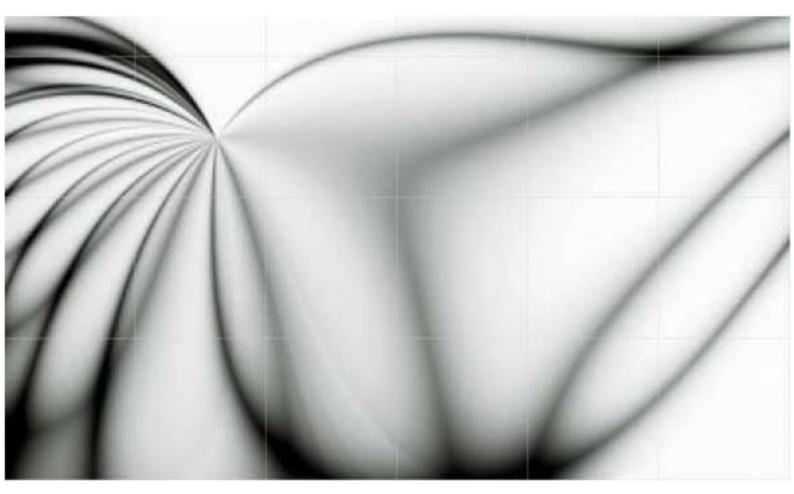


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# An International Journal of Optimization and Control:

## Theories & Applications Volume: 14 Number: 4 October 2024



### CONTENTS

### **RESEARCH ARTICLES**

- 294 List coloring based algorithm for the Futoshiki puzzle Banu Baklan Şen, Oznur Yasar Diner
- 308 Early prediction of fabric quality using machine learning to reduce rework in manufacturing processes Sema Aydın, Koray Altun
- 322 Witte's conditions for uniqueness of solutions to a class of Fractal-Fractional ordinary differential equations

Abdon Atangana, Ilknur Koca

- 336 Influence of rotation on peristaltic flow for pseudoplastic fluid: a wavy channel *Hayat Adel Ali, Mohammed R. Salman*
- 346 A comparative view to H\_infinity-norm of transfer functions of linear DAEs Hasan Gündüz, Ercan Çelik, Mesut Karabacak
- 355 Fuzzy-PID and interpolation: a novel synergetic approach to process control Devashish Jha, Arifa Ahmed, Sanatan Kumar, Debanjan Roy
- 365 Global mathematical analysis of a patchy epidemic model Lahcen Boulaasair, Hassane Bouzahir, Mehmet Yavuz
- 378 An Inverse recursive algorithm to retrieve the shape of the inaccessible dielectric objects *Ahmet Sefer*
- 394 A local differential quadrature method for the generalized nonlinear Schrödinger (GNLS) equation *Meirikim Panmei, Roshan Thoudam*
- 404 Modeling the dependency structure between quality characteristics in multi-stage manufacturing processes with copula functions

Pelin Toktaş, Ömer Lütfi Gebizlioğlu



RESEARCH ARTICLE

# List coloring based algorithm for the Futoshiki puzzle

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### ABSTRACT

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Given a graph G = (V, E) and a list of available colors L(v) for each vertex  $v \in V$ , where  $L(v) \subseteq \{1, 2, \ldots, k\}$ , LIST k-COLORING refers to the problem of assigning colors to the vertices of G so that each vertex receives a color from its own list and no two neighboring vertices receive the same color. The decision version of the problem, LIST k-COLORING, is NP-complete even for bipartite graphs. As an application of list coloring problem we are interested in the Futoshiki Problem. Futoshiki is an NP-complete Latin Square Completion Type Puzzle. Considering Futoshiki puzzle as a constraint satisfaction problem, we first give a list coloring based algorithm for it which is efficient for small boards of fixed size. To thoroughly investigate the efficiency of our algorithm in comparison with a proposed backtracking-based algorithm, we conducted a substantial number of computational experiments at different difficulty levels, considering varying numbers of inequality constraints and given values. Our results from the extensive range of experiments indicate that the list coloring-based algorithm is much more efficient.

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### 1. Introduction

Since the 1980s, there has been significant theoretical analysis and exploration of applications for pencil puzzle games. In recent decades, research has focused on algorithmic solutions and the computational complexity of pencil puzzle games, including optimization versions of various puzzle types. Latin Square Completion-Type Puzzles (LSCP) are among the most common types of these games.

A Latin Square Completion Puzzle (LSCP) is a partial Latin square with empty cells. А Partial Latin Square (PLS) is an  $n \times n$  grid that is partially filled with some numbers from  $[n] = \{1, \ldots, n\}$ . The goal is to fill in all the blank cells with numbers in such a way that the numbers are distinct in each row and each column. The objective of LSCP is to complete the grid by filling the remaining cells with numbers such that each number appears exactly once in

each row and each column. Two notable puzzles in this category are Sudoku and Futoshiki.

The Futoshiki puzzle, also known as Unequal, is a popular Japanese board-based puzzle played on an  $n \times n$  square board with additional inequality constraints between certain cells. The objective is to fill the cells with numbers, satisfying the Latin square property while respecting the specified inequalities. Inequalities can occur between horizontally or vertically neighboring cells, indicating that a number in a particular cell must be greater or smaller than the number in the adjacent cell. Let S denote the set of inequality constraints and T the set of pre-assigned cells.

The decision version of the Futoshiki game, known as the FUTOSHIKI PROBLEM, is defined as follows:

FUTOSHIKI PROBLEM (FUTOSHIKI) *Instance:*  $\mathcal{F}_n(T,S)$ , an  $n \times n$  board, a set T of

<sup>\*</sup>Corresponding Author

pre-assigned cells, and a set S of inequality constraints.

Question: Is the Futoshiki puzzle solvable on  $\mathcal{F}_n(T,S)$ ?

The solvability of a partial Latin square is closely related to Hall's condition. However, Bobga et al. [1] demonstrated that satisfying Hall's condition is insufficient. They provided necessary and sufficient conditions on the configuration of the prescribed cells to ensure the solvability of LSCP. Further results on related topics, such as partial Latinized rectangles, can be found in [2] and [3].

Both the decision version of the Latin Square completion problem and the FUTOSHIKI PROB-LEM have been proven to be NP-Complete [4,5]. Let us define the optimization version of FU-TOSHIKI PROBLEM.

### MAXIMUM FUTOSHIKI (MAXFUTOSHIKI)

Input:  $\mathcal{F}_n(T, S)$  and sign set  $S \subseteq S_L$ .

*Output:* A Futoshiki board  $\mathcal{F}_n(T, S)$  filled with maximum number of valid entries.

Various studies examine the computational complexity of problems defined on partial latin squares. The Latin Square completion problem is NP-Complete by reduction from 3-SAT [4]. In particular the Futoshiki problem is also known to be NP-Complete, as proved by Haraguchi et al. [5]. As for the optimization version of the Futoshiki, Haraguchi and Ono [5] examined the approximability of LSCPs and formulated three LSCP puzzles as maximization problems, presenting polynomial-time approximation algorithms. These maximization problems aim to fill as many cells as possible, instead of determining whether it is possible to complete the entire board. MAXFU-TOSHIKI was shown to be NP-Hard by Haraguchi [5], and related work on optimization versions of LSCP problems is reviewed by Donovan [6].

Properties of Latin squares and improvements to Galvin's solution [7] have been explored by Ivanyi and Nemeth [8]. Yato and Seta [9] investigated the computational complexity and completeness of finding alternative solutions to LSCP problems and proposed two algorithms.

The solvability of LSCP puzzles has been extensively studied in terms of time complexity, and numerous algorithmic solutions have been proposed. Sudoku, a well-known puzzle, has been approached using various algorithmic techniques for both deterministic and metaheuristic approaches. A deterministic algorithm does not contain any randomness or probabilistic elements. It always produces the same output and follows a fixed sequence of steps. Some major deterministic approaches to solve LSCP type problems are the exact cover problem with, Norvig's work with constraint propagation [10] and constraint programming that Crawford gave [11]. As for nondeterministic approaches, one can refer to the "Dancing Links" algorithm that Knuth presented [12].

The term "Metaheuristic" was first used in the study of Glover [13]. Metaheuristics are known as one of the best methods for finding sufficiently good solutions to NP-Hard problems. Traveling salesman problems, scheduling problems, and assignment problems are some of the examples that metaheuristics are used. Sudoku has been solved with one of the metaheuristic methods that are artificial bee colony algorithm [14], particle swarm optimisation [15], and ant colony optimisation algorithm [16]. Moreover, as a heuristics, we can show the study of Musliu [17] that proposes a hybrid method for solving Sudoku.

In this work, we concentrate on deterministic approaches rather than solving the puzzle with metaheuristic methods. One of the most common techniques to solve PLSs as a combinatorial optimization problem is coloring [4]. Furthermore, many graph coloring variants have been utilized to solve LSCP puzzles. For instance, in [18], the Sudoku puzzle is shown to illustrate the precoloring extension problem [19]. Precoloring extension is a variant of the precoloring problem in which some vertices are precolored and others are assigned lists of allowed colors. Notice that the NP-Completeness of the list coloring problem for general graphs [20] and bipartite graphs [21] has been proven.

Our motivation for studying the list coloring approach for the Futoshiki puzzle game stems from the fact that while Sudoku has been extensively studied as a graph coloring problem, Futoshiki has not been analyzed in the same context. In this paper, we adapt the Futoshiki puzzle game to a new variant of the list coloring problem, which we refer to as the *list precoloring extension problem* (formally defined in Section 2). We propose a list precoloring extension algorithm and discuss its complexity.

The rest of the paper is organized as follows. Section 2 provides problem definitions. Section 3 explores applications related to the Futoshiki game. Section 4 establishes the equivalence between the list precoloring extension instance and the Futoshiki problem instance. Section 5 presents an algorithm to solve the Futoshiki problem when the board size is fixed. Section 6 analyzes the experimental results. Finally, Section 7 concludes the paper.

### 2. Problem definitions

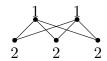
In this section, we provide formal notation and terminology related to graph coloring and introduce a new graph coloring problem that models the Futoshiki problem. The notation and basic terminology used in this section follow Diestel [22].

We consider simple, finite, undirected graphs G = (V, E) with a vertex set V and an edge set E. A coloring of a graph G is a labeling of its vertices. A k-coloring is a coloring that uses at most k colors from the set  $[k] = 1, 2, \ldots, k$ . A coloring is proper if no two adjacent vertices have the same color. The decision version of the graph coloring problem is defined as follows:

COLORING (COL)

*Instance:* A graph G = (V, E) and an integer  $k \ge 1$ .

Question: Does G have a k-coloring?



**Figure 1.** A graph *G* and a valid coloring for it.

In coloring, k is a part of the input. On the other hand, when k is fixed, i.e., when k is not a part of the input, we have the k-coloring problem. As an example, a 2-coloring is given in Figure 1: vertices in one part receive one color, while vertices in the other part receive a different color. It is worth noting that every bipartite graph can be colored using only two colors.

 $\frac{k\text{-COLORING }(k\text{-COL})}{Instance: A \text{ graph } G} = (V, E).$ Question: Does G have a k-coloring? k-COL is

NP-Complete for  $k \geq 3$  [23] and polynomial time solvable when k = 1 or 2 [24]. List coloring is a generalization of graph coloring. It is a proper coloring in which each vertex v receives a color from its own list of allowed colors. The list coloring problem is defined by Vizing [23] and Erdös, Rubin and Taylor [25] independently.

### LIST-COLORING (LICOL)

Instance: A graph G = (V, E) and a list assignment L for G.

Question: Does G have a coloring where each vertex v receives a color from its list L(v)?

A list assignment of a graph G = (V, E) is a mapping L that assigns each vertex  $v \in V$  a List  $L(v) \subseteq \{1, 2, \ldots\}$  of admissible colors for v. When  $L(v) \subseteq [k] = \{1, 2, \ldots k\}$  for every  $v \in V$  we say that L is a k-list assignment of G. Thus, the total number of available colors is bounded by kin a k-list assignment. On the other hand, when  $|L(v)| \leq k$  for every  $v \in V$ , then we say that L is a list k-assignment of G. Thus, the size of each list is bounded by k in a list k-assignment.

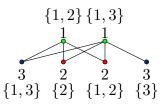


Figure 2. A list assignment L for the vertices of G, and a coloring that respects L.

The List k-Coloring problem is to decide whether a graph G = (V, E) with a list  $L(u) \subseteq \{1, \ldots, k\}$ for each  $u \in V$  has a coloring c such that  $c(u) \in$ L(u) for every  $u \in V$ . It is clearly a generalization of k-coloring, and hence it is NP-Complete for  $k \geq 3$ . Refer to Figure 2 for an example. It is important to note that, despite the graph being bipartite in Figure 2, two colors were not enough to color it while satisfying the constraints imposed by the assigned lists L.

### LIST k-COLORING (LI k-COL)

Instance: A graph G = (V, E) and a k-list assignment L.

Question: Does G have a coloring where each vertex v receives a color from its list L(v)?

A k-precoloring of a graph G = (V, E) is a mapping  $c_W : W \to \{1, 2, \ldots k\}$  for some subset  $W \subseteq V$ . We say that a k-coloring c of G is an extension or a k-extension of a k-precoloring  $c_W$  of G if  $c(v) = c_W(v)$  for each  $v \in W$ . For a given graph G, a positive integer k and a kprecoloring  $c_W$  of G, the Precoloring Extension problem (PREXT) asks whether  $c_W$  can be extended to a k-coloring of G. If k is fixed we denote this problem as the k-Precoloring Extension problem (k-PREXT). Let us define the latter problem formally. k-Precoloring Extension (k-PrExt)

Instance: A graph G = (V, E) and a k-precoloring  $c_W$ .

Question: Is there a k-extension for  $c_W$ ?

For general graphs PREXT is NP-Complete [26]. In fact, the NP-Completeness of the LSCP problem is shown via its equivalence to the k-PREXT when it is restricted to the cartesian product of  $K_n$  with itself [4].

We define a new coloring problem called the List *k*-Precoloring Extension problem (LI *k*-PREXT).

LIST k-PRECOLORING EXTENSION (LI k-PREXT) *Instance:* A graph  $G = (V, E), W \subseteq V$ , a k-precoloring  $c_W$ , and a list k-assignment L for each  $v \in V/W$ 

Question: Is there a k-extension for  $c_W$  that obeys the list L?

Notice that when the list L is not assigned to the vertices in V/W, then LI k-PREXT reduces to k-PREXT. Let us denote an instance of LI k-PREXT with  $\mathcal{L}_G(c_W, L)$ .

### 3. Applications

In this section, we will first provide a brief overview of some notable applications related to the problems under consideration, namely the Futoshiki problem, list coloring, and its variants. Subsequently, we will introduce a novel application of the Futoshiki problem in the field of scheduling, specifically to optimize the efficiency of the job assignment problem.

Applications of the Futoshiki problem: The Futoshiki problem has found applications in various domains. Mahmood [27] proposed a random number generator that utilizes the Futoshiki problem to generate numbers satisfying given conditions. This generator, with good linear complexity, has potential application as an encryption key in mathematical analysis, security systems, and simulations. Additionally, Haraguchi [28] explored the evaluation values achievable in a Futoshiki puzzle with a high number of inequality signs.

The Futoshiki configuration technique, considering partial shading conditions in photovoltaic (PV) systems, has been proposed by Sahu et al. [29]. They observed that incorporating the Futoshiki structure increases the power generation of PV arrays, leading to improved energy efficiency. The technique avoids the need for changing the electrical connection of modules by rearranging them, and it effectively reduces mismatch loss under different shading models. Applications of List Coloring and its Variants: The list coloring problem has been widely applied to solve optimization and scheduling problems [30]. In Orden and Moreira's work [31], the problem of minimizing interference threshold and the number of colors respecting that threshold was modeled as list coloring. They demonstrated that the problems are NP-Hard and proposed DSATUR, a graph coloring algorithm, to tackle them.

Garg et al. [32] tackled the channel frequency allocation problem in mobile communication networks by modeling it as a generalized list coloring problem. Their solutions prevented signal interference by selecting channels for neighboring base stations in a way that they did not overlap. This approach effectively addressed the crash failures caused by distance limitations.

In the domain of register assignment, Zeitlhofer et al. [33] presented a list-coloring algorithm that optimally assigns a large number of target variables to a small number of CPU registers. This algorithm preserves the structure of the interference graph, ensuring the retention of interval graph properties.

Sudoku puzzles can also be formulated as list coloring problems. Each cell corresponds to a vertex, and the relationships between cells are represented as edges in rows and columns. The numbers used in Sudoku can only appear once in each row and column, making it an instance of the list coloring problem. Additionally, Lastrina et al. [18] demonstrated how the precoloring extension problem can be used to illustrate the Sudoku puzzle.

### 4. LI *k*-PREXT and FUTOSHIKI

In this section, we show that the Futoshiki problem can be reduced to the list precoloring extension problem for the Futoshiki graph G. In the reduction the revealed cells given in the Futoshiki problem are used to construct the pre-coloring for G. In addition, the list assignment is obtained using the inequality constraints.

Let  $n \geq 2$  be a positive integer. A Partial Latin Square is an  $n \times n$  grid that is partially filled with some numbers from  $[k] = \{1, \ldots, n\}$ . Let us denote a cell that is in the i'th row and the j'th column of a grid as (i, j). Each cell (i, j) is represented in the graph with a vertex  $v_{ij}$ . Two cells (i, j) and (i', j') are adjacent whenever they are in the same column or in the same row. Thus, a Latin square is represented as a graph G = (V, E) such that  $V = \{v_{ij} : 1 \le i, j \le n\}$ , and  $E = \{(v_{ij}, v_{i'j'}) : ((i = i') \land (j \ne j')) \lor ((j = j') \land (i \ne i')\}$  [34]. This graph is called the *Fu*toshiki graph of size n. Notice that the Futoshiki graph G has  $n^2(n-1)$  edges. The graph G is isomorphic to the graph  $K_n \boxtimes K_n$ , which is the strong product of  $K_n$  with itself [18] and it is (2n-2)regular.

Recall that the Futoshiki problem of size n,  $\mathcal{F}_n(T,S)$ , is defined on the Futoshiki graph of size n where S is the set of inequality constraints. Thus there are at most 2n(n-1) inequality signs. In Figure 3, for n = 4, there are  $n^2 = 16$  vertices and  $n^2(n-1) = 48$  edges. An instance of the problem on this graph can take up to 24 inequality constraints in total, yet in this instance, there are only 5 inequality constraints.

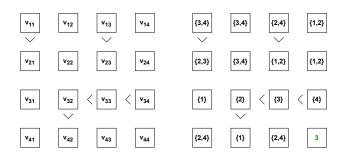


Figure 3. Vertices of the Futoshiki Puzzle.

**Theorem 1.** For every Futoshiki problem  $\mathcal{F}_n(T, S)$  there exists an equivalent instance of the LIST k-PRECOLORING EXTENSION problem  $\mathcal{L}_G(c_W, L)$  on the Futoshiki graph where k = n.

**Proof.** We give a polynomial time reduction that converts a Futoshiki problem  $\mathcal{F}_n(T, S)$  of size  $n \times n$ to a Futoshiki graph G and a list-assignment Lthat corresponds to the list k-precoloring extension problem  $\mathcal{L}_G(c_W, L)$  for some precoloring  $c_W$ . We also show that  $\mathcal{F}_n(T, S)$  is solvable whenever  $\mathcal{L}_G(c_W, L)$  is solvable on G. We do the latter by converting each solution of  $\mathcal{F}_n(T, S)$  to a solution of  $\mathcal{L}_G(c_W, L)$  and vice versa.

Given an instance  $\mathcal{F}_n(T, S)$  of the Futoshiki problem the entries of the  $n \times n$  board cells correspond to vertices of G, occurring exactly once in each row and column. Thus, the graph G will have  $n^2$  vertices. The cells represent vertices and adjacent cells in each row and column represent the edges. At the beginning of the problem, if a number l is revealed in a cell that is represented with a vertex v, then we say v is precolored with color l. This gives a one-to-one correspondence between the revealed cells T and the precoloring  $c_W$ . If no number is revealed in the cell, then the corresponding vertex will be assigned the list  $\{1, 2, \ldots, k\}$ . If, in addition, there is an inequality sign > located between some adjacent cells that are represented with vertices u and v in G, then for every color  $i \in L(u)$ , there must be at least one color  $j \in L(v)$  such that i > j. For the inequality sign <, the construction of the list assignments of the related vertices are done similarly. This gives the construction of the list assignment L, thereby completing the reduction of  $\mathcal{F}_n(T, S)$  to  $\mathcal{L}_G(c_W, L)$ .

Each solution of  $\mathcal{F}_n(T, S)$  will naturally give a proper coloring for G which is an extension of the precoloring  $c_W$  and it will obey the list L. On the other hand, a list coloring solution of  $\mathcal{L}_G(c_W, L)$ yields a solution to the given Futoshiki problem  $\mathcal{F}_n(T, S)$ . Notice that the precoloring and the list assignment L are constructed so that the solution to the list precoloring extension problem gives a number assignment that satisfies the inequalities located between adjacent cells.

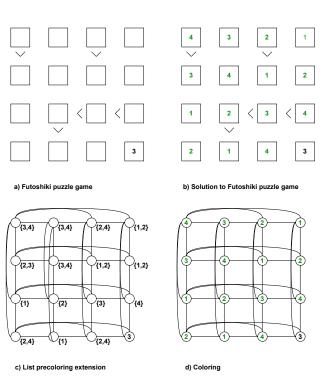


Figure 4. A Futoshiki puzzle instance and the cells that correspond to the vertices in the related Futoshiki Graph.

Figure 4 illustrates an instance of a  $4 \times 4$  Futoshiki problem and the corresponding Futoshiki graph construction along with the list assignment: Figure 4.a shows the initial board of the game, Figure 4.b shows the solution of the game, Figure 4.c shows the list precoloring extension instance and, finally, Figure 4.d shows the corresponding coloring as a solution to the list precoloring extension problem.

# 5. List coloring-based algorithm for the FUTOSHIKI PROBLEM

There are various algorithmic approaches to solve pencil puzzles. The backtracking algorithm is used for the class of Constraint Satisfaction Problems (CSPs). These problems are defined as a set of variables, a set of their respective domains of values, and a set of constraints [10]. The goal of a CSP is to find a consistent assignment of values to variables that satisfies all constraints, subject to certain conditions. CSPs have applications in various domains, including scheduling, planning, configuration, and puzzle-solving. LSCPtype puzzles are seen as constraint satisfaction problem CSPs that find a solution that satisfies all the constraints considering assignment of variables. These problems include Sudoku, Futoshiki, and Kakuro. Sudoku is the most popular one that is solved as CSP by the researchers. Norvig [10]describes two methods to solve Sudoku, namely, constraint propagation (CP) and Local Search. Constraint propagation is a technique that is commonly used in CSPs to efficiently update and reduce the domain of variables based on the constraints imposed by the problem.

In this section, we present two different deterministic algorithms for solving the Futoshiki Puzzle, called FutoshikiBT and ColorFutoshik, each incorporating backtracking, and filtering methods respectively.

### 5.1. BackTracking algorithm

The backtracking algorithm can be seen as the simplest solution for Sudoku puzzles which are the most commonly studied problem. Backtracking uses a recursive approach in which each cell is assigned a number from  $1 \dots n$  when the board size is  $n \times n$ . The backtracking algorithm systematically explores the solution space by iteratively assigning values to empty cells in the puzzle and backtracking when a contradiction or violation of constraints is encountered.

Here, we give a backtracking algorithm that solves the Futoshiki Puzzle to compare its efficiency with the proposed method called ColorFutoshiki which we give in Section 5.2. The backtracking algorithm starts by selecting an empty cell in the puzzle and attempts to assign a value that satisfies the row and column constraints, as well as the inequality constraints associated with neighboring cells. It then moves on to the next empty cell and repeats the process. If a contradiction arises, such as a repeated number in a row or column, or a violation of an inequality constraint, the algorithm backtracks to the previous cell and explores alternative value assignments. Although this method guarantees a solution, it is not efficient in terms of time complexity. Let us present our FutoshikiBT Algorithm.

Alg	Algorithm 1 FutoshikiBT Algorithm					
1: <b>Input:</b> Futoshiki board with constraints.						
	<b>Output:</b> Solution of the puzzle.					
3:	if $colorG(n, list, v = 1, given) == False$					
4:	print ("No solution")					
5:	else					
6:	print (list)					
7:	colorG(n, list, v, given):					
8:	$\mathbf{if}(v == V + 1)$					
9:	return True					
10:	for $c$ in range $(1, n)$					
11:	if $safe(v, list, c, given) == True$					
12:	list[v] = c					
13:	if $colorG(n, list, v + 1, given)$					
14:	return True					
15:	end if					
16:	if $v$ not in given					
17:	list[v] = 0					
18:	end if					
19:	return False					
20:	end if					
21:	end for return False					
22:	safe(v, list, c, given):					
23: 24:	if v in given and list[v] == c					
24: 25:	f v m given and $iist[v] = -creturn True$					
25: 26:	else if v in given					
20: 27:	return False					
21. 28:	end if					
20: 29:	for $(i \text{ in } \operatorname{range}(1, V))$					
$\frac{20}{30}$ :	if $list[i] == c$ and $neighbour(v, i)$					
31:	return False					
32:	end if					
33:	if constraints are not satisfied					
34:	return False					
35:	end if					
36:	end for					
37:	return True					
37:	return 1rue					

### 5.2. ColorFutoshiki algorithm

In this section, using the equivalence between the FUTOSHIKI PROBLEM and the LI k-PREXT problem for the Futoshiki graph, as assured by Theorem 1, we construct the ColorFutoshiki algorithm to solve the FUTOSHIKI PROBLEM. We will observe that, this approach is equivalent to the backtracking algorithm with forward checking for the FUTOSHIKI PROBLEM.

The backtracking algorithm considers every solution by iterating every possible number in each cell under all satisfying conditions, assigns the first available option, backtracks when a solution is not possible for the next cell under consideration, and tries the next possible option for the previous cell. These methods guarantee the solution, but they do not give the solution in optimal time. Here we aim to improve the backtracking algorithm. This is why we need a problem space that helps our solver save us more time. The backtracking method of solving the Futoshiki problem fills each cells from left to right and top to bottom with considering inequality constraints.

The ColorFutoshiki algorithm is an improved version of the FutoshikiBT algorithm. Our aim is to reduce the number of colors in each list by eliminating inconsistent ones. This reduces the search space to be explored. At the beginning of the ColorFutoshiki algorithm, we use a filtering technique. In this filtering step we do forward checking in order to create color lists. Forward checking keeps track of the remaining possible values for unassigned variables after a variable is assigned a value. It propagates constraints by eliminating values from the domains of other variables that conflict with the newly assigned value. This technique is applied to create lists for each cell that they can use. Thus, it will begin coloring the puzzle with the minimum number of colors in the list for each cell.

### 5.3. Analysis of the algorithms

The input parameters for the algorithm are the Futoshiki graph of size n, the inequality constraints, and the pre-assigned entries. The algorithm begins by examining the constraints and pre-assigned numbers of the Futoshiki instance  $\mathcal{F}_n(T, S)$ , which then produces a k-precoloring instance  $\mathcal{L}G(c_W, L)$ . Next, it determines how to color the given Futoshiki graph using the list of colors assigned to each vertex through the reduction process described above. If  $\mathcal{L}G(c_W, L)$  is a YES instance, the algorithm outputs a matrix

 $M_G = [mij]n \times n$  indicating the colors of the vertices of the graph G. Otherwise, it concludes that no solution exists.

First, let us analyze the FutoshikiBT algorithm, which builds candidates for the solutions incrementally and abandons candidates when it determines that they cannot possibly be solved with a valid solution.

The function colorG(n, list, v, given) is a recursive function that ensures the coloring process is completed by checking all vertices. It attempts to use the colors in the list for the corresponding vertex in order. Here, n represents the puzzle dimension, which is equal to the size of the color list. list is the list of colors assigned to vertices (solution). v is the vertex number. V represents the total number of vertices. given denotes the values given before the game starts.

The function safe(v, list, c, given) checks whether the given vertex can be colored with the chosen color by verifying the constraints. In this process, neighbour(v, i) checks the adjacency of the two relevant vertices, ensuring that adjacent vertices are not colored with the same color.

It is worth noting that the FutoshikiBT algorithm does not include a process for creating preassigned color lists. On the other hand, ColorFutoshiki first traverses the graph and creates a list of colors that minimizes the number of candidate colors for each cell. It then attempts to color empty cells, starting from the first vertex  $v_{11}$ .

The ColorFutoshiki algorithm is an improved version of the FutoshikiBT algorithm. Its aim is to reduce the number of colors in each list by eliminating inconsistent ones. This reduction effectively reduces the search space that needs to be explored.

The pseudocode of the algorithm is provided below.

1: Input: Futoshiki board with constraints. 2: **Output:** Solution of the puzzle. 3: if colorG(pcList[1].length, list, v = 1, given)4: print (list) 5: else print ("No solution") 6: 7: end if 8: colorG(n, list, v, given): **if** (v == V + 1)9: return True 10: 11: end if for c in range(1, n)12:if safe(v, list, pcList[v][c], given)13:14: list[i] = pcList[v][c]nextN = pcList[v+1].length15:if colorG(nextN, list, v + 1, qiven)16:return True 17:end if 18:19:if v not in given 20: list[v] = 0end if 21:22: return False end if 23:end for 24:return False 25:26: safe(v, list, c, given): if v in given and list[v] == c27:28:return True else if v in *given* 29:30: return False end if 31: if constraints are not satisfied 32: return False 33: end if 34: for i in range(1,n) 35: if (hNeighbor == c & hNeighbor! = v)36: 37: return False end if 38: if (vNeighbor == c & vNeighbor! = v)39: return False 40: end if 41: 42: end for return True 43:

In the ColorFutoshiki algorithm, first, we perform filtering and create color lists for each cell based on their admissible colors and constraints. Consequently, the algorithm begins coloring the puzzle using the minimum number of colors available in the lists.

Unlike the FutoshikiBT algorithm, Color-Futoshiki uses a recursive structure that does not traverse the entire graph to color the related vertex. Instead, it only checks the horizontal and vertical neighbors of the vertex being colored. It is observed that ColorFutoshiki outperforms the FutoshikiBT algorithm in all instances of varying difficulty levels.

Now, let us explain the ColorFutoshiki algorithm.

In lines 3-7, we call the colorG function, which displays the solution if found. Here pcList is the list that each cell takes.

In lines 8-25, the recursive colorG function checks the termination condition. If this condition is not met, it checks whether the related vertex v can be colored based on the possible color list of v. If v cannot be colored, the algorithm moves on to the next color in its list. If it cannot be colored with any color in the list, the recursive function returns to previous vertex and the color of the previous vertex is updated. If it can be colored, the algorithm moves on to the next vertex, and the admissible color is added to the color list.

In lines 26-43, if the vertex to be colored has a preassigned (given) value, the algorithm proceeds to the next vertex. Then, it checks whether there is a constraint in front of or above the vertex to be colored or not. If there is, it verifies whether the constraint conditions are satisfied. After this step, we check the colors of the adjacent vertices if they have the same color. Instead of traversing all nodes, it only checks the horizontal and vertical neighbors of the relevant vertex.

Now let us analyze the time complexities of the algorithms. The FutoshikiBT algorithm traverses all vertices to check the neighborhood of the vertex being colored and to decide whether the colors are the same or not. For each empty cell, there are n possible options, where n is the total number of colors. As a result, the time complexity becomes  $O(n^{n^2})$ . In the ColorFutoshiki algorithm some values are removed from some domains. Since there will be some early pruning the time taken will be much less than the backtracking algorithm. However, the upper bound time complexity remains the same. The reason is that we don't know how many values are removed. As a result, the time complexity becomes  $O(n^{n^2})$ .

Although the worst case time complexity of the ColorFutoshiki algorithm is only a slight improvement over the FutoshikiBT algorithm, as we will observe below, its speed is remarkably faster in all of the computational experiments that we have done.

### 6. Results and discussion

We aim to solve the FUTOSHIKI as an instance of the LICOL problem. For this reason we first improved the **ColorFutoshiki** algorithm. It is an enumeration algorithm that incorporates additional search space reductions and bounding elements, making it an enhanced version compared to FutoshikiBT. Due to the fact that FUTOSHIKI is classified as an NP-Complete problem, Color-Futoshiki proves to be highly effective and suitable for numerous applications and purposes. Its capabilities make it a valuable tool in addressing the complexity of FUTOSHIKI.

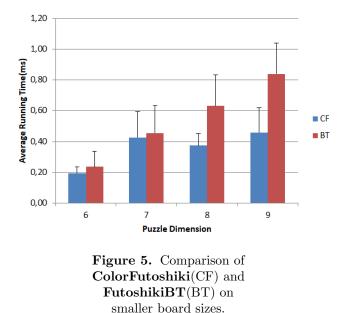
Here, we present the computational experiments conducted to assess the efficiency of the Color-Futoshiki algorithm in solving instances of the Futoshiki problem. All the codes were implemented in the Python programming language, and the experiments were executed on a system with an Intel Core i7-6700HQ CPU operating at 2.60 GHz, with 16GB RAM, running Windows 10 (64-bit). Different instances have been generated and tested on nxn boards for n = 6, 7, 8, 9, 15, 20, 30, 40, 50. We ran the related code 50 times per instance and took their average. In total, 1800 Futoshiki puzzles have been used for each algorithms. Due to space limitations, we are unable to provide a table containing the running times for each individual test. This is why, we present the average experimental results for each algorithm in Table 1 and Table 2.

Solutions to the FUTOSHIKI Problem are of particular interest due to the given application in scheduling on  $n \times n$  boards when the size n is large. As our experimental results demonstrate, the Color-Futoshiki algorithm works much better even on boards of a larger size where the number of inequality constraints is not necessarily restricted to be less than n for an  $n \times n$  board.

A standard deviation denotes the spread of data concerning its mean. When the standard deviation is small, it signifies that the data is tightly clustered around the mean. Conversely, a high or large standard deviation suggests that the data is more widely spread.

All the results and standard deviations can be seen in Table 1. Different numbers of constraints and different numbers of givens are examined for each algorithm.

The performance of the proposed algorithms for standard search algorithms is illustrated in Figure 5 and Figure 6 with standard deviations. In this figures, we maintain a constant number of constraints while showcasing the increasing number of given values. Notably, ColorFutoshiki consistently outperforms FutoshikiBT in solving puzzles, even when the number of constraints is held constant. These results underscore the efficiency of the ColorFutoshiki algorithm, particularly on larger-sized boards, providing a performance comparison with the FutoshikiBT algorithm.



In addition to running times, we also measure the number of operations for both ColorFutoshiki and FutoshikiBT. Since the number of explored nodes provides insights into the efficiency of the algorithm, we show both the number of explored nodes and the number of removed values of each algorithm in Table 2. A lower number of explored nodes generally indicates a more efficient algorithm, as it suggests that the algorithm is able to reach a solution without exhaustively searching through a large portion of the puzzle's solution space. The number explored nodes allows for comparison with other algorithms or approaches for solving the same puzzle. For this reason, we use this parameter to compare the ColorFutoshiki algorithm that we present with FutoshikiBT.

We observe that the number of explored nodes varies significantly across different instances of the puzzle, it may indicate that the algorithm's performance is sensitive to certain characteristics of the puzzle. Similar to the number of explored nodes, the number of removed nodes provides insight into the efficiency of the algorithm. In certain search algorithms, such as backtracking or constraint satisfaction algorithms, removed nodes typically refer to nodes that are pruned from the search space because they are deemed unnecessary or invalid. A lower number of removed nodes indicates that the algorithm is effectively pruning the search space, which can lead to improved

size	inequalities	givens	CF	BT
6	6	1	$1.54\pm0.11$	$1.61 \pm 0.44$
6	6	20	$0.28\pm0.05$	$0.29\pm0.1$
6	6	30	$0.19\pm0.04$	$0.24\pm0.1$
6	1	6	$0.59\pm0.08$	$0.66\pm0.22$
6	20	6	$0.5\pm0.08$	$0.54\pm0.27$
6	30	6	$0.53\pm0.17$	$0.4323 \pm 0.1073$
7	7	1	$1.40\pm0.16$	$1.47\pm0.52$
7	7	30	$0.43\pm0.17$	$0.46\pm0.18$
7	7	40	$0.29\pm0.04$	$0.35\pm0.08$
7	1	7	$1.37\pm0.3$	$1.58\pm0.5$
7	30	7	$2.07\pm0.46$	$2.33\pm0.58$
7	40	7	$1.19\pm0.37$	$1.21\pm0.52$
8	8	1	$3.53\pm0.80$	$3.64 \pm 1.33$
8	8	40	$0.5\pm0.04$	$0.77\pm0.29$
8	8	50	$0.37\pm0.08$	$0.63\pm0.2$
8	1	8	$2.01\pm0.33$	$2.29\pm0.73$
8	40	8	$6.72 \pm 1.71$	$9.33 \pm 2.32$
8	50	8	$5.34 \pm 1.55$	$10.04\pm2.3$
9	9	1	$8.08 \pm 3.11$	$8.11 \pm 3.06$
9	9	70	$0.46\pm0.16$	$0.84\pm0.2$
9	18	35	$1.28\pm0.32$	$1.92\pm0.63$
9	1	9	$3.78 \pm 1.33$	$4.7 \pm 1.69$
9	70	9	$8.86\pm0.3$	$10.71\pm0.92$
9	35	18	$2.27 \pm 3.27$	$2.95 \pm 3.22$
15	15	150	$2.77\pm0.64$	$11.65 \pm 2.54$
15	15	170	$2.25\pm0.86$	$11.75\pm2.86$
15	15	200	$1.44\pm0.45$	$10.52 \pm 3.94$
15	1	150	$11.82\pm0.7$	$12.04 \pm 3.26$
15	90	130	$3.47 \pm 1.10$	$12.61 \pm 3.33$
15	150	15	$2987.7 \pm 336.8$	$3064.9 \pm 103.2$
20	20	300	$4.98 \pm 1.48$	$38.54 \pm 8.12$
20	30	320	$11.58 \pm 1.27$	$62.2\pm3.43$
20	20	370	$1.575 \pm 1.62$	$31.57\pm6.07$
20	30	300	$5.21 \pm 3.48$	$35.98 \pm 8.52$
20	80	250	$349.97 \pm 1.42$	$644.16 \pm 7.26$
20	50	350	$3.55 \pm 27.31$	$33.27 \pm 29.87$
30	30	500	$11.000 \pm 37.377$	$2585.5 \pm 133.84$
30	30	600	$612.73 \pm 34.274$	$1360.2 \pm 441.69$
30	30 7 0	750	$41.852 \pm 4.9579$	$1192.3 \pm 78.302$
30	50	500	$1103.7 \pm 135.63$	$2412.5 \pm 102.47$
30	100	600 750	$608.17 \pm 29.557$	$1274.6 \pm 71.195$
$\frac{30}{40}$	300	750	$40.34 \pm 5.8942$	$\frac{993.95 \pm 34.361}{12150 \pm 402.01}$
40	40	750	$2827.7 \pm 97.233$	$12159 \pm 402.91$
40	40	950 1200	$702.37 \pm 33.654$	$9869.8 \pm 234.02$
40	40	$1300 \\ 750$	$91.642 \pm 8.8446$	$1257.7 \pm 51.235$
40	100	750 050	$2913.0 \pm 599.59$ $427.20 \pm 22.055$	$9359.7 \pm 255.39$
40	300 400	950 050	$437.39 \pm 23.055$	$4845.2 \pm 130.88$ $4005.2 \pm 142.66$
$\frac{40}{50}$	400	950	$\frac{438.99 \pm 27.05}{4442.1 \pm 151.71}$	$\frac{4995.3 \pm 142.66}{27727 \pm 570.75}$
50 50	50 100	1200 1500	$4443.1 \pm 151.71$	$37727 \pm 579.75$
50 50	100	1500	$2158.0 \pm 93.02$ 1817 7 $\pm$ 75 545	$21803.0 \pm 358.64$ $20840 \pm 528.47$
50 50	250 400	2000	$1817.7 \pm 75.545$ $1002.8 \pm 54.712$	$20849 \pm 538.47$ $12270 \pm 162.22$
50 50	400	1600	$1092.8 \pm 54.712$ $1067.5 \pm 20.427$	$13279 \pm 162.22$ 12145 $\pm 262.0$
50 50	400	2000	$1067.5 \pm 39.437$	$13145 \pm 263.9$ 11550 $\pm 284.07$
50	500	2000	$835.95 \pm 40.199$	$11559 \pm 284.97$

 Table 1. Run time for all algorithms reported in milliseconds.

efficiency as it can be seen in Table 2. As the FutoshikiBT algorithm lacks a filtering step, no

values are removed from its domains, unlike the filtering steps in the ColorFutoshiki algorithm.

The running time of the algorithm varies depending on the puzzle's difficulty level. We observe that as the number of inequality signs approaches the maximum limit, the computation time significantly decreases. This behavior can be attributed to the utilization of the backtracking method in the ColorFutoshiki algorithm. Typically, Futoshiki puzzles are played on  $5 \times 5$  to  $9 \times 9$  boards (occasionally on  $15 \times 15$  boards), and existing algorithmic solutions are primarily tested on boards with dimensions up to n = 9.

In Figure 5, we compare the performance of our method with previous solutions employing the FutoshikiBT algorithm on smaller-sized boards.

Motivated by the lack of performance analysis for larger-sized boards, we conducted experiments using the ColorFutoshiki algorithm on larger board sizes. Additionally, we wanted to assess the algorithm's effectiveness on larger-sized boards due to the relationship between the Futoshiki puzzle game and larger scheduling problems, as discussed in Section 3. In Figure 6, we compare the performance of our method with previous solutions employing the FutoshikiBT algorithm on largersized boards. We even conducted experiments for  $50 \times 50$  boards. The results demonstrate that the ColorFutoshiki algorithm efficiently solves even  $30 \times 30$ ,  $40 \times 40$  and  $50 \times 50$  board games as shown in Figure 7.

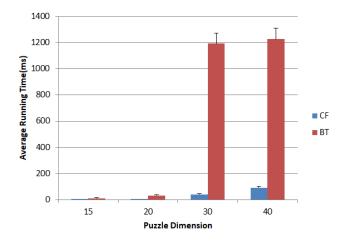


Figure 6. Comparison of ColorFutoshiki(CF) and FutoshikiBT(BT) on larger board sizes.

Overall, these findings highlight the efficiency of the ColorFutoshiki algorithm, especially on larger-sized boards, and provide a performance comparison with the FutoshikiBT algorithm.

### 7. Conclusion

The Futoshiki problem is aimed to be solved as a list coloring problem in ColorFutoshiki. It is an enumeration algorithm that incorporates additional search space reductions and bounding elements, making it an enhanced version compared to FutoshikiBT. Due to the fact that FUTOSHIKI is classified as an NP-Complete problem, Color-Futoshiki proves to be highly effective and suitable for numerous applications and purposes. Its capabilities make it a valuable tool in addressing the complexity of FUTOSHIKI.

A considerable number of experiments were conducted to test ColorFutoshiki and FutoshikiBT, providing a robust foundation for drawing meaningful conclusions. The extensive set of experiments carried out ensures that the findings are sufficiently supported and reliable. Observing Table 1 and Table 2, we see that ColorFutoshiki is much more efficient than FutoshikiBT.

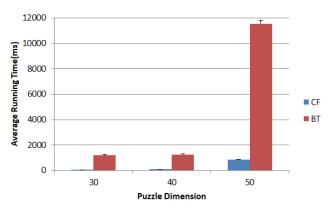


Figure 7. Comparison of ColorFutoshiki(CF) and FutoshikiBT(BT) on larger board sizes.

We incorporate a short discussion on these metaheuristic methods and their applications to Sudoku. This will enhance the comprehensiveness of our paper and provide a broader perspective on the algorithmic techniques used to solve LSCP type puzzles.

We are also interested in studying the Futoshiki problem as an application of the LI *k*-COL problem. To find approximation algorithms for the Futoshiki puzzle, we would like to use metaheuristics.

As for future work related with nature based algorithms, one can see whether an Ant Colony optimization (ACO) algorithm gives a more efficient algorithm to solve the Futoshiki problem. ACO is a Swarm intelligence algorithm which is one of the artificial intelligence techniques. A solution

size	inequalities	givens	FC-EN	FC-RN	BT-EN	BT-RN
6	6	1	528	15	540	NRN
6	6	20	40	173	126	NRN
6	6	30	36	180	126	NRN
6	1	6	151	78	198	NRN
6	30	6	111	81	156	NRN
6	20	6	100	81	144	NRN
7	7	1	456	18	469	NRN
7	7	30	59	276	196	NRN
7	7	40	50	291	196	NRN
7	1	7	298	113	406	NRN
7	40	7	268	125	392	NRN
7	30	7	474	120	392 392	NRN
8	8	1	1145	29	1160	NRN
8	8	50	65	$\frac{29}{446}$	288	NRN
8	8		03 78			NRN
		40		423 156	288 726	
8	1	8	580 1951	156 161	736 2744	NRN NRN
8	40	8	1851	161	2744	NRN
8	50	8	1293	174	2920	NRN
9	9	1	2279	24	2313	NRN
9	9	70	81	647	405	NRN
9	18	35	187	546	603	NRN
9	1	9	988	194	1357	NRN
9	70	9	1629	213	2070	$\mathbf{NRN}$
9	35	18	489	385	855	NRN
15	15	150	286	3040	2010	NRN
15	15	170	239	3102	1800	NRN
15	15	200	229	3139	1800	$\mathbf{NRN}$
15	1	150	286	3028	2010	NRN
15	90	130	331	2975	2025	NRN
15	150	15	674261	7472	240	NRN
20	20	300	472	7589	4200	NRN
20	30	320	760	7484	5940	NRN
20	20	370	408	7588	4220	NRN
20	30	300	472	7484	4200	NRN
20	80	250	21057	6922	49580	NRN
20	50	350	417	7578	4220	NRN
30	30	500	44063	22402	116550	NRN
30	30	600	24682	23577	56400	NRN
30	30	750	1722	25450	48060	NRN
30	50	500	41511	22403	111840	NRN
30	100	600	22654	23580	52560	NRN
30	300	750	1684	25510	41220	NRN
40	40	750	69967	54498	229320	NRN
40	40	950	17714	56006	537760	NRN
40	40	1300	2542	61272	43160	NRN
40	100	750	33348	51448	219360	NRN
40	300	950	11154	561440	219300 220240	NRN
40	400	$950 \\ 950$	11134 11124	56132 56224	220240 220240	NRN
$\frac{40}{50}$	$\frac{400}{50}$	$\frac{930}{1400}$	59494	$\frac{50224}{119420}$	600200	NRN NRN
$\frac{50}{50}$	$\frac{50}{100}$		$\frac{59494}{29404}$			
		$\frac{1600}{2000}$		120771	462900	NRN NRN
50 50	250 400		25673	120862	427900	NRN NRN
50 50	400	1600	16255	120912	302150	NRN
50	400	2000	16255	120912	302150	NRN
50	500	2000	12864	120979	260000	NRN

 Table 2. The count of removed nodes and explored nodes. NRN stands for "No Removed Nodes".

for Sudoku is given using ACO in the study of Huw Lloyd [16]. Another solution which is the first nature-based algorithm for the NP-Complete Nurikabe problem is presented by Amos et al. [35]. This algorithm was developed based on ACO. For future work, it would be interesting to solve the Futoshiki problem using Ant Colony Optimization (ACO) and an Artificial Bee Colony (ABC) algorithm [36]. The performance of these approaches could then be compared with existing solutions, such as the improved constraint programming method developed by Kostyukova and Tchemisova [37].

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RESEARCH ARTICLE

# Early prediction of fabric quality using machine learning to reduce rework in manufacturing processes

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ABSTRACT

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The increasing competition and rapid technological advancements in today's business world have raised customer expectations. People now expect quick delivery, low prices, and high-quality products. As a result, companies must adapt to this competitive environment to survive. Rework, which is a significant cost in production, increases expenses, reduces production efficiency, and can lead to customer attrition. Research shows various efforts across different sectors to reduce rework, although there is still a gap in the textile sector's fabric dyeing units. Common problems in these units include non-retentive colors, customer dissatisfaction with shades, and repeated dyeing due to environmental factors or dye vat issues. This study uses logistic regression and artificial neural networks models from machine learning to predict which fabrics will need rework, using data from a textile company in Bursa. The analysis indicates that artificial neural networks models perform better.



### 1. Introduction

In the textile industry, optimizing fabric dyeing processes is a pivotal challenge. Rework processes within fabric dyeing units are among the most critical factors contributing to cost escalation, low-quality production, and customer dissatisfaction.

"Rework" can be defined as the need for additional processing or corrective measures due to various quality issues. Rework represents a form of waste, driving research into the concept of Zero Defect Manufacturing [1,2]. This concept aims to eliminate defects before they necessitate rework. However, achieving this goal requires proactive measures to anticipate and prevent potential quality issues before they escalate into rework processes.

Machine learning techniques offer promising approaches to identifying patterns in historical data and predicting defects in manufacturing processes. Although there is growing interest in using machine learning for quality assurance and defect detection in manufacturing, a significant gap remains in research on applying these techniques specifically for "rework prediction" in the textile industry.

Correspondingly, this research aims to address this gap

by evaluating the effectiveness of logistic regression and artificial neural networks (ANNs) in predicting rework instances in fabric dyeing processes.

In line with the study's objectives and the research landscape, the following contributions are emphasized:

- This study addresses a critical research gap in the textile industry by exploring the application of machine learning for predicting errors in fabric dyeing processes. While machine learning has been extensively applied in various industries, its use in the textile sector for rework prediction remains relatively underexplored.
- This study focuses on applying machine learning, specifically logistic regression and ANNs, to develop models that predict rework in fabric dyeing units within the textile industry. By leveraging datadriven methods, our goal is to enhance the early detection of potential quality issues and reduce the need for rework before it escalates a bigger problem.

The aim is to proactively predict and mitigate potential quality issues, thereby optimizing production processes and minimizing instances of rework. This study not only contributes to the expanding field of predictive

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analytics and manufacturing optimization but also seeks to advance the application of machine learning within the textile sector.

### 2. Literature review

A review of the literature on early quality prediction and rework reveals numerous studies across various industries. However, the application of these techniques specifically within the textile sector appears to be less common.

A systematic effort was undertaken to conduct a comprehensive literature review. Prominent databases such as Science Direct, Web of Science, and Google Scholar were utilized to identify relevant materials. Two specific search strings were employed to reflect the core focus of the investigation. The first search string, "quality" AND "defect detection" AND "prediction" AND "manufacturing," aimed to cover the scholarly work on predictive methods for quality assurance and defect detection in manufacturing contexts. The second search string, "rework" AND "defect" AND "machine learning," was designed to explore research on the application of machine learning approaches to predict defects and prevent rework processes. By systematically using these search strings and examining the results from the selected databases, the literature review aimed to extract and synthesize relevant insights from the existing body of scholarly work.

A case study [1] was conducted within an automotive company, employing an Early Quality Prediction system grounded in a data-driven approach. In this study, the focus was on applying Convolutional Neural Network (CNN) techniques to time-series data to proactively predict and prevent defects. This approach aimed to minimize rework costs and optimize product quality through predictive insights. A data-driven mathematical model has been developed [3] for a dynamic manufacturing process with multiple rework lines, focusing on calculating production rates and machine efficiency for each machine. This model is designed to address scenarios involving preventive maintenance activities for each machine, with machine efficiencies computed based on real performance data for analysis. Taking into consideration the dynamic states of the production system, including rework productions, a mathematical model has been developed [4] to calculate efficiency of the process. With this model, rework strategies are predicted to ensure the production of products with the desired quality. In the context of assembly lines, rework stations are typically set up at the end of assembly lines for reprocessing faulty products. These rework stations operate within standard production processes when error rates are low. In cases where rework stations operate in dynamic conditions, a nonlinear mixed-integer programming model [5] has been proposed to enhance station efficiency. This model aims to increase the efficiency of rework stations in dynamic situations, thus improving the overall performance of the assembly line. In the automotive industry, various Machine Learning methods have been employed to predict errors in assembly lines. The results obtained from different methods have been compared [6]. To facilitate this comparison, specific metrics were established, and these metrics were contrasted among the six algorithms employed.

To provide a comprehensive overview of the current state of research on early quality prediction and rework processes, a detailed literature summary table (Table-1) has been compiled. This table highlights the key methodologies, applications, and findings from various studies, illustrating the broader landscape of machine learning applications in different sectors.

A review of the literature on the application of artificial neural networks in the textile sector reveals that they have been employed in various studies to predict yarn parameters, optimize weaving processes, enhance finishing stages, and assess fabric comfort parameters [7]. Artificial Neural Networks (ANN) has also been employed to detect fabric defects in weaving [8]. To predict the characteristics of woven fabric (width, weight, weft and warp tensile values), an advanced feedforward recurrent artificial neural network (ANN) model [9] was employed and compared with a linear regression model. Artificial Neural Network (ANN) methods have been employed [10] to predict weft errors that emerge during fabric production in a textile company. ANN methods have been employed [11] to predict the impact of chemical finishing processes on the CIELab value of the fabric color.

This study aims to develop alert systems for the identification of products with a high probability of rework and the implementation of specific actions for their mitigation. Early Quality Prediction systems employ deep learning methods as well as various techniques for this purpose. However, within the textile industry, specifically in a textile company with a fabric dyeing production process, there is a lack of research on using Machine Learning for the prediction of errors. This particular gap forms the distinct aspect of this study.

The remainder of this paper is organized as follows: Section 3 presents the problem statement, detailing the specific challenges addressed in this study. Section 4 provides the methodology. Section 5 discusses the results. Section 6 explores managerial insights and practical implementations, offering actionable recommendations based on the study's outcomes. Finally, Section 7 concludes the paper with a summary of key findings and an outlook on future research directions.

Table 1. Summary	table	of the	literature.
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Ref.	Methods used	Application area	Key findings
[1]	Deep learning, Time series data	Manufacturing	Successful use of deep learning techniques for early quality prediction.
[2]	Various machine learning methods	Zero defect manufacturing	Comprehensive review of current methods to achieve zero defect manufacturing.
[3]	Data-driven modeling and analysis	Multi-stage manufacturing	Used data-driven modeling to analyze quality rework cycles.
[4]	Product traceability and rework analysis	systems Manufacturing systems	Analyzed quality performance considering product traceability and rework.
[5]	Mixed-integer programming	Assembly lines	Developed a model for positioning rework stations to improve efficiency.
[6]	Machine learning	Assembly environment	Applied machine learning for error detection in low-automation assembly environments.
[7]	Artificial neural networks	Textile industry	Reviewed applications of artificial neural networks in the textile industry.
[8]	Artificial neural networks	Weaving technology	Comprehensive review of ANN applications in weaving technology.
[9]	Artificial neural networks	Woven fabric	Used advanced feedforward recurrent neural networks to predict woven fabric properties.
[10]	Artificial neural networks, Multiple linear regression	Fabric defects	Compared ANN and multiple linear regression models for predicting fabric defects.
[11]	Artificial neural networks	Chemical finishing processes	Predicted the impact of chemical finishing on fabric color using ANNs.
[12]	Robust mathematical model	Epidemic modeling	Developed a mathematical model to predict the course of the COVID-19 epidemic.
[13]	Machine learning	Agri-food production forecasting	Used robust and resilient machine learning methods to forecast agri-food production.
[14]	Machine learning, Deep learning	Healthcare	Applied machine learning techniques to improve early disease detection.
[15]	Support vector machines, Neural networks	Manufacturing	Compared the efficiency of SVM and ANN in predicting manufacturing defects.
[16]	Deep learning	Electronics manufacturing	Used deep learning to predict defects in electronics manufacturing.
[17]	Logistic regression, Decision trees	Automotive	Developed predictive models to reduce rework in automotive manufacturing.
[18]	Ensemble learning	Aerospace	Applied ensemble learning techniques for quality prediction in aerospace components.
[19]	Neural networks, Fuzzy logic	Food processing	Combined neural networks and fuzzy logic for defect prediction in food processing.
[20]	Gradient boosting machines	Pharmaceutical	Used gradient boosting machines to predict quality issues in pharmaceutical manufacturing.
[21]	Intelligent quality control system	Surface roughness	Enhanced surface quality control.
[22]	Artificial intelligence techniques	Production cycle	Rework control optimization.
[23]	Machine learning for quality prediction	Injection molding	Prediction of defects in injection molding.
[24]	Real-time quality prediction	process Serial-parallel manufacturing processes	Real-time quality identification and prediction.
[25]	Integration of multisource information	Manufacturing processes	Enhanced quality prediction using multisource information.
[26]	Soft computing techniques	Machining process	Intelligent quality prediction in machining.
[27]	BP neural network	Supply chain quality	Optimized method for supply chain quality prediction
	algorithm	prediction	

#### 3. Problem statement

Fabric dyeing involves several key steps: preparing the fabric, mixing the dyes, dyeing the fabric, washing and rinsing, and drying. First, the fabric is cleaned and treated to ensure it absorbs the dye evenly. Next, the dyes are mixed to achieve the desired color. The fabric is then immersed in the dye mixture, ensuring it is thoroughly soaked. After dyeing, the fabric is washed and rinsed to remove any excess dye, and finally, it is dried.

Fabric dyeing involves several methods, each suited to

different types of fabrics and production scales. Common methods include batch dyeing, where fabric is dyed in a single batch, and continuous dyeing, which is efficient for large quantities as fabric moves continuously through the dyeing process. Pad-dyeing uses rollers to ensure even dye absorption, while jet dyeing employs high-pressure jets for delicate fabrics. Beam dyeing immerses fabric wound on a beam into the dye bath, and tie-dyeing creates unique patterns by tying fabric before dyeing. Solution dyeing integrates dye into the polymer solution for synthetic fibers, and dip dyeing achieves gradient effects by submerging fabric to different levels. Each method offers distinct advantages depending on the desired outcome and fabric type.

Rework processes are often needed in fabric dyeing due to various issues such as uneven dye distribution, incorrect color shades, or dye spots. These problems can arise from improper preparation, inaccurate dye mixing, or inconsistencies in the dyeing process. Reworking involves correcting these defects to meet the required quality standards, ensuring the final product is uniform and meets customer expectations.

The research was conducted within a textile company located in Bursa with a Fabric Dyeing Department. It was found that dyed fabrics frequently required redyeing or additional finishing processes due to various quality issues. These corrective processes are referred to as "Rework" within the operation. To address this issue, historical fabric dyeing job order data from the MRP software, which the company uses, was utilized. A dataset comprising 4,855 entries from the past year was collected for this purpose. The goal is to predict and minimize these rework instances to enhance efficiency and quality in the fabric dyeing process.

### 4. Methodology

As a result of the literature review, the decision of whether a fabric should undergo dyeing was framed as a "Classification" problem. To address this, an algorithm was developed using Logistic Regression and Artificial Neural Networks to determine whether rework is needed or not. Among the Artificial Neural Networks algorithms, the Multilayer Perceptron (MLP) algorithm was selected, specifically the MLPClassifier from the sklearn.neural\_network library in Python. The parameters chosen during the construction of the Artificial Neural Networks model directly impact its accuracy. The steps involved in the study are illustrated in Figure 1.

#### Logistic regression

Regression is a statistical method used to determine the relationship between two variables, where one is dependent (y) and the other is independent (x). In this relationship, y is expressed as a function of x. Given the x attribute values, the continuous variable y is calculated. Regression is a supervised learning technique. Regression analysis helps identify the cause-and-effect relationship between variables.

Logistic regression is a statistical method used to predict binary outcomes. It predicts the probability of a result that can have only two values. The prediction is based on the use of one or several predictors (numerical and categorical). Linear regression is not suitable for values that can be expressed in a binary system such as yes/no or presence/absence because it can predict values outside the range of 0 and 1. Logistic regression produces a logistic curve that is limited to values between 0 and 1.

The logistic regression model aims to minimize the cost function by updating the parameters and learning the parameters that provide the best classification results [28]. In logistic regression analysis, the ratio of the probability of an event occurring to the probability of it not occurring is called the odds ratio, and the probability of not occurring is calculated as follows:

$$1 - P_i = 1 - 1/(1 + e^{-Z_i}) = (1 + e^{-Z_i} - 1)/(1 + e^{-Z_i})$$
$$= e^{-Z_i}/(1 + e^{-Z_i})$$

The odds ratio is obtained by dividing the probability of occurrence by the probability of non-occurrence. The explicit expression of the odds ratio is:

$$P_i/(1 - P_i) = 1/(1 + e^{-Z_i})^*((1 + e^{-Z_i})/(e^{-Z_i})) = e^{Z_i}$$

By taking the natural logarithm of both sides of the logistic function, which becomes usable in linear regression analysis, a linear structure is obtained:

$$g(x) = \ln (P_i / (1 - P_i)) = \ln e^{Z_i} = Z_i = b_1 + b_2 X_i$$
  
$$P_i / (1 - P_i) = 1 / (1 + e^{-Z_i})^* ((1 + e^{-Z_i}) / (e^{-Z_i})) = e^{Z_i}$$

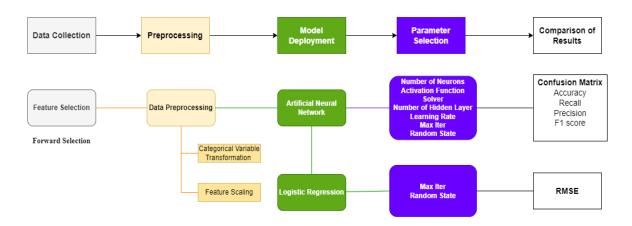


Figure 1. An overview of the methodology.

By taking the natural logarithm of both sides of the logistic function, which becomes usable in linear regression analysis, a linear structure is obtained:

$$g(x) = \ln (P_i / (1 - P_i)) = \ln e^{Z_i} = Z_i = b_1 + b_2 X_i$$

### Artificial Neural Networks (ANNs)

ANNs are computer systems designed to automatically perform tasks such as generating and discovering new knowledge through learning. ANNs can be used for tasks like prediction, classification, data association, data interpretation, and data filtering. ANNs are nonlinear information and data processing systems. They consist of processing units called neurons and the connections between these neurons.

The three main components of ANNs are neurons, the connections between these neurons, and functions. ANNs are made up of layers; the input layer is where data enters the network, and hidden layers process the data received in the input layer. There can be multiple hidden layers. The output layer is where the processed data is expressed as output. When a structure has multiple hidden layers, deep neural networks are used [29]. Figure 2 shows the working principle of the ANN model.

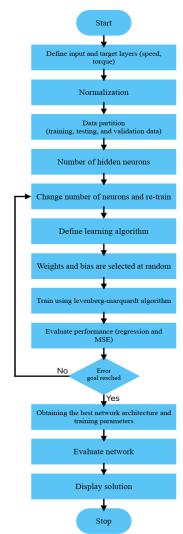


Figure 2. A typical ANN modeling workflow.

An MLP model has three layers: an input layer, hidden layers, and an output layer. Each layer can have one or more neurons, and all neurons in one layer can influence all neurons in the next layer. This relationship can be expressed as:

$$y_k = f\left(\sum_i w_{ki} \cdot x_i\right)$$

Where:

 $y_k$  is the output value of neuron k

 $w_{ki}$  is the weight value between input  $x_i$  and output neuron k

*x<sub>i</sub>* is the input value *i* 

In ANN, various transfer functions such as linear, logsigmoid, and tan-sigmoid can be used to convert input values to output values. In our study, we selected the ReLU (Rectified Linear Unit) and logistic transfer functions to transform the weighted input values into output values.

ReLU activation function

f(x) = max(0,x)

This function returns 0 if x is less than 0, otherwise, it returns x.

Logistic activation function

 $f(x) = 1 / 1 + e^{-x}$ 

Here, e is the base of the natural logarithm, and x is the input value. This function converts the input value into an output between 0 and 1, allowing the output to be interpreted as a probability.

In this implementation, the behaviors of the parameters listed below have been examined, and based on the performance of the proposed model, suitable values for these parameters have been selected. Some of these parameters were considered together, leading to the execution of 61 different experiments. The findings of these experiments are detailed in the Results section (in Table 3).

#### The parameters studied

Batch size and iteration count (max\_iter), Learning rate (learning\_rate), Weight initialization (random\_state), Neuron activation function and solver, Neuron count in the hidden layer.

When constructing the artificial neural networks model, there is no fixed formula for determining the number of hidden layers, neuron count, or activation function. Instead, a trial-and-error approach using test data is employed to determine the values that yield the best results for the model.

Test models have been created using the Relu and Logistic activation functions. Additionally, models have been built using the Adam and lbfgs optimizers. It is important to avoid setting a high learning rate, as it may lead to overfitting in the model. Therefore, through necessary testing, a learning rate of 0.001 has been selected for the model.

Generally, lbfgs tends to give optimal results on smaller datasets, while Adam is more suitable for larger datasets [30].

ReLU is a commonly used activation function, especially in deep neural networks. When used with lbfgs, ReLU often performs well because its derivative is non-zero, which can speed up training and reduce the vanishing gradient problem [31].

The logistic activation function is commonly used for binary classification problems. Using lbfgs with the logistic activation function is a good choice for small or medium-sized datasets. However, for deep neural networks or large datasets, activation functions like ReLU might be preferred due to their better performance [32, 33].

One of the important factors affecting the success of artificial neural networks is the selection of the number of neurons in each layer. There is no precise mathematical formula to determine this number, and it is often found through trial and error. Various factors should be considered when determining the number of neurons in a layer. Increasing or decreasing the number of neurons in an artificial neural network can affect the model's performance, error rate, and generalization ability. For instance, using too many neurons can lead to overfitting, where the model fits the training data too closely and fails to generalize well to real-world data [34]. Conversely, using too few neurons may cause the model to underfit, failing to capture the complexity of the dataset, which can decrease performance and increase computational costs [35]. The number of hidden layers and the number of neurons per layer have been determined through trial and error.

The Long Short Term Memory (LSTM) method, a type of deep learning technique, has been employed for realtime defect detection and texture classification on fabrics. This method aims to identify defects on fabrics using digital images.

Through a comprehensive review of literature and expert opinions, a set of 13 candidate features has been identified. The "IsTamir" outcome data serves as the target variable. Among the candidate attributes, a feature selection process has been conducted.

The Forward Selection method was employed for feature selection. This approach was chosen due to its remarkable success in classification tasks. The model commences with the most crucial variable concerning the dependent variable. Initially, the model incorporates solely one variable. Subsequent variables are incrementally added to the model. If the inclusion of a variable enhances the model's performance, it is retained within the model. Employing this process, all variables are examined, ultimately shaping the final model. List of the features are presented in Table 1.

Normalization is a technique commonly applied as part of data preprocessing in machine learning. Its purpose is to transform the values of numerical columns in a dataset onto a common scale without distorting the inherent differences in value ranges. Not every dataset requires normalization for machine learning purposes. The normalization process can be used to reduce data dimensionality, perform operations at appropriately scaled intervals with normalized values, and attain more meaningful and interpretable results.

In literature, various forms of data normalization exist. These include but are not limited to methods like minimum-maximum (min-max) scaling, decimal scaling, z-score normalization, and sigmoid normalization [36].

Table 2. Identified features.

Rework (Response variable)
Fabric quality name (Categorical)
Raw fabric pattern name (Categorical)
Color code (Categorical)
Finished fabric formation type code (Categorical)
Planned length (Numerical)
Raw fabric code (Categorical)
Master recipe name (Categorical)
Process name (Categorical)
Machine name (Categorical)
Operation flow code (Categorical)

Scaling is used to address the magnitude differences between various features in a dataset. When features have different scales, some may exert a stronger influence than others. This imbalance in feature scales can distort their equal contribution and potentially hinder algorithm performance.

The scaling process is implemented to compress feature values within a specific range. In the case of Logistic Regression and Artificial Neural Networks models, scaling has been deemed necessary. The StandardScaler scaling method from the Python sklearn.preprocessing library has been utilized to scale the features.

There are two crucial steps in prediction: first is the preparation of the data for prediction, and second is the comparison of different predictive models. The criteria for comparing models include; accuracy, speed, robustness, scalability, and interpretability.

Fundamental performance indicators employed in assessing the performance of Artificial Neural Networks and machine learning methods include R2, MSE, RMSE, and MAE [37].

To compare the models, Accuracy and F1 Score metrics were used.

Accuracy: The ratio of correctly predicted instances to the total instances.

Accuracy = (TP + TN) / (TP + TN + FP + FN)TP:True Positive TN:True Negative

FP:False Positive

FN:False Negative

Precision: Indicates how many of the instances predicted as positive are actually positive. It measures the model's ability to correctly classify the positive class.

Precision = TP / (TP + FP)

Recall: Indicates how many of the actual positive instances are correctly classified. It is the ratio of correctly predicted positive instances to all actual positive instances.

Recall = TP / (TP + FN)

F1 Score: The harmonic mean of Precision and Recall.

F1 Score=2\*((Precision\*Recall) / (Precision+Recall))

Visualization of Class Distribution: To visualize the distribution of the dataset (Figure 3) in Python, the code block was used:

```
import matplotlib.pyplot as plt
import numpy as np
```

```
# Visualize class distribution
plt.bar(np.unique(y), np.bincount(y))
plt.xlabel('Class')
plt.ylabel('Number of Samples')
plt.title('Class Distribution')
plt.show()
```

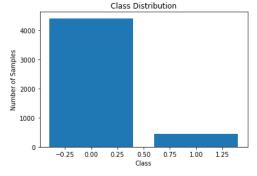


Figure 3. Class distribution.

Given that the dataset is imbalanced, the F1 Score is a more appropriate performance metric to use, as it provides a better measure of the model's performance on datasets with uneven class distributions.

### 5. Results

In this study, Python programming is used to implement machine learning algorithms. The process begins with handling missing and outlier data. Confirmation from the LEO MRP program ensures that no missing data is anticipated for the relevant attributes.

The get\_dummy function is used for categorical data transformation. The get\_dummies function takes each category of a categorical variable as a separate column and assigns a value of 1 to the rows corresponding to that category, and 0 to other rows. This way, each category becomes a distinct feature that can be utilized by machine learning models.

### Logistic regression implementation

The logistic regression model was implemented using Python, with the following steps:

Data Loading and Preprocessing: The data was loaded from a CSV file and categorical variables were converted into dummy variables. The dependent variable (IsTamir) was encoded using label encoding. Feature Engineering: The independent variables were selected and the dataset was split into training and testing sets. The data was scaled using StandardScaler.

Model Training and Prediction: A logistic regression model was trained and used to make predictions on the test set.

Evaluation Metrics: Accuracy and F1 Score metrics were used to evaluate the model's performance. Additionally, a confusion matrix and root mean squared error (RMSE) were computed.

The complete Python code is given in Appendix.

The accuracy of the logistic regression model is 92.64%. This means that the model correctly predicts the class of 92.64% of the samples in the test dataset. While accuracy is a commonly used metric, it may not be sufficient for evaluating the performance of models on imbalanced datasets.

The F1 score, which considers both precision and recall, is 0.4779. The F1 score is a better metric for imbalanced datasets because it takes into account false positives and false negatives. A higher F1 score indicates better overall performance of the model.

The confusion matrix provides insight into the model's performance across different classes. It reveals that the model correctly predicted 1431 samples as true positives and 54 samples as true negatives. However, it misclassified 36 samples as false positives and 82 samples as false negatives.

The RMSE value is 0.2713, reflecting the average difference between the actual and predicted values. Lower RMSE values indicate better model performance. However, in the context of classification, RMSE might not be the most informative metric.

While the accuracy of the logistic regression model is relatively high, the F1 score and confusion matrix reveal that the model's performance may be impacted by the imbalanced nature of the dataset. It's important to consider these results in the context of the dataset characteristics and the specific goals of the classification task.

### ANNs implementation

The Python code (in Appendix) implements an Artificial Neural Network (ANN) model, starting from data preprocessing steps and extending to training the model and evaluating its performance.

The values obtained from the results based on the parameters selected during the creation of the Artificial Neural Networks models are presented in Table 3 (in appendix).

Table 3 presents the evaluation results of 61 different models based on various configurations, including the activation function, solver, number of hidden layers, and number of neurons.

Upon examining the results, it's evident that there is a wide range of performance across different configurations. Some models achieve high accuracy and F1 Score values, indicating robust classification performance, while others exhibit lower values, suggesting potential areas for improvement.

These results provide valuable insights into the effectiveness of different configurations in training artificial neural network models for the given task. Further analysis and experimentation may help identify optimal configurations for maximizing classification performance.

### Comparison of Logistic Regression and Artificial Neural Network Results

Logistic Regression and Artificial Neural Networks methods were analyzed in Python. The results were compared using the Accuracy metric. Accuracy values for multiple Artificial Neural Network models were calculated and are presented in Table 3. The accuracy and F1 Score obtained from the Logistic Regression model were compared with those from the Artificial Neural Network model with the highest accuracy.

For Logistic Regression, the Accuracy is calculated at 0.90, while for the Artificial Neural Networks (Model 1), the Accuracy is found to be 0.92. This indicates that the Artificial Neural Networks model achieves higher accuracy compared to the Logistic Regression model.

Similarly, the F1 Score performance metric was evaluated. For Logistic Regression, the F1 Score is 0.48, while for the Artificial Neural Networks (Model 1), it is 0.47. Although there is only a slight difference in the F1 Score between the two methods, the Artificial Neural Networks model has a small advantage over

Logistic Regression.

In conclusion, the Artificial Neural Networks (Model 1) method achieves higher accuracy compared to Logistic Regression, while the F1 Score values are similar. These results suggest that, for this specific classification problem, the Artificial Neural Networks method may be more effective.

### 6. Managerial insights and practical implications

The findings of this study can inform strategic planning initiatives aimed at reducing rework costs in fabric dyeing processes. By leveraging predictive analytics, textile companies can proactively identify potential rework needs at the planning stage, enabling preemptive measures to optimize production processes and reduce rework expenses.

Implementing AI-based algorithms for predicting rework needs allows textile companies to optimize operational efficiency by streamlining production processes and minimizing downtime associated with rework activities. This, in turn, enhances overall productivity and cost-effectiveness.

Insights derived from predictive models can facilitate informed resource allocation and risk management strategies. By identifying high-risk production batches or processes prone to rework, companies can allocate resources more efficiently and implement targeted interventions to mitigate risks and minimize rework occurrences.

Model	Activation	Solver	Number of	Number	Accuracy	F1 Score
No	function		hidden layers	of neuron	8	
1	Relu	Adam	2	3,2	0.92	0.39
2	Relu	Adam	2	3,3	0.92	0.24
3	Relu	Adam	2	3,6	0.91	0.45
4	Relu	Adam	2	6,6	0.91	0.38
5	Relu	Adam	1	6	0.91	0.36
6	Relu	Adam	2	6,5	0.91	0.33
7	Relu	Adam	2	3,4	0.91	0.26
8	Relu	Adam	2	4,7	0.91	0.25
9	Relu	Adam	2	3,5	0.91	0.07
10	Logistic	Adam	2	7,7	0.9	0.47
11	Logistic	Adam	2	6,6	0.9	0.45
12	Logistic	Adam	2	8,8	0.9	0.45
13	Logistic	lbfgs	1	2	0.9	0.45
14	Logistic	Adam	2	5,5	0.9	0.44
15	Logistic	lbfgs	1	7	0.9	0.44
16	Relu	lbfgs	1	4	0.9	0.44
17	Relu	Adam	1	3	0.9	0.43
18	Logistic	Adam	2	7,8	0.9	0.43
19	Relu	lbfgs	2	4,4	0.9	0.42
20	Relu	Adam	4	4	0.9	0.4
21	Relu	Adam	2	4,6	0.9	0.37
22	Logistic	lbfgs	2	5,6	0.9	0.37
23	Relu	Adam	2	4,4	0.9	0.34

Table 3. Different configurations and obtained results.

Model	Activation	Solver	Number of	Number	Accuracy	F1 Score
No	function		hidden layers of neurons			
24	Relu	Adam	2	5,6	0.9	0.34
25	Logistic	lbfgs	2	4,5	0.9	0.33
26	Relu	Adam	2	4,3	0.9	0.3
27	Logistic	lbfgs	1	5	0.89	0.47
28	Logistic	Adam	3	8,8,8	0.89	0.46
29	Logistic	Adam	2	4,4	0.89	0.44
30	Logistic	Adam	1	6	0.89	0.44
31	Logistic	Adam	1	9	0.89	0.44
32	Relu	Adam	2	2,3	0.89	0.43
33	Logistic	Adam	2	8,9	0.89	0.43
34	Logistic	Adam	2	7,5	0.89	0.42
35	Logistic	lbfgs	2	5,5	0.89	0.39
36	Logistic	Adam	2	8,7	0.88	0.44
37	Logistic	lbfgs	1	9	0.87	0.42
38	Logistic	Adam	2	6,7	0.87	0.41
39	Logistic	lbfgs	2	7,7	0.87	0.37
40	Logistic	lbfgs	2	6,7	0.86	0.34
41	Logistic	lbfgs	2	2,2	0.86	0.31
42	Logistic	lbfgs	1	6	0.85	0.43
43	Logistic	lbfgs	1	11	0.85	0.42
44	Logistic	lbfgs	1	10	0.85	0.41
45	Logistic	lbfgs	1	8	0.85	0.4
46	Relu	Adam	2	6,7	0.85	0.39
47	Relu	Adam	2	6,7	0.85	0.39
48	Relu	lbfgs	2	4,3	0.85	0.39
49	Logistic	Adam	1	1	0.85	0.37
50	Relu	Adam	2	3,7	0.85	0.25
51	Logistic	lbfgs	1	12	0.84	0.4
52	Relu	Adam	2	5,5	0.84	0.38
53	Logistic	lbfgs	1	4	0.84	0.36
54	Relu	lbfgs	1	3	0.83	0.4
55	Relu	lbfgs	2	3,3	0.82	0.37
56	Relu	lbfgs	1	5	0.82	0.37
57	Relu	lbfgs	2	3,3	0.82	0.37
58	Relu	lbfgs	1	2	0.8	0.38
59	Logistic	lbfgs	1	3	0.79	0.33
60	Relu	lbfgs	2	6,6	0.77	0.35
61	Relu	Adam	2	7,7	0.73	0.25

Table 3. Different configurations and obtained results. (continued)

### 7. Conclusions and outlook

The primary objective of this study was to develop an algorithm capable of predicting rework needs at the planning stage for textile companies with fabric dyeing processes, with the goal of minimizing rework costs due to faulty productions. Machine Learning methods, including Logistic Regression and Artificial Neural Networks, were employed to tackle this issue as a classification problem. Both Logistic Regression and Artificial Neural Networks achieved successful outcomes.

Future studies could develop a more effective method for textile companies to predict rework needs. For instance, an algorithm could be designed to create alternative production routes before engaging in redyeing or repair processes. Additionally, developing a model that suggests the use of different chemical compositions could significantly reduce rework costs.

In conclusion, this study takes a pivotal step towards solving a significant issue in the textile sector by providing a potential solution for predicting the need for reprocessing in fabric dyeing processes using AIbased algorithms. Future efforts could further enhance this algorithm, ultimately optimizing production processes for textile companies in terms of efficiency and cost-effectiveness.

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### Appendices

```
1. Logistic Regression in Python Code
import pandas as pd
import numpy as np
# Data loading
veriler = pd.read csv('RW Data 1.csv')
print(veriler)
# Converting categorical variables to dummy variables
df KumasKaliteAdi = pd.get dummies(veriler["KumasKaliteAdi"], prefix="Kalite",
drop first=True)
df_KumasDesen = pd.get_dummies(veriler["HamKumasDesenAdi"], prefix="KumasDesen",
drop first=True)
df UretimPartiNo = pd.get dummies(veriler["UretimPartiNo"], prefix="PartiNo",
drop first=True)
df RenkKodu = pd.get dummies(veriler["RenkKodu"], prefix="RenkKodu",
drop first=True)
df LotNo = pd.get dummies(veriler["LotNo"], prefix="LotNo", drop first=True)
df MamulOlusumTipKodu = pd.get dummies(veriler["MamulOlusumTipKodu"],
prefix="MamulOlusumTipKodu", drop first=True)
df HamUrunKodu = pd.get dummies(veriler["HamUrunKodu"], prefix="HamUrunKodu",
drop first=True)
```

```
df MasterReceteAdi = pd.get dummies(veriler["MasterReceteAdi"],
prefix="MasterReceteAdi", drop_first=True)
df ProsesAdi = pd.get dummies(veriler["ProsesAdi"], prefix="ProsesAdi",
drop first=True)
df IslemAkisKodu = pd.get dummies(veriler["IslemAkisKodu"], prefix="IslemAkisKodu",
drop first=True)
df MakinaAdi = pd.get dummies(veriler["MakinaAdi"], prefix="MakinaAdi",
drop_first=True)
# Creating a DataFrame for PlanMt
PlanMt = veriler.iloc[:, 8:9].values
mt = pd.DataFrame(data=PlanMt, index=range(4855), columns=['PlanMt'])
# Encoding the dependent variable
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
IsTamir = le.fit transform(veriler.iloc[:, 0])
tamir = pd.DataFrame(data=IsTamir, index=range(4855), columns=['IsTamir'])
# Merging DataFrames
sonuc = pd.concat([df KumasKaliteAdi, df KumasDesen, df UretimPartiNo, df RenkKodu,
df_LotNo, df_MamulOlusumTipKodu, df_HamUrunKodu, df_MasterReceteAdi, df_ProsesAdi,
df IslemAkisKodu, df MakinaAdi, mt, tamir], axis=1)
print(sonuc)
# Splitting into independent and dependent variables
x = sonuc.iloc[:, 0:-1].values # independent variables
y = \text{sonuc.iloc}[:, -1]
                                # dependent variable
# Splitting the data into training and testing sets
from sklearn.model selection import train test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33,
random state=0)
# Scaling the data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(x_train)
X test = sc.transform(x test)
# Logistic regression
from sklearn.linear model import LogisticRegression
logr = LogisticRegression(random_state=0, max_iter=1000)
logr.fit(X_train, y_train) # training the model
# Predictions
y_pred = logr.predict(X test)
print(y pred)
print(y test)
# Evaluation
from sklearn.metrics import confusion_matrix, mean_squared_error, accuracy_score,
fl score
# Confusion matrix
cm = confusion matrix(y test, y pred)
print(cm)
# Root mean squared error
RMSE = np.sqrt(mean_squared_error(y_test, y_pred))
print("RMSE:", RMSE)
# Accuracy
accuracy = accuracy score(y test, y pred)
print("Accuracy:", accuracy)
# F1 Score
f1 = f1_score(y_test, y_pred)
```

# Visualization of class distribution import matplotlib.pyplot as plt plt.bar(np.unique(y), np.bincount(y)) plt.xlabel('Class') plt.ylabel('Number of Samples') plt.title('Class Distribution') plt.show() 2. ANN in Python Code # -\*- coding: utf-8 -\*-..... import pandas as pd import numpy as np #The CSV file should be located in the same directory as the Python code. veriler=pd.read\_csv('RW\_Data\_1.csv') print(veriler) df KumasKaliteAdi=pd.get dummies(veriler["KumasKaliteAdi"],prefix="Kalite",drop fir st=True) #print(df KumasKaliteAdi) df KumasDesen=pd.get dummies(veriler["HamKumasDesenAdi"],prefix="KumasDesen",drop f irst=True) #print(df KumasDesen) df UretimPartiNo=pd.get dummies(veriler["UretimPartiNo"],prefix="PartiNo",drop firs t=True) #print(df UretimPartiNo) df\_RenkKodu=pd.get\_dummies(veriler["RenkKodu"],prefix="RenkKodu",drop\_first=True) #print(df RenkKodu) df LotNo=pd.get dummies(veriler["LotNo"],prefix="LotNo",drop first=True) #print(df LotNo) df MamulOlusumTipKodu=pd.get dummies(veriler["MamulOlusumTipKodu"],prefix="MamulOlu sumTipKodu",drop first=True) #print(df\_MamulOlusumTipKodu) df HamUrunKodu=pd.get dummies(veriler["HamUrunKodu"],prefix="HamUrunKodu",drop firs t = True) #print(df HamUrunKodu) df MasterReceteAdi=pd.get dummies(veriler["MasterReceteAdi"],prefix="MasterReceteAd i",drop first=True) #print(df\_MasterReceteAdi) df\_ProsesAdi=pd.get\_dummies(veriler["ProsesAdi"],prefix="ProsesAdi",drop\_first=True #print(df ProsesAdi) df IslemAkisKodu=pd.get dummies(veriler["IslemAkisKodu"],prefix="IslemAkisKodu",dro p first=True) #print(df IslemAkisKodu) df MakinaAdi=pd.get dummies(veriler["MakinaAdi"],prefix="MakinaAdi",drop first=True ) #print(df MakinaAdi) PlanMt=veriler.iloc[:,8:9].values mt=pd.DataFrame(data=PlanMt,index=range(4855),columns=['PlanMt']) IsTamir=veriler.iloc[:,0:1].values tamir=pd.DataFrame(data=IsTamir,index=range(4855),columns=['IsTamir'])

```
320
```

print("F1 Score:", f1)

from sklearn import preprocessing

```
# DataFrame merging is used to create a new DataFrame by combining multiple
DataFrames.
sonuc=pd.concat([df KumasKaliteAdi,df KumasDesen,df UretimPartiNo,df RenkKodu,df Lo
tNo, df MamulOlusumTipKodu,df HamUrunKodu,df MasterReceteAdi,df ProsesAdi,
df_IslemAkisKodu, df_MakinaAdi,mt,tamir],axis=1)
#print(sonuc)
x=sonuc.iloc[:,0:-1].values #independent variables
y=sonuc.iloc[:,-1] #dependent variables
#print(x)
#print(y)
# splitting the data into training and testing sets
from sklearn.model selection import train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=0)
# scaling the data
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train=sc.fit_transform(x_train) #eğitim uyguluyor
X test=sc.transform(x_test)
#Let's create our artificial neural network model and configure our hidden layer.
from sklearn.neural network import MLPClassifier
#iki katman ve her katman 6 nörondan oluşacak şekilde model kurulmuştur
mlpcl = MLPClassifier(hidden layer sizes=(3,3),activation='relu', solver='lbfgs',
max iter=1000,random state=42,learning rate='constant', learning rate init=0.001)
#model = MLPClassifier(hidden_layer_sizes=(64, 64), activation='relu',
solver='adam', max_iter=1000, random_state=42)
mlpcl.fit(X_train, y_train.values.ravel())
# Let's make predictions on our test data.
predictions = mlpcl.predict(X test)
print(predictions)
# Let's evaluate the performance of our predictions - our algorithm.
from sklearn.metrics import classification report, confusion matrix
print(confusion_matrix(y_test, predictions))
print(classification report(y test, predictions))
from sklearn.metrics import accuracy score
# Calculate accuracy using your predictions and the actual labels.
accuracy = accuracy score(y test, predictions)
# print accuracy
print("Accuracy:", accuracy)
from sklearn.metrics import f1 score
# calculate accuracy
f1 = f1_score(y_test, predictions, pos label='T')
print("F1 Score:", f1)
```

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RESEARCH ARTICLE

### Witte's conditions for uniqueness of solutions to a class of Fractal-Fractional ordinary differential equations

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### ABSTRACT

In this paper, Witte's conditions for the uniqueness solution of nonlinear differential equations with integer and non-integer order derivatives are investigated. We present a detailed analysis of the uniqueness solutions of four classes of nonlinear differential equations with nonlocal operators. These classes include classical and fractional ordinary differential equations in fractal calculus. For each case, theorems and lemmas and their proofs are presented in detail.

### 1. Introduction

Nonlinear differential equations are powerful mathematical tools used to model real-world problems arising in several fields of study [1, 2]. The analysis of their solutions is of great importance, as they are for comparison with the collected data [3]. It is worth noting that, most of the time, obtaining their exact solutions is sometimes impossible. Researchers have therefore developed different approaches to help guarantee the existence and uniqueness of these solutions [4–7]. We note that several researchers have provided different conditions in the case of uniqueness in the last decades. For existence, many iterative approaches have been suggested, for example, Picard, Toneli, and others. For uniqueness, Witte provided several conditions that can be tested to conclude that a given nonlinear ordinary differential equation with a classical derivative has a

unique solution. Several other researchers, like Caratheordory, Nagumo, and others, have also provided some important conditions [8,9]. While several works have been published for ordinary differential equations with integer-order derivatives, much attention has not been devoted to classical and fractional nonlinear ordinary differential equations in fractal calculus [10, 11]. Fractional calculus and fractal calculus are interconnected fields, primarily through their shared focus on non-integer dimensions and scales. Fractional calculus extends the concept of differentiation and integration to non-integer orders, allowing for more flexible mathematical modeling of complex systems. A key connection is that fractional calculus provides the mathematical tools needed to describe the dynamics of processes on fractal structures. For example, the study by Metzler and Klafter [12] titled "The random walk's guide

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to anomalous diffusion: a fractional dynamics approach" discusses how fractional calculus can be applied to model diffusion processes on fractal media . Whereas these equations are suitable for the depiction of several complex real-world problems that cannot be modeled using classical ordinary differential equations. In this paper, we shall consider four classes of nonlinear ordinary differential equations, including those with classical differentiation in fractal calculus, those with power law, exponential decay, and generalized Mittag-Leffler kernels in fractal calculus. For each case, we will find conditions of uniqueness based on the framework of Witte [9].

### 2. Preliminaries

We shall provide some definitions that will be used in this paper.

$$\frac{df(t)}{dt^{\beta}} = \lim_{t_1 \to t} \frac{f(t_1) - f(t)}{t_1^{\beta} - t^{\beta}}, \, \beta > 0, \qquad (1)$$

which the fractal derivative of the function f with respect to a fractal measure t with scaling indice  $\beta$  [11]. We note that if f is differentiable then,

$$\frac{df(t)}{dt^{\beta}} = \frac{f'(t)}{\beta t^{\beta-1}}.$$
(2)

Fractal-fractional derivatives of the function f with power law, exponential decay and Mittag-Leffler kernel are given below respectively [10].

$${}^{FFP}_{t_0} D^{\alpha,\beta}_t f(t) = \frac{d}{dt^\beta} \frac{1}{\Gamma(1-\alpha)} \int\limits_{t_0}^t f(\tau) (t-\tau)^{-\alpha} d\tau,$$
(3)

$${}^{FFE}_{t_0} D^{\alpha,\beta}_t f(t) = \frac{d}{dt^\beta} \frac{1}{(1-\alpha)} \int\limits_{t_0}^{\circ} f(\tau) \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) d\tau,$$
(4)

$${}^{FFM}_{t_0} D^{\alpha,\beta}_t f(t) = \frac{d}{dt^\beta} \frac{1}{(1-\alpha)} \int\limits_{t_0}^t f(\tau) E_\alpha \left(\frac{-\alpha}{1-\alpha} (t-\tau)^\alpha\right) d\tau,$$
(5)

where  $(\alpha, \beta) \in (0, 1]$ .

Their respective integrals are given as below:

$${}^{FFP}_{t_0}J^{\alpha,\beta}_t f(t) = \frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t (t-\tau)^{\alpha-1} \tau^{\beta-1} f(\tau) d\tau,$$
(6)

$$F_{t_0}^{FFE} J_t^{\alpha,\beta} f(t) = (1-\alpha)\beta t^{\beta-1} f(t) + \alpha \beta \int_{t_0}^{b} \tau^{\beta-1} f(\tau) d\tau,$$
(7)

$${}^{FFM}_{t_0} D_t^{\alpha,\beta} f(t) = (1-\alpha)\beta t^{\beta-1} f(t)$$
(8)

$$+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t (t-\tau)^{\alpha-1} \tau^{\beta-1} f(\tau) d\tau.$$

We note that, when  $\beta = 1$ , we recover all the fractional differential and integral operators.

### 3. The Witte's uniqueness conditions for classical fractal ordinary differential equations

In this section, we are interested in the following general fractal differential equation.

$$\begin{cases} {}^{F}_{t_0} D^{\alpha}_t y(t) = f(t, y(t)), & t > t_0. \\ y(t_0) = y_0, \end{cases}$$
(9)

The aim is to establish uniqueness conditions based on the Witte's uniqueness.

**Theorem 1.** Let assume that f(t, y) is continuous in  $S_+ = \{(t, y) \mid t_0 < t \le a, |y| < \infty\}$  and satisfies

$$i) \ \forall (t,y), (t,\overline{y}) \in S_{+} \\ |f(t,y) - f(t,\overline{y})| \le h(t) |y - \overline{y}|, \qquad (10)$$
$$ii)|f(t,y)| \le \varphi(t)h(t) \exp\left(\int_{a}^{t} h(\tau)d\tau\right) in S_{+},$$

where h(t) > 0 is continuous in  $[t_0, a]$  and  $\varphi(t)$  is continuous in  $[t_0, a]$  and  $\varphi(t_0) = 0$ .

Then the considered equation has almost one solution.

**Proof.** To proof the above, we shall first provide the proof of the following Lemma.  $\Box$ 

**Lemma 1.** Let  $\Omega(t)$  be a nonnegative continuous function on  $[t_0, a]$  and let

i) h(t) > 0 be continuous functions in  $[t_0, a]$ ,

ii) There exists a function H(t) in  $[t_0, a]$  such that H'(t) = h(t) for almost all  $t \in [t_0, a]$  and  $\lim_{t \to t_0^+} H(t)$  exists, it can be finite,

*iii)* 
$$\Omega(t) \leq \int_{t_0}^t h(\tau)\Omega(\tau)d\tau, t \in [t_0, a],$$
  
*iv)*  $\Omega(t) = o\left(\exp\left(t^{\alpha}H\left(t\right)\right)\right)$  as  $t \to t_0^+$ . Then  $\Omega(t) = 0.$ 

**Proof.** Let the mentioned conditions hold, then

$$\Psi(t) = \alpha \int_{t_0}^t \tau^{\alpha - 1} h(\tau) \Omega(\tau) d\tau.$$
(11)

Thank to the hypothesis of the Lemma  $\Psi(t)$  exists and is continuous on  $[t_0, a]$ . Then

We define

$$F(t) = \exp\left(-t^{\alpha}H(t)\right)\Psi(t). \tag{13}$$

$$F_{t_0} D_t^{\alpha} F(t) \tag{14}$$

$$\begin{split} &= \frac{1}{\alpha t^{\alpha-1}} \frac{d}{dt} \int_{t_0}^{t} F(\tau) d\tau = \frac{1}{\alpha t^{\alpha-1}} F'(t), \\ &= \frac{1}{\alpha t^{\alpha-1}} \\ &\times \left[ \begin{array}{c} \Psi'(t) \exp\left(-t^{\alpha}H(t)\right) \\ -\Psi(t) \left( \begin{array}{c} -\alpha t^{\alpha-1}H(t) \\ -t^{\alpha}h(t) \end{array} \right) \exp\left(-t^{\alpha}H(t)\right) \right], \\ &= \frac{1}{\alpha t^{\alpha-1}} \exp\left(-t^{\alpha}H(t)\right) \\ &\times \left[ \begin{array}{c} \Psi'(t) \\ -\Psi(t) \left[ \begin{array}{c} \alpha t^{\alpha-1}H(t) \\ -t^{\alpha}h(t) \end{array} \right] \right], \\ &\leq \frac{1}{\alpha t^{\alpha-1}} \exp\left(-t^{\alpha}H(t)\right) \\ \left[ \begin{array}{c} h(t)\Psi(t)\alpha t^{\alpha-1} \\ -\Psi(t) \left[ \begin{array}{c} \alpha t^{\alpha-1}H(t) \\ -t^{\alpha}h(t) \end{array} \right] \right], \\ &\leq \frac{\Psi(t) \exp\left(-t^{\alpha}H(t)\right) }{\alpha t^{\alpha-1}} \left[ \begin{array}{c} \alpha t^{\alpha-1}h(t) \\ -\alpha t^{\alpha-1}H(t) - t^{\alpha}h(t) \end{array} \right], \\ &\leq \frac{\Psi(t) \exp\left(-t^{\alpha}H(t)\right) }{\alpha t^{\alpha-1}} \left[ \begin{array}{c} t^{\alpha}h(t) \\ -\alpha t^{\alpha-1}H(t) - t^{\alpha}h(t) \end{array} \right], \\ &\leq -H(t)\Psi(t) \exp\left(-t^{\alpha}H(t)\right), \\ &\leq -H(t)F(t) \leq 0. \end{split}$$

We can say that  $\forall t \in [t_0, a], \Psi(t) \exp(-t^{\alpha} H(t))$ is decreasing. We now choose  $\varepsilon > 0$  with t small enough

$$\Psi(t) \exp(-t^{\alpha} H(t))$$
(15)  
=  $\exp(-t^{\alpha} H(t)) \int_{t_0}^t \alpha \tau^{\alpha-1} h(\tau) \Omega(\tau) d\tau,$ 

$$\leq \varepsilon \exp(-t^{\alpha}H(t))\alpha \int_{t_0}^t \tau^{\alpha-1}h(\tau)\exp(\tau^{\alpha}H(\tau))d\tau,$$
  
$$\leq \varepsilon \exp(-t^{\alpha}H(t))\alpha \int_{t_0}^t \tau^{\alpha}h(\tau)\exp(\tau^{\alpha}H(\tau))d\tau,$$
  
$$\leq \varepsilon \exp(-t^{\alpha}H(t))\alpha \int_{t_0}^t \left(\begin{array}{c}\tau^{\alpha}h(\tau)\\+\alpha\tau^{\alpha-1}H(\tau)\end{array}\right)$$
  
$$\times \exp(\tau^{\alpha}H(\tau))d\tau,$$
  
$$= \varepsilon \alpha \exp(-t^{\alpha}H(t))\exp(t^{\alpha}H(t)),$$
  
$$= \varepsilon \alpha.$$

thus

$$\exp(-t^{\alpha}H(t))\Psi(t) \le 0 \text{ for } t > 0, \qquad (17)$$

 $\lim_{t \to 0} \exp(-t^{\alpha}H(t))\Psi(t) = 0,$ 

this also implies that

 $t \rightarrow t_0^+$ 

$$\alpha \int_{t_0}^t \tau^{\alpha-1} h(\tau) \Omega(\tau) d\tau \le 0.$$
 (18)

Therefore we should have

$$\Omega(t) = 0. \tag{19}$$

(16)

The new uniqueness criteria will be presented below. This is more general that the previous condition of the theorem.

**Theorem 2.** Let f(t, y) be continuous in  $\overline{S}_+$  in addition to the hypothesis in theorem 1, we have

$$|f(t,y) - f(t,\overline{y})| = o\left(\exp(t^{\alpha}H(t))\right), \qquad (20)$$

as  $t \to t_0^+$  uniformly with respect to  $y, \overline{y} \in [-\lambda, \lambda]$ ,  $\lambda > 0$  arbitrary with h(t) and H(t) the same like in Lemma 1. Then the considered equation has almost one solution in  $[t_0, a]$ .

**Proof.** Let y(t) and  $\overline{y}(t)$  be two different solutions of one equation

$$y(t) = y(t_0) + \alpha \int_{t_0}^t \tau^{\alpha - 1} f(\tau, y(\tau)) d\tau,$$
(21)

$$\begin{aligned} |y(t) - \overline{y}(t)| &\leq \alpha \int_{t_0}^t \tau^{\alpha - 1} \left| f(\tau, y(\tau)) - f(\tau, \overline{y}(\tau)) \right| d\tau, \\ &\leq \alpha \int_{t_0}^t \tau^{\alpha - 1} h(\tau) \left| y - \overline{y} \right| d\tau, \end{aligned}$$

$$\leq \alpha \int_{t_0}^{t} \left( \tau^{\alpha - 1} H(\tau) + \tau^{\alpha} h(\tau) \right) \exp\left( \tau^{\alpha} H(\tau) \right) d\tau,$$
  
$$\leq \varepsilon \exp\left( t^{\alpha} H(t) \right).$$

From the Lemma, the result is obtained.  $\Box$ 

**Corollary 1.** Let f satisfies the following conditions;  $\forall (t, \overline{y}), (t, y) \in S_+, \beta \in (1, 2]$  and  $\alpha \in (0, 1]$ :

i) 
$$(f(t,\overline{y}) - f(t,y)) (\overline{y} - y)^{\beta-1} \leq \frac{\beta}{\alpha} th(t) (\overline{y} - y)^{\beta}$$
,  
ii)  $f(t,\overline{y}) - f(t,y) = o(\exp(t^{\alpha}H(t)))$ ,  
as  $t \to t_0^+$  uniformly with respect to  $y,\overline{y} \in [-\delta,\delta], \delta > 0$  arbitrary. Then the considered

equation has almost one solution.

**Proof.** Let  $\overline{y}$  and y be different solutions in  $\overline{S}_+$ . Let put  $\Phi(t) = (\overline{y}(t) - y(t))^{\overline{\beta}}$  then we have that,

$$\begin{split} {}_{t_0}^F D_t^{\alpha} \Phi(t) &= \frac{1}{\alpha t^{\alpha - 1}} \frac{d}{dt} \left[ \Phi(t) \right], \\ &= \frac{1}{\alpha t^{\alpha - 1}} \left( \overline{\beta} \left( \overline{y}(t) - y(t) \right) \right)' \left( \overline{y}(t) - y(t) \right)^{\overline{\beta} - 1}, \\ &= \overline{\beta} \left( {}_{t_0}^F D_t^{\alpha} \overline{y}(t) - {}_{t_0}^F D_t^{\alpha} y(t) \right) \left( \overline{y}(t) - y(t) \right)^{\overline{\beta} - 1}, \\ &= \overline{\beta} \left( f \left( t, \overline{y}(t) \right) - f(t, y(t)) \right) \left( \overline{y}(t) - y(t) \right)^{\overline{\beta} - 1}. \end{split}$$

$$(22)$$

By the hypothesis (i), we have that

$$F_{t_0} D_t^{\alpha} \Phi(t) \leq \overline{\beta} h(t) \left( \overline{y}(t) - y(t) \right)^{\overline{\beta}}, \qquad (23)$$
$$= \frac{\overline{\beta}}{\alpha} t h(t) \Phi(t).$$

Therefore

$${}_{t_0}^F D_t^{\alpha} \Phi(t) \le \frac{\overline{\beta}}{\alpha} h(t) \Phi(t) t.$$
(24)

Note that

$$\begin{aligned} & \frac{F}{t_0} D_t^{\alpha} \left( \Phi(t) \exp\left(-\overline{\beta}t^{\alpha} H(t)\right) \right) \\ &= \frac{1}{\alpha t^{\alpha-1}} \begin{bmatrix} \Phi'(t) \exp\left(-\overline{\beta}t^{\alpha} H(t)\right) \\ &+ \Phi(t) \begin{bmatrix} -\overline{\beta}t^{\alpha} h(t) \\ -\overline{\beta}\alpha t^{\alpha-1} H(t) \end{bmatrix} \exp\left(-\overline{\beta}t^{\alpha} H(t)\right) \end{bmatrix} \\ &= \exp\left(-\overline{\beta}t^{\alpha} H(t)\right) \begin{bmatrix} F_{0} D_t^{\alpha} \Phi(t) \\ &- \Phi(t) \begin{pmatrix} \frac{\overline{\beta}}{\alpha} th(t) \\ &+ \overline{\beta} H(t) \end{pmatrix} \end{bmatrix}, \\ &\leq \exp\left(-\overline{\beta}t^{\alpha} h(t)\right) \begin{bmatrix} F_{0} D_t^{\alpha} \Phi(t) \\ &- \overline{\beta} \frac{t}{\alpha} h(t) \Phi(t) \end{bmatrix}, \\ &\leq 0. \end{aligned}$$

$$(25)$$

Since

l t

$${}^{F}_{t_0} D^{\alpha}_t \Phi(t) - \overline{\beta} \frac{t}{\alpha} h(t) \Phi(t) \le 0, \qquad (26)$$

$$\int_{0}^{\overline{r}} D_{t}^{\alpha} \left( \exp\left(-\overline{\beta}t^{\alpha}H(t)\right) \Phi(t) \right) \leq 0.$$
 (27)

The conclusion is that the function  $\exp\left(-\overline{\beta}t^{\alpha}\right)\Phi(t)$  is non increasing for almost  $\forall t \in [t_0, a]$ . On the other hand we have that

$$\exp\left(-\overline{\beta}t^{\alpha}H(t)\right)\Phi(t)$$
(28)  
=  $\exp\left(-\overline{\beta}t^{\alpha}H(t)\right)(\overline{y}(t) - y(t))^{\overline{\beta}},$   
=  $\exp\left(-\overline{\beta}t^{\alpha}H(t)\right)$   
 $\times\left(\alpha\int_{t_{0}}^{t}\tau^{\alpha-1}\left(f\left(\tau,\overline{y}\right) - f\left(\tau,y\right)\right)d\tau\right)^{\overline{\beta}}.$ 

However by hypothesis (ii), we can find  $\varepsilon>0$  small enough such that

$$\begin{split} \exp\left(-\overline{\beta}t^{\alpha}H(t)\right)\Phi(t) & (29) \\ \leq \exp\left(-\overline{\beta}t^{\alpha}H(t)\right)\alpha^{\overline{\beta}} \\ \times \left(\int_{t_{0}}^{t}\varepsilon\beta\left(\begin{array}{c}\alpha\tau^{\alpha-1}H(\tau)\\+\tau^{\alpha}h\left(\tau\right)\end{array}\right)\exp\left(\tau^{\alpha}\overline{\beta}H(\tau)\right)d\tau\right)^{\overline{\beta}}, \\ \leq \exp\left(-\overline{\beta}t^{\alpha}H(t)\right)\alpha^{\overline{\beta}}\varepsilon^{\overline{\beta}} \\ \times \left(\int_{t_{0}}^{t}\exp\left(\tau^{\alpha}\overline{\beta}H(\tau)\right)'d\tau\right), \\ \leq \exp\left(-\overline{\beta}t^{\alpha}H(t)\right)\alpha^{\overline{\beta}}\varepsilon^{\overline{\beta}}\exp\left(t^{\alpha}\overline{\beta}H(t)\right), \\ = \alpha^{\overline{\beta}}\varepsilon^{\overline{\beta}} = (\alpha\varepsilon)^{\overline{\beta}}, \end{split}$$

and then

$$\lim_{t \to t_0^+} \exp\left(-\overline{\beta}t^{\alpha}H(t)\right)\Phi(t) = 0.$$
 (30)

Therefore  $\Phi(t) = 0$  so we get

$$\overline{y}(t) = y(t), \tag{31}$$

which completes the proof.

We shall now evaluation the above condition in the case of the fractal fractional with power law.This will be acheived in the next section

# 4. The Witte's uniqueness conditions for Fractal-Fractional ordinary differential equations with exponential kernel

We shall consider in this section, the following fractal-fractional differential equation

$$\begin{cases} FFE_{t_0}^{\alpha,\beta} y(t) = f(t, y(t)), & \text{if } t > t_0, \\ y(t_0) = y_0, & \text{if } t = t_0. \end{cases}$$
(32)

that under the witte's condition  $\alpha, \beta \in (0, 1]$ . The aim of this section is to show that under the Witte's condition equation has a unique solution if such solution exists in  $[t_0, a]$ . We will start our investigation on with the following lemma.

**Lemma 2.** Let f(t, y(t)), h(t) and H(t) satisfy the properties presented before

$$i) \quad \Phi(t) \leq (1 - \alpha)\beta t^{\beta - 1}h(t)\Phi(t) + \alpha\beta \int_{t_0}^t \tau^{\beta - 1}h(\tau) \Phi(\tau)d\tau,$$
  
$$::) \quad \Phi(t) = (-(H(t))) = t \Rightarrow t^{\frac{1}{2}} + t = \Phi(t) = 0$$

*ii*)  $\Phi(t) = o(\exp(H(t)))$  as  $t \to t_0^+$ , then  $\Phi(t) = 0$ in  $[t_0, a]$ . Therefore

$$FFE_{t_0}^{FFE} D_t^{\alpha,\beta} \left[ \Omega(t) \exp\left(-H(t)\right) \right]$$

$$= \frac{1}{\beta t^{\beta-1}} \left[ \begin{array}{c} \frac{1}{1-\alpha} \int_{t_0}^t \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) \\ \times \left[ \begin{array}{c} \Omega'(\tau) \exp(-H(\tau)) \\ -h(\tau) \Omega(\tau) \exp(-H(\tau)) \end{array} \right] \end{array} \right] d\tau,$$

$$= \frac{1}{\beta t^{\beta-1}} \left[ \begin{array}{c} \frac{1}{1-\alpha} \int_{t_0}^t \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) \\ \times \left[ \Omega'(\tau) - h(\tau) \Omega(\tau) \right] \exp(-H(\tau)) \end{array} \right] d\tau,$$

$$\leq 0.$$

$$(38)$$

In reference [9] it was shown that under the condition prescribed here

$$\Omega'(t) - h(t) \Omega(t) \le 0, \qquad (39)$$

therefore

$$_{t_0}^{FFE} D_t^{\alpha,\beta} \left[ \exp\left(-H(t)\right) \Omega(t) \right] \le 0.$$
 (40)

Since by the hypothesis the integral is positive therefore

$$_{t_0}^{FFE} D_t^{\alpha,\beta} \left[ \exp\left(-H(t)\right) \Omega(t) \right] \le 0, \qquad (41)$$

almost every where in  $[t_0, a]$ .

$$\begin{split} &\exp\left(-H(t)\right)\Omega(t) \\ &= \exp\left(-H(t)\right) \left[ \begin{array}{c} \left(1-\alpha\right)\beta h\left(t\right)\Phi\left(t\right)t^{\beta-1} \\ +\beta\alpha \int\limits_{t_0}^t \tau^{\beta-1}h\left(\tau\right)\Phi(\tau)d\tau \end{array} \right]. \end{split}$$

For a sufficient small t, we choose  $\varepsilon > 0$  such that in the view of (iv), we get

$$\begin{split} \Omega(t) \exp\left(-H(t)\right) &\leq \exp\left(-H(t)\right) \\ &\times \left[ \begin{array}{c} (1-\alpha)\,\beta h\left(t\right)t^{\beta-1}\exp\left(H(t)\right)\varepsilon' \\ +\beta\alpha\varepsilon'\int\limits_{t_0}^t\tau^{\beta-1}h\left(\tau\right)\exp\left(H(\tau)\right)d\tau \end{array} \right], \\ &\leq \exp\left(-H(t)\right) \\ &\times \left[ \begin{array}{c} (1-\alpha)\,\beta h\left(t\right)\left(\bar{t}_0\right)^{\beta-1}\exp\left(H(t)\right)\varepsilon' \\ +\left(\bar{t}_0\right)^{\beta-1}\beta\alpha\varepsilon'\exp\left(H(t)\right) \end{array} \right] \\ &\leq (1-\alpha)\,\beta h\left(t\right)\left(\bar{t}_0\right)^{\beta-1}\varepsilon' + \left(\bar{t}_0\right)^{\beta-1}\beta\alpha\varepsilon'. \end{split}$$

Using the continuity of h(t) in  $[t_0, a]$ .  $\exists t_1 \in [t_0, a]$ such that  $\forall t \in [t_0, a]$ 

$$h(t_1) \ge h(t), \qquad (42)$$

**Proof.** Let set  

$$\Omega(t) = (1 - \alpha)\beta h(t)t^{\beta - 1}\Phi(t) \qquad (33)$$

$$+ \alpha \beta \int_{t_0}^t \tau^{\beta - 1} h(\tau) \Phi(\tau) d\tau.$$

From the hypothesis, we have that  $\Omega(t)$  exists and is continuous in  $[t_0, a]$ . We recall that

$$_{t_0}^{FFE} D_t^{\alpha,\beta} \left( {}_{t_0}^{FFE} J_t^{\alpha} u(t) \right) = u(t).$$
 (34)

Thus applying  $_{t_0}^{FFE} D_t^{\alpha,\beta}$  on both sides yields

$${}_{t_0}^{FFE} D_t^{\alpha,\beta} \Omega(t) = h(t) \Phi(t) \le h(t) \Omega(t).$$
(35)

Now, we shall find the sign of the

$$F_{t_0}^{FFE} D_t^{\alpha,\beta} \left[ \Omega(t) \exp\left(-H(t)\right) \right]$$
(36)  
$$= \frac{1}{\beta t^{\beta-1}} C_{t_0}^{FR} D_t^{\alpha} \left[ \Omega(t) \exp\left(-H(t)\right) \right],$$
  
$$= \frac{1}{\beta t^{\beta-1}} C_{t_0}^{F} D_t^{\alpha} \left[ \Omega(t) \exp\left(-H(t)\right) \right].$$

Since  $\Omega(t_0) = 0$ , therefore, we have that

$${}^{CFR}_{t_0} D^{\alpha}_t \Omega(t) = {}^{CF}_{t_0} D^{\alpha}_t \Omega(t).$$
(37)

therefore

$$\exp\left(-H(t)\right)\Omega(t) \leq \left(\bar{t}_{0}\right)^{\beta-1}\beta\left(h\left(t_{1}\right)\varepsilon'\left(1-\alpha\right)+\alpha\varepsilon'\right),\\ \leq \mu\varepsilon' = \frac{\mu}{\mu}\varepsilon = \varepsilon.$$
(43)

where

$$\varepsilon' = \frac{\varepsilon}{\mu} = \frac{\varepsilon}{\left(\bar{t}_0\right)^{\beta-1} \beta \left(h\left(t_1\right)\left(1-\alpha\right) + \alpha\beta\right)}.$$
 (44)

Therefore

$$\Phi(t) = 0. \tag{45}$$

**Theorem 3.** Let f(t, y) be continuous in  $\overline{S}_+$  in addition to Theorem 2 and Lemma 2 we have

$$\forall \varepsilon' > 0,$$
  

$$\varepsilon' = \frac{\varepsilon}{(1-\alpha)\beta h(t)(\overline{t}_0)^{\beta-1} + (\overline{t}_0)^{\beta-1}\beta\alpha}.$$
 (46)

Then the initial value problem (32) has almost one solution.

We have that 
$$\Psi(t_0) = 0$$
, thus

$$\begin{split} & \stackrel{FFE}{t_0} D_t^{\alpha,\beta} \Psi(t) \qquad (49) \\ &= \frac{1}{\beta t^{\beta-1}} \stackrel{CFR}{t_0} D_t^{\alpha} \Psi(t) = \frac{1}{\beta t^{\beta-1}} \stackrel{CF}{t_0} D_t^{\alpha} \Psi(t), \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{1-\alpha} \int_{t_0}^t \Psi'(\tau) \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) d\tau, \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{1-\alpha} \int_{t_0}^t \left[ \overline{\beta} \left( \overline{y} - y \right)' \left( \overline{y} - y \right)^{\overline{\beta}-1} \right] \\ &\times \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) d\tau, \\ &\leq \overline{\beta} \delta \left[ \stackrel{FFE}{t_0} D_t^{\alpha,\beta} \overline{y} - \stackrel{FFE}{t_0} D_t^{\alpha,\beta} y \right], \\ &\leq \overline{\beta} \delta \left| f(t, \overline{y}(t)) - f(t, y(t)) \right|, \\ &\leq \overline{\beta} \delta h(t) \Psi(t), \end{split}$$

here

$$\delta = \begin{cases} \max_{t \in [t_0, a]} |\overline{y} - y|^{\overline{\beta} - 1}, & \text{if } y' - \overline{y}' > 0, \\ \min_{t \in [t_0, a]} |\overline{y} - y|^{\overline{\beta} - 1}, & \text{if } y' - \overline{y}' < 0. \end{cases}$$

In the view of the first hypothesis. Thus

$${}_{t_0}^{FFE} D_t^{\alpha,\beta} \Psi(t) \le \overline{\Delta} \Psi(t), \tag{50}$$

**Proof.** Let y(t) and  $\overline{y}(t)$  be two different solutions of our equation, then *G* 1

$$\begin{split} |\Phi(t)| &= |\overline{y}(t) - y(t)| \leq (1 - \alpha)\beta t^{\beta^{-1}} |f(t, \overline{y}(t)) - f(t, y(t))| \text{ almost every where in } [t_0, a]. \\ &+ \alpha \beta \int_{t_0}^t \tau^{\beta^{-1}} |f(\tau, \overline{y}(\tau)) - f(\tau, y(\tau))| d\tau, \\ &\leq (1 - \alpha)\beta t^{\beta^{-1}} h(\tau) \Phi(\tau) d\tau, \\ &\leq (1 - \alpha)\beta h(t) (\overline{t_0})^{\beta^{-1}} \varepsilon' \exp(H(t)) \\ &+ (\overline{t_0})^{\beta^{-1}} \beta \alpha \varepsilon' \exp(H(t)), \\ &\leq \left( \begin{pmatrix} (1 - \alpha)\beta h(t) (\overline{t_0})^{\beta^{-1}} \varepsilon' \exp(H(t)) \\ + (\overline{t_0})^{\beta^{-1}} \beta \alpha \end{pmatrix} \varepsilon' \exp(H(t)), \\ &\leq \left( \begin{pmatrix} (1 - \alpha)\beta h(t) (\overline{t_0})^{\beta^{-1}} \\ + (\overline{t_0})^{\beta^{-1}} \beta \alpha \end{pmatrix} \varepsilon' \exp(H(t)), \\ &\leq \mu \varepsilon' \exp(H(t)) = \varepsilon \exp(H(t)). \end{split}$$

$$\end{split}$$

$$\begin{aligned} & (47) \\ &\times \left( \Psi(\tau) \exp\left(-\overline{\beta}H(\tau)\right) \right)' d\tau \\ &= \frac{1}{\beta t^{\beta^{-1}}} \frac{1}{1 - \alpha} \Psi(t_0) \exp\left(-\overline{\beta}H(t_0)\right) \exp\left(\frac{-\alpha}{1 - \alpha}t\right). \end{aligned}$$

**Theorem 4.** Let f(t, y) satisfies all the condition described in Theorem 3.

**Proof.** Let y(t) and  $\overline{y}(t)$  be two different solution of equation (32). We set as before

$$\Psi(t) = (\overline{y} - y)^{\beta} \,. \tag{48}$$

 $\Psi(t_0) = 0,$ (52)

therefore

But

(51)

$$FFE_{t_0}^{FFE} D_t^{\alpha,\beta} \left[ \exp\left(-\overline{\beta}H(t)\right) \Psi(t) \right]$$
(53)  
$$= \frac{1}{(1-\alpha)\beta t^{\beta-1}} \int_{t_0}^t \exp\left(-\frac{\alpha}{1-\alpha} (t-\tau)\right)$$
$$\times \left( \exp\left(-\overline{\beta}H(\tau)\right) \Psi(\tau) \right)' d\tau,$$
$$= \frac{1}{(1-\alpha)\beta t^{\beta-1}} \int_{t_0}^t \exp\left(-\frac{\alpha}{1-\alpha} (t-\tau)\right)$$
$$\times \left( \frac{\Psi'(\tau) \exp\left(-\overline{\beta}H(\tau)\right)}{-\overline{\beta}H(\tau) \exp\left(-\overline{\beta}H(\tau)\right)} \Psi(\tau) \right) d\tau.$$

In reference [9], it was shown that

$$\Psi'(t) \exp\left(-\overline{\beta}H(t)\right) - \overline{\beta}H(t) \exp\left(-\overline{\beta}H(t)\right)\Psi(t) < 0.$$
(54)

Therefore

$$_{t_{0}}^{FFE}D_{t}^{\alpha,\beta}\left[\Psi(t)\exp\left(-\overline{\beta}H(t)\right)\right]\leq0.$$

$$\begin{split} & F^{FE} D_{t}^{\alpha,\beta} \left[ \exp\left(-\overline{\beta}H(t)\right) \Psi(t) \right] \quad (55) \\ &= \frac{1}{\beta t^{\beta-1}} \mathop{}_{t_{0}}^{CFR} D_{t}^{\alpha} \left[ \exp\left(-\overline{\beta}H(t)\right) \Psi(t) \right], \\ &= \frac{1}{\beta t^{\beta-1}} \mathop{}_{t_{0}}^{CF} D_{t}^{\alpha} \left[ \exp\left(-\overline{\beta}H(t)\right) \Psi(t) \right], \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{1-\alpha} \int_{t_{0}}^{t} \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) \\ &\times \left[ \begin{array}{c} -\Psi'(\tau)\overline{\beta} \exp\left(-\overline{\beta}H(\tau)\right) \\ -\overline{\beta}h(\tau) \exp\left(-\overline{\beta}H(\tau)\right) \Psi(\tau) \end{array} \right] d\tau, \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{1-\alpha} \int_{t_{0}}^{t} \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) \\ &\times \left[ \left[ \Psi'(\tau) + h(\tau)\Psi(\tau) \right] \exp\left(-\overline{\beta}H(\tau)\right) \right] d\tau, \\ &= \frac{1}{\beta t^{\beta}} \frac{1}{1-\alpha} \int_{t_{0}}^{t} \exp\left(\frac{-\alpha}{1-\alpha}(t-\tau)\right) \\ &\times \left[ \left[ \Psi'(\tau) - h(\tau)\Psi(\tau) \right] \exp\left(-\overline{\beta}H(\tau)\right) \right] d\tau, \\ &\leq 0. \end{split}$$

Therefore, we have

$$_{t_0}^{FFE} D_t^{\alpha,\beta} \left[ \exp\left(-\overline{\beta}H(t)\right) \Psi(t) \right] < 0.$$
 (56)

Following the routine presented earlier we shall have for  $\varepsilon'$ 

$$\begin{split} \exp\left(-\overline{\beta}H(t)\right)\Psi(t) \\ &= \exp\left(-\overline{\beta}H(t)\right)\left(\overline{y}(t) - y(t)\right)^{\overline{\beta}}, \\ &= \exp\left(-\overline{\beta}H(t)\right)\left(\begin{pmatrix} (1-\alpha)\beta t^{\beta-1}\left(f(t,\overline{y}(t)) - f(t,y(t))\right) \\ +\alpha\beta\int\limits_{t_0}^t \tau^{\beta-1}\left(f(\tau,\overline{y}(\tau)) - f(\tau,y(\tau))\right)d\tau \end{pmatrix}\right)^{\overline{\beta}}, \\ &\leq \exp\left(-\overline{\beta}H(t)\right)\left(\begin{pmatrix} (1-\alpha)\beta t^{\beta-1}\varepsilon'\exp\left(H(t)\right)h(t) \\ +\alpha\beta\int\limits_{t_0}^t h(\tau)\tau^{\beta-1}\varepsilon'\exp\left(H(\tau)\right)d\tau \end{pmatrix}\right)^{\overline{\beta}}, \\ &\leq \exp\left(-\overline{\beta}H(t)\right)\left(\begin{pmatrix} (1-\alpha)\beta\left(\overline{t}_0\right)^{\beta-1}\varepsilon'\exp\left(H(t)\right)h(t) \\ +\left(\overline{t}_0\right)^{\beta-1}\alpha\beta\varepsilon'\int\limits_{t_0}^t h(\tau)\exp\left(H(\tau)\right)d\tau \end{pmatrix}\right)^{\overline{\beta}}, \\ &\leq \exp\left(-\overline{\beta}H(t)\right)\left(\begin{pmatrix} (1-\alpha)\overline{\beta}\left(\overline{t}_0\right)^{\beta-1}\varepsilon'\exp\left(H(t)\right)h(t) \\ +\left(\overline{t}_0\right)^{\beta-1}\alpha\overline{\beta}\varepsilon'\exp\left(H(t)\right)\end{pmatrix}\right)^{\overline{\beta}}, \\ &\leq \exp\left(-\overline{\beta}H(t)\right)\left(\begin{pmatrix} (1-\alpha)\beta\left(\overline{t}_0\right)^{\beta-1}\varepsilon'\exp\left(H(t)\right)h(t) \\ +\left(\overline{t}_0\right)^{\beta-1}\alpha\beta\varepsilon'\exp\left(H(t)\right)\end{pmatrix}\right)^{\overline{\beta}}, \\ &\leq \exp\left(-\overline{\beta}H(t)\right)\left(\begin{pmatrix} (1-\alpha)\beta\left(\overline{t}_0\right)^{\beta-1}\varepsilon'\exp\left(H(t)\right)h(t) \\ +\left(\overline{t}_0\right)^{\beta-1}\alpha\beta\varepsilon'\exp\left(H(t)\right)\end{pmatrix}\right)^{\overline{\beta}}, \\ &\leq \exp\left(-\overline{\beta}H(t)\right)\exp\left(\beta H(t)\right)(\varepsilon')^{\overline{\beta}}\left((1-\alpha)\beta\left(\overline{t}_0\right)^{\beta-1}+\left(\overline{t}_0\right)^{\beta-1}\alpha\beta\right)^{\overline{\beta}} \\ &\leq (\varepsilon')^{\overline{\beta}}\mu^{\overline{\beta}}, \ \mu=((1-\alpha)\beta+\alpha\beta)\left(\overline{t}_0\right)^{\beta-1}. \end{split}$$

We choose

$$\varepsilon' = \frac{\varepsilon}{\mu},$$
 (58)

such that

$$\exp\left(-\overline{\beta}H(t)\right)\Psi(t) \le \varepsilon^2.$$
(59)

Therefore

$$\lim_{t \to 0^+} \exp\left(-\overline{\beta}H(t)\right)\Psi(t) = 0.$$
 (60)

So we conclude that

$$\Psi(t) = 0 \tag{61}$$
$$\Rightarrow \overline{y}(t) = y(t),$$

which concludes the proof.

# 5. The Witte's uniqueness conditions for Fractal-Fractional ordinary differential equations with power-law kernel

In this section, we shall consider the following differential equation

$$\begin{cases} FFP_{t_0} D_t^{\alpha,\beta} y(t) = f(t, y(t)), & \text{if } t > t_0, \\ y(t_0) = y_0, & \text{if } t = t_0. \end{cases}$$
(62)

We aim to show that if the solution of the above equation exists in  $S_+ =$  $\{(t,y) \mid t_0 < t \leq a, |y| < \infty\}, \alpha \in (0,1], \beta \in$ (0,1] then it is unique. **Lemma 3.** Let  $\Phi(t)$  be a non negative continuous in  $(t_0, a]$  such that  $\Phi(t_0) = 0$ . Let

i) 
$$h(t) > 0$$
 be continuous function in  $(t_0, a]$ ,

ii) We can find a function H(t) in  $(t_0, a]$  such that H'(t) = h(t) for almost all  $t \in (t_0, a]$  and  $\lim_{t \to t_0^+} H(t)$  exists,

*iii)* 
$$\Phi(t) \leq \frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau) \Phi(\tau) d\tau,$$
  
 $\forall t \in (t_0, a] and$ 

 $\forall t \in (t_0, a] and$ 

iv) 
$$\Phi(t) = o\left(\exp(H(t))\right)$$
 as  $t \to t_0^+$ . Then  
 $\Phi(t) = 0,$  (63)

 $\Omega(t) = \frac{\beta}{\Gamma(\alpha)} \int_{t_{-}}^{t} \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau) \Phi(\tau) d\tau.$  (64)

The existence and the continuty of the function  $\Omega(t)$  is assumed since the hypothesis of the

 ${}_{t_0}^{FFP} D_t^{\alpha,\beta} \Omega(t) = h(t) \Phi(t) \le h(t) \Phi(t).$ 

 $= \frac{\beta}{\Gamma(\alpha)} \mathop{}_{t_0}^{FFP} D_t^{\alpha,\beta} \left[ \int_{\tau}^{t} \tau^{\beta-1} \left(t-\tau\right)^{\alpha-1} h(\tau) \Phi(\tau) d\tau \right],$ 

 $\times \left( \int_{\tau}^{t} \tau^{\beta-1} (t-\tau)^{-\alpha} \left[ \int_{\tau}^{\tau} l^{\beta-1} (\tau-l)^{\alpha-1} h(l) \Phi(l) dl \right] d\tau \right),$ 

Lemma. Therefore we have that

*in*  $(t_0, a]$ .

**Proof.** Let

We note that

 $FFP_{t_0}^{FFP} D_t^{\alpha,\beta} \Omega(t)$ 

 $=\frac{\beta}{\Gamma(\alpha)\,\beta t^{\beta-1}}\frac{d}{dt}\frac{1}{\Gamma(1-\alpha)}$ 

 $=\frac{\beta t^{\beta-1}h(t)\Phi(t)}{\beta t^{\beta-1}},$ 

 $= h(t)\Phi(t).$ 

 $= \frac{\beta}{\beta t^{\beta-1}} \mathop{}_{t_0}^{RL} D_t^{\alpha} \left[ \mathop{}_{t_0}^{RL} J_t^{\alpha} \left( t^{\beta-1} h(t) \Phi(t) \right) \right],$ 

We recall that  $\Omega(t_0) = 0$ , then

$$\begin{split} & F^{FP}_{t_0} D_t^{\alpha,\beta} \left[ \exp(-H(t))\Omega(t) \right] \\ &= \frac{1}{\beta t^{\beta-1}} \frac{RL}{t_0} D_t^{\alpha} \left[ \exp(-H(t))\Omega(t) \right], \\ &= \frac{1}{\beta t^{\beta-1}} \frac{C}{t_0} D_t^{\alpha} \left[ \exp(-H(t))\Omega(t) \right], \\ &= \frac{1}{\beta t^{\beta}} \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t \left( t - \tau \right)^{-\alpha} \left[ \begin{array}{c} \Omega'(\tau) \exp(-H(\tau)) \\ -h(\tau)\Omega(\tau) \exp(-H(\tau)) \end{array} \right] d\tau, \\ &= \frac{1}{\beta t^{\beta}} \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t \left( t - \tau \right)^{-\alpha} \exp(-H(\tau)) \left[ \Omega'(\tau) - h(\tau)\Omega(\tau) \right] d\tau, \end{split}$$
 (68)

We have due to reference [9] that

$$\Omega'(\tau) - h(\tau)\Omega(\tau) \le 0.$$
(69)

Therefore

$$_{t_0}^{FFP} D_t^{\alpha,\beta} \left[ \exp(-H(t))\Omega(t) \right] \le 0.$$
 (70)

We can now have for a small t

$$\exp(-H(t))\Omega(t) = \exp(-H(t))\frac{\beta}{\Gamma(\alpha)}\int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau)\Phi(\tau)d\tau,$$

$$\leq \frac{\exp(-H(t))\beta}{\Gamma(\alpha)}\int_{t_0}^t \tau^{\beta} (t-\tau)^{\alpha} h(\tau)\Phi(\tau)d\tau,$$

$$\leq \frac{\exp(-H(t))\beta a^{\beta+\alpha}}{\Gamma(\alpha)}\int_{t_0}^t h(\tau)\Phi(\tau)d\tau.$$
(71)

By hypothesis (iv), we have

$$\exp(-H(t))\Omega(t) \le \frac{\exp(-H(\tau))\beta a^{\beta+\alpha}}{\Gamma(\alpha)} \varepsilon \exp\left(H(\tau) \times \frac{\Gamma(\alpha)}{\beta a^{\beta+\alpha}}\right)$$
$$\le \varepsilon.$$
(72)

$$\lim_{t \to 0^+} \exp(-H(t))\Omega(t) = 0.$$
 (73)

This leads to

(65)

(66)

$$\exp(-H(t))\Omega(t) \le 0, \ \forall t > t_0, \tag{74}$$

which implies

$$\frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} \left(t-\tau\right)^{\alpha-1} h(\tau) \Phi(\tau) d\tau \le 0, \quad (75)$$

which is a contradiction therefore

$$\Phi(t) = 0. \tag{76}$$

$${}^{RL}_{t_0} D^{\alpha}_t \Omega(t) = {}^{C}_{t_0} D^{\alpha}_t \Omega(t).$$
(67)

**Theorem 5.** Let f be continuous in  $S_+ = \{(t, y) \mid t_0 < t \le a, \mid y \mid < \infty\}$  such that  $\forall (t, y), (t, \overline{y}) \in S_+$   $i)|f(t, y) - f(t, \overline{y})| \le h(t) \mid y - \overline{y}|,$   $ii)f(t, y) - f(t, \overline{y}) = o(\exp(H(t))),$   $as t \to t_0^+$  uniformly with respect to  $y, \overline{y} \in [-\delta, \delta],$  $\delta > 0$  arbitrary, where h(t) = H'(t) are the same

o > 0 arourary, where h(t) = H(t) are the same as in above. Then the considered equation has almost one solution.

**Proof.** Let  $\overline{y}(t)$  and y(t) be two different solutions, we have that

$$\begin{aligned} |\overline{y}(t) - y(t)| &\leq \frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta - 1} (t - \tau)^{\alpha - 1} \left| \begin{array}{c} f(\tau, \overline{y}(\tau)) \\ -f(\tau, y(\tau)) \end{array} \right| d\tau \\ &\leq \frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta - 1} (t - \tau)^{\alpha - 1} h(\tau) |y - \overline{y}| d\tau, \\ &\leq \frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta - 1} (t - \tau)^{\alpha} h(\tau) |y - \overline{y}| d\tau. \end{aligned}$$

$$(77)$$

In the view of (ii), we have

$$\begin{aligned} |\overline{y}(t) - y(t)| &\leq \varepsilon \frac{\beta \Gamma(\alpha)}{\beta a^{\beta + \alpha} \Gamma(\alpha)} \int_{t_0}^t a^{\beta + \alpha} h(\tau) \exp(H(\tau)) d\tau, \\ &\leq \varepsilon \exp(H(t)). \end{aligned}$$
(78)

The result of the previous lemma leads to

$$\overline{y}(t) = y(t). \tag{79}$$

**Theorem 6.** Let f be continuous in  $\overline{S}_+ = \{(t,y) \mid t_0 < t \leq a, |y| < \infty\}$  such that  $\overline{\beta} \in (1,2]$ ,  $\alpha, \beta \in (0,1], \forall (t,y), (t,\overline{y}) \in \overline{S}_+$ , we have

$$\begin{array}{l} i) \ (f(t,\overline{y}) - f(t,y)) \ (\overline{y} - y) \leq h(t) \ (\overline{y} - y)^{\overline{\beta}} \ ,\\ ii) \ f(t,\overline{y}) - f(t,y) = o \left(h(t) \exp \left(H(t)\right)\right),\\ uniformly \ with \ respect \ to \ y, \overline{y} \ \in \ [-\delta,\delta] \ , \ \delta \ > \ 0\\ arbitrary \ then \end{array}$$

$$\overline{y}(t) = y(t). \tag{80}$$

**Proof.** Let  $\overline{y}$  and  $\underline{y}$  be two solutions, we put  $\Phi(t) = (\overline{y}(t) - y(t))^{\overline{\beta}}$ . We have that at  $t = t_0$ ,  $\Phi(t_0) = 0$  initial condition then we will have that

$${}^{C}_{t_{0}}D^{\alpha}_{t}\Phi(t) = {}^{RL}_{t_{0}}D^{\alpha}_{t}\Phi(t).$$
(81)

However,

$$\begin{split} {}^{FFP}_{t_0} D_t^{\alpha,\beta} \Phi(t) \\ &= \frac{1}{\beta t^{\beta-1}} \, {}^{RL}_{t_0} D_t^{\alpha} \Phi(t) = \frac{1}{\beta t^{\beta-1}} \, {}^{C}_{t_0} D_t^{\alpha} \Phi(t), \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t (t-\tau)^{-\alpha} \, \Phi'(\tau) d\tau, \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t (t-\tau)^{-\alpha} \left[ \overline{\beta} \, (\overline{y} - y)' \, (\overline{y} - y)^{\beta-1} \right] d\tau, \\ &= \frac{1}{\beta t^{\beta-1}} \left[ \begin{array}{c} \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t \overline{\beta} \, (\overline{y})' \, (\overline{y} - y)^{\beta-1} \, (t-\tau)^{-\alpha} \, d\tau \\ &- \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t \overline{\beta} y' \, (\overline{y} - y)^{\beta-1} \, (t-\tau)^{-\alpha} \, d\tau \\ &- \frac{1}{\Gamma(1-\alpha)} \int_{t_0}^t \overline{\beta} y' \, (\overline{y} - y)^{\beta-1} \, (t-\tau)^{-\alpha} \, d\tau \end{array} \right], \\ &\leq \overline{\beta} \Lambda \left( {}^{FFP}_{t_0} D_t^{\alpha,\beta} \overline{y}' \, - {}^{FFP}_{t_0} D_t^{\alpha,\beta} y \right), \\ &\leq \overline{\beta} \Lambda \left| f(t, \overline{y}(t)) - f(t, y(t)) \right|, \\ &\leq \overline{\beta} \Lambda h(t) \, (\overline{y}(t) - y(t))^{\overline{\beta}}. \end{split}$$

$$\tag{82}$$

here

$$\Lambda = \begin{cases} \max_{t \in [t_0,a]} |\overline{y} - y|^{\overline{\beta} - 1}, & \text{if } y' - \overline{y}' > 0, \\ \min_{t \in [t_0,a]} |\overline{y} - y|^{\overline{\beta} - 1}, & \text{if } y' - \overline{y}' < 0. \end{cases}$$

By the hypothesis (i), thus

$$\frac{FFP}{t_0} D_t^{\alpha,\beta} \Phi(t) \le \overline{\beta} \Lambda h(t) \Phi(t), \qquad (83)$$

$$\le \overline{\beta} \overline{\Lambda} h(t) \Phi(t).$$

$$FFP_{t_0} D_t^{\alpha,\beta} \Phi(t) - \overline{\beta} \overline{\Lambda} h(t) \Phi(t) \le 0.$$

$$FFP_{t_0} D_t^{\alpha,\beta} \left[ \exp(-\overline{\beta} H(t)) \Phi(t) \right]$$

$$(84)$$

$$\begin{split} t_{0} &= \mathcal{D}_{t} \quad \left[ \exp\left(-\overline{\beta}H(t)\right) \Gamma(t) \right] \\ &= \frac{1}{\beta t^{\beta-1}} \frac{RL}{t_{0}} D_{t}^{\alpha} \left[ \exp\left(-\overline{\beta}H(t)\right) \Phi(t) \right], \\ &= \frac{1}{\beta t^{\beta-1}} \frac{C}{t_{0}} D_{t}^{\alpha} \left[ \exp\left(-\overline{\beta}H(t)\right) \Phi(t) \right], \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{\Gamma \left(1-\alpha\right)} \int_{t_{0}}^{t} \left(t-\tau\right)^{-\alpha} \left( \exp\left(-\overline{\beta}H(\tau)\right) \Phi(\tau) \right)' d\tau, \\ &= \frac{1}{\beta t^{\beta-1}} \frac{1}{\Gamma \left(1-\alpha\right)} \int_{t_{0}}^{t} \left(t-\tau\right)^{-\alpha} \left[ \begin{array}{c} -\overline{\beta}h(\tau) \Phi(\tau) \\ -\beta \left(\overline{y}-y\right)' \left(\overline{y}-y\right)^{\beta-1} H(\tau) \end{array} \right] d\tau, \\ &= \frac{-1}{\beta t^{\beta-1}} \frac{1}{\Gamma \left(1-\alpha\right)} \int_{t_{0}}^{t} \left(t-\tau\right)^{-\alpha} \left[ \begin{array}{c} \overline{\beta}h(\tau) \Phi(\tau) \\ +\beta \left(\overline{y}-y\right)' \left(\overline{y}-y\right)^{\beta-1} H(\tau) \end{array} \right] d\tau, \\ &\leq 0, \end{split}$$

$$(85)$$

for almost all  $t \in [0, a]$ . This shows that  $\exp(-\overline{\beta}H(t))\Phi(t)$  is non increasing for a small t.

$$\exp(-\overline{\beta}H(t))\Phi(t) = \exp(-\beta H(t)) (\overline{y} - y)^{\overline{\beta}},$$
  
$$= \exp(-\beta H(t))$$
$$\times \left(\frac{\beta}{\Gamma(\alpha)} \int_{t_0}^{t} \tau^{\beta - 1} (t - \tau)^{\alpha - 1} \left| \begin{array}{c} f(\tau, \overline{y}(\tau)) \\ -f(\tau, y(\tau)) \end{array} \right| d\tau \right)^{\overline{\beta}}.$$
  
(86)

In the view of the second hypothesis, we will have that

$$\exp(-\overline{\beta}H(t))\Phi(t) \leq \left(\frac{\beta}{\Gamma(\alpha)}\frac{\Gamma(\alpha)a^{\beta+\alpha}}{\beta a^{\beta+\alpha}}\right)^{\overline{\beta}}\varepsilon^{\overline{\beta}}\exp(\overline{\beta}H(t))\exp(-\overline{\beta}H(t)),$$
$$=\varepsilon^{\overline{\beta}}.$$
(87)

Therefore

$$\exp(-\overline{\beta}H(t))\Phi(t) \le \varepsilon^{\beta}, \qquad (88)$$

$$\lim_{t \to 0^+} \exp(-\beta H(t))\Phi(t) = 0.$$

Therefore

$$\Phi(t) = 0,$$

$$\implies \overline{y}(t) = y(t) \text{ in } [t_0, a].$$

$$\square$$

# 6. The Witte's uniqueness conditions for Fractal-Fractional ordinary differential equations with the Mittag Leffler kernel

In this section, we will consider the following fractal-fractional differential equation

$$\begin{cases} FFM D_t^{\alpha,\beta} y(t) = f(t, y(t)), & \text{if } t > t_0, \\ y(t_0) = y_0, & \text{if } t = t_0. \end{cases}$$
(90)

Assuming the existence of the solution y(t), we shall show that y(t) is unique.

**Lemma 4.** Let  $\Phi(t)$  be a nonnegative continuous in  $[t_0, a]$  and

i) Let h(t) > 0 be a continuous function in  $(t_0, a]$ such that  $1 - zh(t_1) > 0$ ,

$$ii) \quad \Phi(t) \leq (1 - \alpha)t^{\beta - 1}\beta h(t)\Phi(t) + \int_{0}^{t} \int_{0}^{t} dt dt = 0$$

$$\frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0} \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau) \Phi(\tau) d\tau,$$
  
*iii)* and  $\frac{\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau) d\tau,$  exists Then  

$$\Phi(t) = 0.$$
(91)

*in*  $[t_0, a]$ .

**Proof.** Let  $\Phi(t)$  and h(t) satisfy the condition of the theorem, then, we set

$$\Omega(t) = (1-\alpha)t^{\beta-1}\beta h(t)\Phi(t) + \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau)\Phi(\tau)d\tau.$$
(92)

We have from the fundamental theorem of fractalfractional calculus that

$${}^{FFM}_{t_0} D^{\alpha,\beta}_t \left( {}^{FFM}_{t_0} J^{\alpha,\beta}_t f(t) \right) = f(t).$$
(93)

Therefore

$$F^{FM}_{t_0} D_t^{\alpha,\beta} \Omega(t) = t_0^{FFM} D_t^{\alpha,\beta} \left( t_0^{FFM} J_t^{\alpha,\beta} \left( h(t) \Phi(t) \right) \right) = h(t) \Phi(t)$$
(94)

which produces

$$\sum_{t_0}^{FFM} D_t^{\alpha,\beta} \Omega(t) \le h(t) \Omega(t).$$
(95)

Then, we obtain  $\Omega(t)$  as

$$\begin{split} \Omega(t) &\leq (1-\alpha)\beta t^{\beta-1}h(t)\Omega(t) \\ &+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau)\Omega(\tau) d\tau, \\ &\leq (1-\alpha)\beta \left(\bar{t}_0\right)^{\beta-1} h(t_1)\Omega(t) \\ &+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau)\Omega(\tau) d\tau, \end{split}$$

$$\Omega(t) \le \frac{\alpha\beta}{\Gamma(\alpha)\left(1 - zh(t_1)\right)} \int_{t_0}^{s} \tau^{\beta - 1} \left(t - \tau\right)^{\alpha - 1} h(\tau)\Omega(\tau) d\tau$$
(96)

We put

$$\Delta = \frac{\alpha\beta}{\Gamma(\alpha)\left(1 - zh(t_1)\right)}.$$
(97)

By the Gronwall inequality

$$\Omega(t) \le o \exp\left(\Delta \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau) d\tau\right),$$

$$= o \exp\left(\frac{\alpha}{(1-zh(t_1))} \int_{t_0}^{FFM} J_t^{\alpha,\beta} h(t)\right),$$

$$= 0.$$
(98)

 $z = (1 - \alpha)\beta (\bar{t}_0)^{\beta - 1}$ , which is contraction. Therefore

$$\Omega(t) = 0 \Rightarrow \Phi(t) = 0, \tag{99}$$

in 
$$[t_0, a]$$
.

**Lemma 5.** Let  $\Phi(t)$ , h(t) and H(t) be the same like before and  $\Phi(t_0) = 0$ . i)  $\Phi(t) = o\left(\exp\left(t^{\beta}H(t)\right)\right)$  as  $t \to t_0^+$  then

$$\Phi(t) = o\left(\exp\left(t^{\beta}H(t)\right)\right) as t \to t_{0}^{+} then$$
  
$$\Phi(t) = 0, \ \forall t \in [t_{0}, a].$$
(100)

**Proof.** Let  $\Phi(t)$  and h(t) satisfy the condition above, then

$$\begin{split} \Omega(t) &= (1-\alpha)\beta t^{\beta-1}h(t)\Phi(t) \\ &+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} \left(t-\tau\right)^{\alpha-1} h(\tau)\Phi(\tau)d\tau, \end{split}$$

exists

$$_{t_0}^{FFM} D_t^{\alpha,\beta} \Omega(t) \le h(t) \Omega(t).$$
 (101)

$$\begin{split} & \stackrel{FFM}{t_0} D_t^{\alpha,\beta} \left( \Omega(t) \exp\left(-H(t)\right) \right) \\ & = \frac{1}{(1-\alpha)\beta t^{\beta-1}} \frac{d}{dt} \int_{t_0}^t E_\alpha \left( -\frac{\alpha}{1-\alpha} \left(t-\tau\right)^\alpha \right) \Omega(\tau) \exp\left(-H(\tau)\right) d\tau. \end{split}$$
(102)

Since  $\Phi(t_0) = 0$ , we will have  $\Omega(t_0)$  therefore,

whereas from [9], we have that

$$\Omega(\tau) - h(\tau)\Omega(\tau) \le 0. \tag{104}$$

Therefore since  $E_{\alpha}\left(-\frac{\alpha}{1-\alpha}\left(t-\tau\right)^{\alpha}\right) > 0$ , we concluded that

$$\begin{split} & FFM D_{t}^{\alpha,\beta} \left( \Omega(t) \exp\left(-H(t)\right) \right) < 0. \tag{105} \\ & \exp\left(-t^{\beta}H(t)\right) \Omega(t) \\ & = \exp\left(-t^{\beta}H(t)\right) \left[ \begin{array}{c} (1-\alpha)\beta t^{\beta-1}h(t)\Phi(t) \\ + \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_{0}}^{t} \tau^{\beta-1} (t-\tau)^{\alpha-1}h(\tau)\Phi(\tau)d\tau \end{array} \right] \\ & = \exp\left(-t^{\beta}H(t)\right) (1-\alpha)\beta t^{\beta-1}h(t)\Phi(t) \\ & + \frac{\alpha\beta\exp\left(-t^{\beta}H(t)\right)}{\Gamma(\alpha)} \int_{t_{0}}^{t} \tau^{\beta-1} (t-\tau)^{\alpha-1}h(\tau)\Phi(\tau)d\tau, \\ & \leq \exp\left(-t^{\beta}H(t)\right) (1-\alpha)\beta t^{\beta}h(t)\Phi(t) \\ & + \frac{\alpha\beta\exp\left(-t^{\beta}H(t)\right)}{\Gamma(\alpha)} \int_{t_{0}}^{t} \tau^{\beta} (t-\tau)^{\alpha-1}h(\tau)\Phi(\tau)d\tau, \\ & \leq \exp\left(-t^{\beta}H(t)\right) (1-\alpha)\beta t^{\beta}h(t)\Phi(t) \\ & + \frac{\exp\left(-t^{\beta}H(t)\right)}{\Gamma(\alpha)} \int_{t_{0}}^{t} \tau^{\beta} (t-\tau)^{\alpha-1} \left[ \begin{array}{c} \beta\tau^{\beta-1}H(\tau) \\ +\tau^{\beta}h(\tau) \end{array} \right] \end{split}$$

 $\times \exp\left(-\tau^{\beta}H(\tau)\right)d\tau.$ 

(106)

$$\leq \exp\left(-t^{\beta}H(t)\right)(1-\alpha)\varepsilon'\beta t^{\beta}h(t)\exp\left(t^{\beta}H(t)\right) \\ + \frac{\alpha\beta\varepsilon'a^{\alpha}}{\Gamma(\alpha)}\exp\left(t^{\beta}H(t)\right)\exp\left(-t^{\beta}H(t)\right), \\ \leq \varepsilon'\left(\begin{pmatrix}(1-\alpha)\beta a^{\alpha}h(t_{1})\\ +\frac{\alpha\beta a^{\alpha}}{\Gamma(\alpha)}\end{pmatrix}\right), \\ \leq \frac{\varepsilon}{\left((1-\alpha)\beta a^{\alpha}h(t_{1})+\frac{\alpha\beta a^{\alpha}}{\Gamma(\alpha)}\right)}\left(\begin{pmatrix}(1-\alpha)\beta a^{\alpha}h(t_{1})\\ +\frac{\alpha\beta a^{\alpha}}{\Gamma(\alpha)}\end{pmatrix}\right) \\ \leq \varepsilon.$$
(107)

Therefore

$$\lim_{t \to t_0^+} \exp\left(-t^\beta H(t)\right) \Omega(t) = 0.$$
 (108)

Thus

$$\exp\left(-t^{\beta}H(t)\right)\Omega(t) \le 0 \text{ for } t > t_0, \qquad (109)$$

which implies

$$(1-\alpha)\beta t^{\beta-1}h(t)\Phi(t)$$

$$+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau)\Phi(\tau)d\tau,$$

$$\leq 0.$$
(110)

contradiction, thus

$$\Phi(t) = 0. \tag{111}$$

**Theorem 7.** Let f(t, y(t)) be as presented before and  $exp(t^{\beta}H(t))$  as  $t \to t_0^+$  uniformly with respect to  $y, \overline{y} \in [-\delta, \delta], \delta > 0$  arbitrary h(t) and H(t) are the same as previously. Then equation (92) has a unique solution.

**Proof.** Let y(t) and  $\overline{y}(t)$  be solutions of equation (92).

$$\begin{aligned} |y(t) - \overline{y}(t)| &\leq (1 - \alpha)\beta t^{\beta - 1} \left| f\left(t, y(t)\right) - f\left(t, \overline{y}(t)\right) \right| \\ &+ \frac{\alpha\beta}{\Gamma\left(\alpha\right)} \int_{t_0}^t \tau^{\beta - 1} \left(t - \tau\right)^{\alpha - 1} \left| f\left(\tau, y(\tau)\right) - f\left(\tau, \overline{y}(\tau)\right) \right| d\tau, \\ &\leq (1 - \alpha)\beta t^{\beta - 1} \left| f\left(t, y(t)\right) - f\left(t, \overline{y}(t)\right) \right| \\ &+ \frac{\beta}{\Gamma\left(\alpha\right)} \int_{t_0}^t \tau^{\beta - 1} \left(t - \tau\right)^{\alpha - 1} h\left(\tau\right) \left| y - \overline{y} \right| d\tau, \\ &\leq (1 - \alpha)\beta t^{\beta - 1} \left| f\left(t, y(t)\right) - f\left(t, \overline{y}(t)\right) \right| \\ &+ \frac{\beta}{\Gamma\left(\alpha\right)} \int_{t_0}^t \tau^{\beta - 1} \left(t - \tau\right)^{\alpha} h\left(\tau\right) \left| y - \overline{y} \right| d\tau. \end{aligned}$$

$$(112)$$

In the view (i)

In the view of (i), we get

$$\begin{split} |y(t) - \overline{y}(t)| &\leq (1 - \alpha)\beta t^{\beta - 1}h(t) |y(t) - \overline{y}(t)| \\ &+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta - 1} (t - \tau)^{\alpha - 1} h(\tau) |y(\tau) - \overline{y}(\tau)| d\tau, \\ &\leq (1 - \alpha)\beta t^{\beta - 1}h(t) |y(t) - \overline{y}(t)| \\ &+ \frac{\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta} (t - \tau)^{\alpha} h(\tau) |y(\tau) - \overline{y}(\tau)| d\tau, \\ &\leq (1 - \alpha)\beta \varepsilon' h(t) t^{\beta} \exp\left(t^{\beta} H(t)\right) \\ &+ \frac{\alpha\beta\varepsilon'}{\Gamma(\alpha)} \int_{t_0}^t a^{\alpha}\tau^{\beta} h(\tau) \exp\left(\tau^{\beta} H(\tau)\right) d\tau. \end{split}$$
(113)  
$$\begin{aligned} &|y(t) - \overline{y}(t)| \leq (1 - \alpha)\beta\varepsilon' h(t) a^{\beta} \exp\left(t^{\beta} H(t)\right) \\ &+ \frac{\alpha\beta\varepsilon' a^{\alpha}}{\Gamma(\alpha)} \int_{t_0}^t \left(\tau^{\beta} h(\tau) + \beta\tau^{\beta - 1} H(\tau)\right) \exp\left(\tau^{\beta} H(\tau)\right) d\tau, \\ &\leq \left((1 - \alpha)\beta\varepsilon' h(t) a^{\beta} + \frac{\alpha\beta\varepsilon' a^{\alpha}}{\Gamma(\alpha)}\right) \exp\left(t^{\beta} H(t)\right), \\ &\leq \left((1 - \alpha)\beta\varepsilon' h(t) a^{\beta} + \frac{\alpha\beta\varepsilon' a^{\alpha}}{\Gamma(\alpha)}\right) \exp\left(t^{\beta} H(t)\right), \\ &\leq \frac{\varepsilon\left((1 - \alpha)\beta h(t_1) a^{\beta} + \frac{\alpha\beta\alpha}{\Gamma(\alpha)}\right)}{\left((1 - \alpha)\beta h(t_1) a^{\beta} + \frac{\alpha\beta\alpha}{\Gamma(\alpha)}\right)} \exp\left(t^{\beta} H(t)\right), \end{split}$$

$$\frac{\frac{\alpha\beta a^{\alpha}}{\Gamma(\alpha)}}{\Gamma(\alpha)} \exp\left(t^{\beta}H(t)\right),$$
(114)

From the above Lemma

 $\leq \varepsilon \exp\left(t^\beta H(t)\right).$ 

$$y(t) - \overline{y}(t) = 0. \tag{115}$$

**Corollary 2.** Let the condition in above theorem hold, then

i) 
$$(f(t,y) - f(t,\overline{y})) (y - \overline{y}) \leq h(t) (y - \overline{y})^{\beta},$$
  
 $\forall (t,\overline{y}), (t,y) \in S_{+}, \ \beta \in (1,2].$   
ii)  $h(t_{1}) = \max_{t \in (t_{0},a)} h(t),$ 

$$\begin{aligned} 1 &- \overline{\beta} (1-\alpha) \beta \left( \overline{t}_0 \right)^{\beta-1} \Lambda > 0, \\ \text{iii)} \ {}_{t_0}^{FFM} J_t^{\alpha,\beta} h(t) \ exists. \end{aligned}$$

**Proof.** Let y(t) and  $\overline{y}(t)$  be two solutions of equation (92) then, let set  $\overline{\Omega}(t_0) = 0$  then we get

$$\begin{split} {}^{FFM}_{t_0} D^{\alpha,\beta}_t \overline{\Omega}(t) &= \frac{1}{\beta t^{\beta-1}} \, {}^{ABC}_{t_0} D^{\alpha}_t \overline{\Omega}(t), \\ &= \frac{1}{\beta t^{\beta-1} (1-\alpha)} \int_{t_0}^t E_\alpha \left( -\frac{\alpha}{1-\alpha} \left( t-\tau \right)^\alpha \right) \overline{\Omega}' d\tau \\ &= \frac{1}{\beta t^{\beta-1} (1-\alpha)} \int_{t_0}^t E_\alpha \left( -\frac{\alpha}{1-\alpha} \left( t-\tau \right)^\alpha \right) \\ &\times \left[ \overline{\beta} \left( y-\overline{y} \right)^{\overline{\beta}} \left( y-\overline{y} \right)' \right] d\tau. \end{split}$$
(116)

Let  $m = \min_{\overline{t} \in [t_0, t]} |y - \overline{y}|^{\beta - 1}, \quad M = \max_{\overline{t} \in [t_0, t]} |y(\overline{t}) - \overline{y}(\overline{t})|.$  We define

$$\Lambda = \begin{cases} m, & \text{if } y' - \overline{y}' < 0, \\ M, & \text{if } y' - \overline{y}' > 0. \end{cases}$$
(117)

Therefore

$$\begin{aligned}
& F^{FM}_{t_0} D^{\alpha,\beta}_t \overline{\Omega}(t) \leq \frac{\overline{\beta}\Lambda}{\beta t^{\beta-1} (1-\alpha)} \int_{t_0}^t E_\alpha \left( -\frac{\alpha}{1-\alpha} (t-\tau)^\alpha \right) (y-\overline{y})' \, d\tau, \\
& \leq \overline{\beta}\Lambda \left( \int_{t_0}^{FFM} D^{\alpha,\beta}_t y(t) - \int_{t_0}^{FFM} D^{\alpha,\beta}_t \overline{y}(t) \right), \\
& \leq \overline{\beta}\Lambda \left( f(t,y) - f(t,\overline{y}) \right), \\
& \leq \overline{\beta}\Lambda h(t) \left( y - \overline{y} \right)^{\overline{\beta}}.
\end{aligned}$$
(118)

$$\begin{array}{l}
\overset{RL}{t_0} D_t^{\alpha} \overline{\Omega}(t) = \overline{\beta} \Lambda \beta t^{\beta - 1}, \quad (119) \\
\leq \overline{\beta} \Lambda h(t) \overline{\Omega}(t), \\
\overset{ABR}{t_0} D_t^{\alpha} \overline{\Omega}(t) \leq \beta t^{\beta - 1} \Lambda h(t) \overline{\Omega}(t) \overline{\beta}.
\end{array}$$

$$\overline{\Omega}(t) \leq \overline{\beta}(1-\alpha)\beta t^{\beta-1}\Lambda h(t)\overline{\Omega}(t)$$

$$+ \frac{\alpha\beta\overline{\beta}}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1}\Lambda h(\tau)\overline{\Omega}(\tau)d\tau,$$

$$\leq \overline{\beta}(1-\alpha)\beta(\overline{t_0})^{\beta-1}\Lambda h(t_1)\overline{\Omega}(t)$$

$$+ \frac{\Lambda\alpha\beta\overline{\beta}}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1}h(\tau)\overline{\Omega}(\tau)d\tau.$$
(120)

If we take as

\_\_\_\_\_

$$A = \frac{\Lambda \overline{\beta}}{1 - \overline{\beta} (1 - \alpha) \beta (\overline{t}_0)^{\beta - 1} \Lambda},$$
 (121)

$$\overline{\Omega}(t) \le \frac{A\alpha\beta}{\Gamma(\alpha)} \int_{t_0}^t \tau^{\beta-1} (t-\tau)^{\alpha-1} h(\tau)\overline{\Omega}(\tau) d\tau.$$
(122)

By the Gronwall inequality we set

$$\overline{\Omega}(t) \le o \exp\left(A_{t_0}^{FFP} J_t^{\alpha,\beta} h(t)\right), \qquad (123)$$
  
$$\overline{\Omega}(t) \le 0.$$

Therefore we have  $\overline{\Omega}(t) \leq 0$  which is a contraction therefore

$$\overline{\Omega}(t) = 0 \Rightarrow y(t) = \overline{y}(t), \ \forall t \in [t_0, a].$$
(124)

# 7. Conclusion

Witte provided a set of conditions under which a given nonlinear ordinary differential equation admits unique solutions. This was established when the differential operator was in integer order. Based on the framework of Witte, we have presented a detailed analysis of the uniqueness of nonlinear ordinary differential equations with fractal-fractional derivatives.

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RESEARCH ARTICLE

# Influence of rotation on peristaltic flow for pseudoplastic fluid: a wavy channel

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#### ARTICLE INFO

#### ABSTRACT

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The phenomenon of rotation serves multiple purposes in cosmic and geophysical phenomena. It offers insights into the formation of galaxies and the circulation patterns of oceans. Moreover, rotational diffusion elucidates the orientation of nanoparticles within fluid mediums. Investigating the dynamics of fluid peristalsis under the influence of rotational forces holds significant relevance in addressing challenges associated with the transportation of conductive physiological fluids such as blood, polymeric materials, and saline water. This study focused on studying the impact of rotation on the peristaltic transport of non-Newtonian pseudoplastic fluids through a wavy channel. The complexity of flow equations, including the continuity and motion equations, is mathematically formulated and transformed into dimensionless nonlinear ordinary differential equations depending on the assumption of low Reynolds number and long wavelength approximation. Perturbation technique is employed to solve the problem for the stream function and the resulted system is implemented and plotted using MATHEMATICA software along with the boundary conditions. Graphical discussion is involved to utilize the impact of the emerging parameters in the flow characteristic, encompassing the velocity profile, pressure gradient, pressure rise, and trapping phenomenon. The research revealed that rotation significantly influences the fluid flow within the channel, diminishing the regressive and inhibitory impact of the fluid parameter, consequently enhancing the fluid flow within the channel.

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# 1. Introduction

Extensive research has been conducted on peristaltic motion in recent years due to the fact that it involves the study of wave-like motion in physiological fluids resulting from interaction with surrounding boundaries. Such phenomena are evident during the process of food ingestion through the esophagus, the propagation of lymphocytes within the lymphatic system, the circulation of blood through vessels, the movement of urine toward the bladder, and numerous other instances that collectively contribute to our understanding of peristalsis. Moreover, peristaltic transport has wide applications in medical engineering, science, and modern industry, such as aggressive chemicals, high solid slurries, noxious fluids (nuclear industries), heart-lung machines, blood pump machines, and dialysis machines [1–4]. The initial effort to elucidate this phenomenon was attributed to [5]. Subsequent to this progress, numerous studies, delving into the exploration of peristaltic flow of various fluid types under diverse influencing factors, were illustrated by many researchers. [6] discussed the impact of long wavelengths and the low Reynolds number assumption on peristaltic pumping. [7] determined the impact

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of the elastic wall of a hollow cylinder's channel of Jeffrey's fluid by peristaltic flow. [8] studied the heat transfer analysis of magnetohydrodynamic (MHD) peristaltic transport of Jeffrey fluid in an inclined tapered asymmetric channel. For more information, see [9–13].

Non-Newtonian fluids, including molten plastics, artificial fibers, polymeric materials, foodstuffs, blood, slurries, and synovial liquids, exhibit shear-stress-strain relationships that diverge significantly from the traditional viscous model, finding numerous applications in manufacturing and commerce [14–17]. Significant literature exists on the study of peristaltic motion in the presence of non-Newtonian fluids. Many of these types of fluids exhibit characteristics of shearthinning yield stress materials [18], such as pseudoplastic fluid which is found in blood plasma, latex paint, polymer solutions, and similar solutions of high molecular weight substances. At low shear rates, these fluids experience the formation of shear stress that results in the reordering of the molecules to reduce the overall stress. [9] analyzed the impact of Soret and Dufour on the peristaltic flow of magnetohydrodynamic (MHD) pseudoplastic nanofluid in a tapered asymmetric channel. The impact of pseudoplasticity and dilatancy of fluid on the peristaltic flow of non-Newtonian fluid in a non-uniform asymmetric channel was investigated [19]. In 2014, [20] studied the impact of wall properties and slip conditions on the peristaltic flow of pseudoplastic fluid in a curved channel. An effect of magnetohydrodynamic (MHD) and thermal radiation on the peristaltic flow of a pseudoplastic nanofluid through a porous medium asymmetric canal with convection boundary conditions was depicted by [21].

A rotational phenomenon plays a pivotal role in various cosmic and geophysical phenomena. It aids in comprehending the emergence of galaxies and the circulation of oceans. Nanoparticles' orientation in fluids is attributed to rotational diffusion. Moreover, rotation is noteworthy in specific flow scenarios within physiological fluids like saline water and blood. This synergy of rotation facilitates the movement of biological fluids within the intestines, ureters, and arterioles. Several studies focused on the rotational system's impact on the peristaltic flow of various fluids. [22] analyzed the flow of non-Newtonian fluid with a porous medium under the effect of rotation and magnetic force. [23] was concerned with the peristaltic flow of a Jeffrey fluid in an asymmetric rotating channel. [24] illustrated the influence of magnetic force, rotation, and nonlinear heat radiation on the peristaltic transport of hybrid bio-nanofluids through a symmetric channel. [25] investigated the peristaltic flow of Bingham plastic fluid under the effect of rotation and induced magnetic field. For more information, see Refs. [26–30].

Lately, there has been a lack of attention given to studying peristaltic flows under conditions where both the fluid and the channel experience solid body rotation, i.e., the entire system, comprising both the fluid and the channel, is situated within a rotating frame characterized by a consistent angular velocity. The aforementioned studies have primarily focused on peristaltic flows involving different non-Newtonian fluids, addressing rotational effects. Nevertheless, there remains a gap in the previous literature concerning the impact of the rotation frame on the peristaltic transport of pseudoplastic fluids. In this study, We extended the inquiry delineated in [19] by elucidating the physical alterations observed in our fluid during the flow, which experiences a reduction in viscosity as the shear rate increases during rotation. As a consequence, its velocity increases, which finds application in various contexts such as in blood apheresis machine and water treatment. In this article, physical modeling governing the equation of peristaltic flow of pseudoplastic under the effect of rotation is described and reduced to the differential equation by using long wavelength and low Reynolds number assumptions. The closed-form analytic solution for the stream function and fluid velocity is provided. Subsequently, a graphical analysis is conducted using codes from the Mathematica package to illustrate the impact of key parameters on flow characteristics.

#### 2. Mathematical model of the problem

Assuming the incompressible peristaltic motion of a non-Newtonian, electrically conducting, pseudoplastic fluid through a two-dimensional asymmetric a wavy channel of width 2 d in which the channel rotates about the horizontal with uniform angular velocity  $\Omega$  see Fig. 1. The induced sinusoidal propagation waves of wavelength  $\lambda$  are advancing with a constant speed c in the  $\overline{X}$  - axis, and the  $\overline{Y}$ -axis is normal to it.

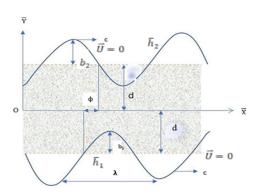


Figure 1. Geometry of problem

The mathematical equations for the channel walls are provided as follows [25]:

$$\bar{Y} = \bar{h}_1(\bar{X}, \bar{t}) = d + b_1 \operatorname{Sin}\left(\frac{2\pi}{\lambda}(\bar{X} - c\bar{t})\right), \quad (1)$$
$$\bar{Y} = \bar{h}_2(\bar{X}, \bar{t}) = -d - b_2 \operatorname{Sin}\left(\frac{2\pi}{\lambda}(\bar{X} - c\bar{t}) + \phi\right). \quad (2)$$

where  $\bar{h}_1$  and  $\bar{h}_2$  are the lower and upper walls respectively,  $b_1$  and  $b_2$  denote the waves' amplitudes,  $\bar{t}$  stands for time,  $\phi \in [0, \pi]$  and represents the phase difference. When  $\phi = 0$ , it indicates waves out of phase for a symmetric channel, and when  $\phi = \pi$  the waves are in phase. Additionally, the values of  $d, b_1, b_2$  and  $\phi$  satisfy the inequity.

$$b_1^2 + b_2^2 + b_1 b_2 \operatorname{Cos} \phi \le (d)^2,$$
 (3)

The governing equations for an incompressible fluid in the fixed frame are formulated as follows: The continuity equation is:

$$\nabla . \vec{V} = 0, \tag{4}$$

The motion equation is:

$$\rho \left( \frac{\partial \vec{V}}{\partial \bar{t}} + (\vec{V} \cdot \nabla) \vec{V} \right) + \rho [\Omega \times (\Omega \times \vec{V}) + 2\Omega \times \vec{V}] \\
= -\nabla \bar{P} + \nabla \cdot \bar{S},$$
(5)

Associated with the no- slip boundary condition bellows:

$$\dot{U} = 0 \text{ at } h_1 \text{ and } h_2. \tag{6}$$

In which  $\vec{V} = (\bar{U}, \bar{V})$  is the fluid velocity vector in  $\bar{X}$  and  $\bar{Y}$  coordinates respectively,  $\rho, \bar{P}$  are the fluid density and the pressure,  $\vec{\nabla} = \left(\frac{\partial}{\partial \bar{X}}, \frac{\partial}{\partial \bar{Y}}\right)$  is the gradient vector,  $\rho(\Omega \times (\Omega \times \vec{V}))$  denotes the centrifugal force while the term  $\rho(2\Omega \times \vec{V})$  refers to the Coriolis force,  $\bar{S}$  is the Cauchy stress tensor for pseudoplastic fluid which defined as [9,19]:

$$\bar{S} + \lambda^*{}_1 \left( \frac{\partial \bar{S}}{\partial \bar{t}} - \nabla \overrightarrow{V} \cdot \bar{S} - \bar{S} \cdot (\nabla \vec{V})^T \right) + \frac{1}{2} \left( \lambda^*{}_1 - \mu^*{}_1 \right) \left( \check{A}_1 \bar{S} + \bar{S} \check{A}_1 \right) = \mu \check{A}_1, \tag{7}$$

$$\check{A}_1 = \nabla \vec{V} + (\nabla \vec{V})^T.$$
(8)

where  $\mu$  is the fluid viscosity,  $\lambda_1^*, \mu^*_1$  are the relaxation times,  $\breve{A}_1$  is the first Rivlin- Ericksen tensor. Consider the wave frame  $(\bar{x}, \bar{y})$  traveling with speed *c* away from the laboratory frame. The transformation of coordinates and flow properties between fixed and wave frame is given by:

$$\bar{x} = \bar{X} - c\bar{t}, \bar{y} = \bar{Y}, \bar{u} = \bar{U} - c, \bar{v} = \bar{V}, \bar{p}(\bar{x}) = \bar{p}(\bar{X}, \bar{t}).$$

$$\tag{9}$$

Now, defining the dimensionless parameters and variables in the following manner.

$$x = \frac{\bar{x}}{\lambda}, y = \frac{\bar{y}}{d}, u = \frac{\bar{u}}{c}, v = \frac{\bar{v}}{c}, h_1 = \frac{H_1(X)}{d},$$
$$h_2 = \frac{\bar{H}_2(X)}{d}, d = \frac{d_2}{d_1}, \delta = \frac{d}{\lambda}, a = \frac{b_1}{d}, b = \frac{b_2}{d},$$
$$\lambda_1 = \frac{c\lambda_1^*}{d}, p = \frac{d^2\bar{p}}{\lambda\mu c}, Re = \frac{\rho cd}{\mu}, s_{ij} = \frac{d}{\mu c}\bar{S}_{ij},$$
$$\mu_1 = \frac{c\mu_1^*}{d}, \Omega = \frac{b_1^2\bar{\Omega}}{\mu}, Ta = \frac{\Omega dRe}{c}.$$
(10)

where Re and  $\delta$  are the Reynolds number and the dimensionless number of waves respectively. Introducing the dimensionless stream function  $\psi(x, y)$ , in which,

$$u = \frac{\partial \psi}{\partial y}, v = -\delta \frac{\partial \psi}{\partial x}.$$
 (11)

The continuity equation is identically achieved. By substituting Eq. (9) and Eq. (10) into Eqs. (2 - 7), we get:

$$\operatorname{Re} \delta \left( (u+1)\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} \right) - 2\operatorname{Ta}(u+1) = -\frac{\partial p}{\partial x} + \delta \frac{\partial s_{xx}}{\partial x} + \frac{\partial s_{xy}}{\partial y}, \qquad (12)$$

$$\operatorname{Re} \delta^{2} \left( (u+1) \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} \right) - 2 \operatorname{Ta} \delta v = -\frac{\partial p}{\partial y} + \delta \frac{\partial s_{yy}}{\partial y} + \delta^{2} \frac{\partial s_{yx}}{\partial x} - \frac{1}{\kappa} \delta^{2} v,$$
(13)

$$s_{xx} + \lambda_1 \left( \delta \left( u \frac{\partial s_{xx}}{\partial x} + v \frac{\partial s_{xx}}{\partial y} \right) - 2\delta s_{xx} \frac{\partial u}{\partial x} - 2s_{xy} \frac{\partial u}{\partial y} \right) + \frac{1}{2} \left( \lambda_1 - \mu_1 \right) \left( 2s_{xy} \left( \frac{\partial u}{\partial y} + \delta^2 \frac{\partial v}{\partial x} \right) + 4\delta s_{xx} \frac{\partial u}{\partial x} \right) = 2\delta \frac{\partial u}{\partial y}, \tag{14}$$

$$s_{xy} + \lambda_1 \left( \delta \left( u \frac{\partial s_{xy}}{\partial x} + v \frac{\partial s_{xy}}{\partial y} \right) - \delta^2 s_{xx} \frac{\partial v}{\partial x} - s_{yy} \frac{\partial u}{\partial y} \right) + \frac{1}{2} \left( \lambda_1 - \mu_1 \right) \left( s_{xx} + s_{yy} \right) \left( \frac{\partial u}{\partial y} + \delta^2 \frac{\partial v}{\partial x} \right) = \frac{\partial u}{\partial y} + \delta^2 \frac{\partial v}{\partial x^2}, \tag{15}$$

$$s_{yy} + \lambda_1 \left( \delta \left( u \frac{\partial s_{yy}}{\partial x} + v \frac{\partial s_{yy}}{\partial y} \right) - 2 \delta s_{xx} \frac{\partial v}{\partial y} + 2 \delta^2 s_{xy} \frac{\partial v}{\partial x} \right) + \frac{1}{2} \left( \lambda_1 - \mu_1 \right) \left( 2 s_{xy} \left( \frac{\partial u}{\partial y} + \delta^2 \frac{\partial v}{\partial y} \right) + 4 \delta s_{yy} \frac{\partial v}{\partial y} \right) = 2 \delta \frac{\partial v}{\partial y}.$$
(16)

Employing Eq. (11) and assuming a low Reynolds number and a large wavelength approximation (  $\delta \ll 1$ ), Eqs. (12 - 16) are reduced as follows:

$$\frac{\partial p}{\partial x} = \frac{\psi_{yy}}{\left(1 + \xi \left(\psi_{yy}\right)^2\right)} + 2Ta\left(\frac{\partial \psi}{\partial y} + 1\right), \quad (17)$$

$$\frac{\partial p}{\partial y} = 0. \tag{18}$$

Through Eq. (18), we conclude that pressure is not a function of y, i.e.,  $P \neq P(y)$ . Neglecting pressure from Eq. (17), we get:

$$\psi_{yyyy} + 3\xi (\psi_{yy})^2 \psi_{yyyy} + 6\xi (\psi_{yyy})^2 \psi_{yy} + 2 \operatorname{Ta} \psi_{yy} = 0,$$
(19)

$$s_{xx} = (\lambda_1 + \mu_1) \frac{(\psi_{yy})^2}{\left(1 + \xi \left(\psi_{yy}\right)^2\right)^2},$$
 (20)

$$s_{xy} = \frac{\psi_{yy}}{\left(1 + \xi \left(\psi_{yy}\right)^2\right)},\tag{21}$$

$$s_{yy} = -(\lambda_1 - \mu_1) \frac{(\psi_{yy})^2}{\left(1 + \xi (\psi_{yy})^2\right)^2}.$$
 (22)

Linked to the subsequent dimensionless boundary condition.

$$\psi = -\frac{F}{2}, \psi_y = 0 \text{ at } y = h_1(x),$$
 (23)

$$\psi = \frac{F}{2}, \psi_y = 0 \text{ at } y = h_2(x).$$
 (24)

where  $h_1(x) = 1 + a \operatorname{Sin}(2\pi x)$  and  $h_2(x) = 1 + b \operatorname{Sin}(2\pi x + \Phi)$ . where  $\xi = (\lambda^2 - \mu^2)$  is the Basedonlectic fluid particular

where  $\xi = (\lambda_1^2 - \mu_1^2)$  is the Pseudoplastic fluid parameter.

= The parameter F refers to the dimensionless mean flows and it is given by:

$$F = \int_{h_1}^{h_2} u(x, y) dy = \int_{h_1}^{h_2} \frac{\partial \psi}{\partial y} dy = \psi(h_2) - \psi(h_1),$$
(25)

Additionally, the connection between F and the nondimensional mean flows in the moving frame,  $\theta$ , can be derived as:

$$F = \theta + a \operatorname{Sin}(2\pi x + \Phi) + b \operatorname{Sin}(2\pi x).$$
 (26)

The pressure rise per unit wavelength is:

$$\Delta p = \int_0^1 \frac{dp}{dx} dx. \tag{27}$$

#### 3. Solution of the problem

Eq. (19) poses a complex nonlinear differential challenge, rendering an exact solution unattainable. In the field of fluid science, various techniques [31–37] are available to find the desired solution. Therefore, we turn to perturbation technique to calculate series solutions when dealing with a small parameter. Consequently, we applied perturbation to stream function  $\psi$  and dimensionless mean flow F, considering them up to the first order with respect to the Pseudoplastic fluid parameter  $\xi$  as:

$$\psi = \psi_0 + \xi \psi_1 + O\left(\xi^2\right), \qquad (28)$$

$$F = F_0 + \xi F_1 + O\left(\xi^2\right).$$
 (29)

#### 3.1. Zeroth order system

$$\psi_{0yyyy} + 2Ta\psi_{0yy} = 0, \tag{30}$$

With the boundary conditions.

$$\psi_0 = -\frac{F_0}{2}, \psi_{0y} = 0, \text{ at } y = h_1(x),$$
 (31)

$$\psi_0 = \frac{F_0}{2}, \psi_{0y} = 0 \text{ at } y = h_2(x).$$
 (32)

where

$$F_0 = \theta + a\operatorname{Sin}(2\pi x + \Phi) + b\operatorname{Sin}(2\pi x).$$
(33)

# 3.2. First order system

$$\psi_{1yyyy} + 3 (\psi_{0yy})^2 \psi_{0yyyy} + 6 (\psi_{0yyy})^2 \psi_{0yy} + 2Ta\psi_{1yy} = 0, \qquad (34)$$

With the following boundary conditions.

$$\psi_1 = -\frac{F_1}{2}, \psi_{1y} = 0, \text{ at } y = h_1(x),$$
 (35)

$$\psi_1 = \frac{F_1}{2}, \psi_{1y} = 0, \text{ at } y = h_2(x).$$
 (36)

Solving the two resulting systems by writing suitable codes in Mathematica software, the explicit expression of stream functions  $\psi_0$  and  $\psi_1$  obtained.

$$\psi_0(x,y) = \frac{e^{-\sqrt{A}y} \left(e^{2\sqrt{A}y} c_1 + c_2\right)}{A} + c_3 + yc_4,$$
(37)

$$\psi_{1}(x,y) = c_{7} + yc_{8} + \frac{1}{8A}e^{-3\sqrt{A}y} \left(-c_{2}^{3} + 30c_{1}c_{2}^{2}e^{2\sqrt{A}y} + 30c_{1}^{2}c_{2}e^{4\sqrt{A}y} - c_{1}^{3}e^{6\sqrt{A}y} + 8e^{4\sqrt{A}y}c_{5} + 8e^{2\sqrt{A}y}c_{6} - 6c_{1}c_{2}e^{2\sqrt{A}y} \left(-c_{2} + c_{1}e^{2\sqrt{A}y}\right)\log\left(e^{2\sqrt{A}y}\right)\right).$$
(38)

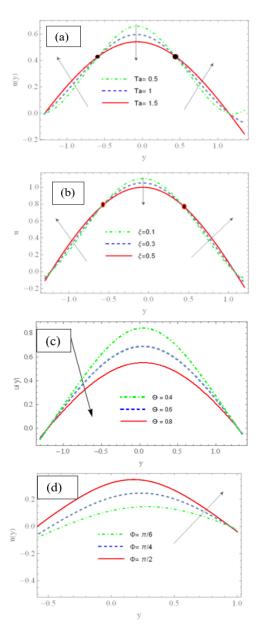
where A = -2Ta, and the coefficients  $c_1, c_2, c_3, c_4, c_5, c_6, c_7$  and  $c_8$  consist of complex expressions that will not be detailed here.

#### 4. Results analysis and discussion

In this section, we examine the outcomes of different physical parameters by utilizing the visual representations provided. The analysis includes the variation in the velocity profile, the gradient of pressure, the pressure rise and the trapping phenomenon as a result of the increase in the values of the rotation parameter Ta, the pseudoplastic fluid parameter  $\xi$ , the non- dimensional mean flows  $\theta$ , the phase difference parameter  $\Phi$ , the lower wall amplitude parameter a, and upper wall amplitude parameter b.

# 4.1. Velocity profile

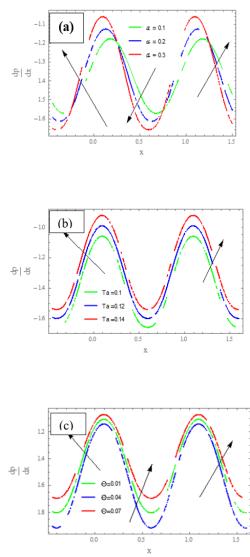
Figs. 2(a)-(d) illustrate a consistent pattern where the maximum velocity is consistently near the center of the channel, and all velocity profiles exhibit a parabolic shape. Figs. 2(a) and 2(b) depict a decrease in velocity profile at the central part of the channel whereas an increasing effect is noticed toward the boundaries, as well as inflection points appearing via ascending values of Ta and  $\xi$ . This outcome arises from the physical phenomenon wherein viscosity decreases as shear rate escalates during rotational motion. As a consequence, its velocity increases. It's worth noting from Fig. 2(c) that as  $\theta$  enlarges, the fluid velocity reduces. However, an opposite reaction on velocity profile is observed from Fig. 2(d), that means as the phase difference between waves increases ( $\Phi$ ), the axial velocity increases across the entire range of the y-axis.



profile Figure **2.** Velocity for ascending values of (a) rotation parameter (b) Pseudoplastic parameter (c) nondimensional mean flows parameter (d) phase difference parameter fixed and b = 0.3, a = 0.6, x = 0.5, t = 0.2.

## 4.2. Gradient of pressure

Figs. 3(a)-(d) record the fluctuations in the axial pressure gradient (dp/dx), exhibiting sinusoidal behavior across the entire x-axis range when it is analyzed under the impact of increasing values of the lower wall wave amplitude a, the rotation parameter Ta, non- dimensional mean flows  $\theta$ , and the Pseudoplastic fluid parameter  $\xi$ . It is noticed from Fig. 3(a) The observed elevation in the magnitude of the pressure gradient towards the central region of the channel compared to its boundaries is attributed to the augmentation of a, leading to an expansion in the dimensions of the channel wall. While from Figs. 3(b) and 3(c), we conclude that the rate of change for (dp/dx) with respect to Ta and  $\theta$  means the flow can smoothly pass without requiring a significant pressure gradient. Fig. 3(d) illustrated that as  $\xi$  increases, a reversal in the situation is depicted, as this parameter inversely correlates with the velocity of the fluid. Consequently, a notable pressure gradient is necessitated to ensure fluid flow remains smooth.



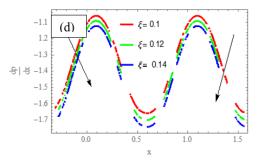
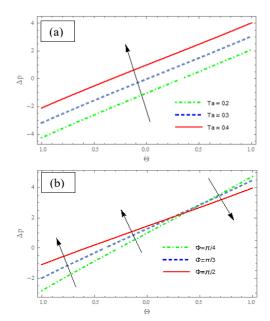


Figure 3. Pressure gradient profile for ascending values of (a) low wall amplitude parameter (b) rotation parameter (c) non- dimensional mean flows parameter (d) Pseudoplastic parameter and fixed b = 0.3, a = 0.6, x = 0.5, t = 0.2.

#### 4.3. Pressure rise profile

Figs. 4(a)-(d) elucidate the behavior of nondimensional pressure rise  $\Delta p$  versus the dimensionless mean flow rate  $\theta$  through plotting  $\Delta p$  profile with various values of the rotation parameter Ta, the phase difference parameter  $\Phi$ , the lower wall amplitude a, and the upper wall amplitude b. It is clear from Fig. 4(a) that the pumping rate  $\Delta p$ is enlarged in the whole region as the value of Ta is increased. Whereas the impact of enhancing  $\Phi$  and a on pumping rate anticipated in Figs. 4(b) and 4(c). The plots recorded a decay in peristaltic pumping region with  $(\theta > 0, \Delta p > 0)$  while an increment impact is noticed in the retrograde pumping area ( $\theta < 0, \Delta p > 0$ ) and no flow area  $(\theta < 0, \Delta p < 0)$ . The opposite scene is depicted with an increasing b, that means the peristaltic pumping region is enhanced while the retrograde pumping and no flow areas are dampened, see Fig. 4(d).



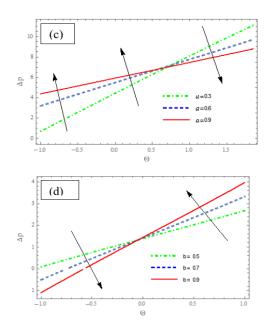


Figure 4. Pressure rise profile for ascending values of (a) rotation parameter (b) phase difference parameter (c) lower wall amplitude parameter (d) upper wall amplitude parameter (d) and fixed  $\{\xi = 0.3, \theta = 0.6, x = 0.5, t = 0.2\}$ .

#### 4.4. Trapping phenomenon

Streamlines depict the paths followed by fluid particles within a flow. The creation of an enclosed, circulating mass of fluid due to the closed streamlines is referred to as trapping phenomenon. Figs. 5-8 are sketched to elucidate the influence of the rotation parameter Ta, the nondimensional mean flow parameter  $\theta$ , the Pseudoplastic fluid parameter  $\xi$ , and the phase difference parameter  $\Phi$  on the absolute value of stream function  $|\psi|$ . Moreover, we noticed from the graphs that the trapped bolus is composed and focused near the channel's walls. Figs. 5 and 6 illustrate that as the Ta and  $\theta$  values increase, the trapped bolus size increases. This outcome correlates with the observation that an increase in these parameters leads to a rise in the flow rate, thereby resulting in the generation of more streamlines and boluses. Figs. 7 and 8 reveal a decrease in the size and number of the trapped bolus as the magnitude of  $\xi$  and  $\Phi$  are enlarged. This result aligns well with findings from previous studies conducted by [9] and [19].

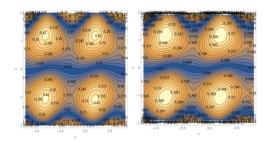


Figure 5. Stream lines for ascending values of rotation parameter  $\{Ta = 0.1, Ta = 0.3\}$ .

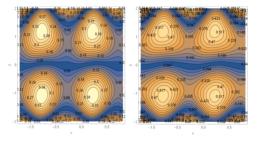


Figure 6. Stream lines for ascending values of rotation parameter  $\{\theta = 0.2, \theta = 0.5\}$ .

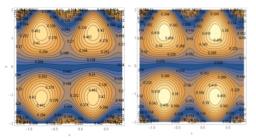


Figure 7. Stream lines for ascending values of pseudoplastic fluid parameter  $\{\xi = 0.1, \xi = 0.3\}$ .

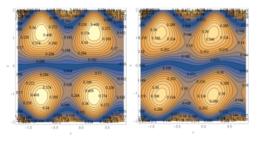


Figure 8. Stream lines for ascending values phase difference parameter  $\{\Phi = \pi/6, \Phi = \pi/4\}.$ 

# 5. Conclusions

The influence of rotation on peristaltic motion for non-Newtonian pseudoplastic fluid in a wavy channel has yielded significant insights. By modeling and transforming the basic governing equations and employing perturbation method, we have obtained analytical expressions for key parameters such as stream function, velocity, pressure gradient, and pressure rise. The study has led to several noteworthy findings:

- 1. The velocity profile exhibits a parabolic shape, with a decrease in velocity profile attributed to an increase in the pseudoplastic fluid parameter  $\xi$ . This decrease is due to the shear-thickening effect or reduction in fluid viscosity as the rate of deformation increases, thereby opposing the flow.
- 2. The velocity profile exhibits a reduction in the central region with increasing rotation parameter Ta and phase difference  $\Phi$ , while it increases towards the boundaries. This phenomenon arises from the enhancement of kinematic forces induced by rotation, and wave phase difference particularly at the boundaries, thereby accelerating fluid flow.
- 3. Because of the direct effect of Ta parameter on the fluid velocity, a smooth flow can occur without requiring a significant pressure gradient with increasing Ta and mean flow rate  $\theta$ , while an opposite trend is observed as  $\xi$  increases, necessitating a substantial pressure gradient.
- 4. The peristaltic pumping region contracts with an increase in the lower wall amplitude a, while it strengthens with an increase in the upper wall amplitude b.
- 5. The size of the trapped bolus increases with increasing values of Ta and  $\theta$ , while its volume and number decrease with the magnitude of  $\xi$  and  $\Phi$ .
- 6. These findings offer valuable insights into the behavior of peristaltic motion in complex fluid systems, with potential applications in various fields such as biomedical engineering, microfluidics, and industrial processes. Understanding these phenomena can aid in the design and optimization of systems involving fluid transport, leading to improved efficiency and performance.

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RESEARCH ARTICLE

ARTICLE INFO

# A comparative view to $\mathcal{H}_\infty\text{-norm}$ of transfer functions of linear DAEs

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ABSTRACT

#### Article History: In this paper, bisection and extended-balanced singular perturbation methods Received 31 March 2024 are used to calculate the $\mathcal{H}_{\infty}$ -norm of the transfer function of a linear DAEs Accepted 9 July 2024 system for the particular case D = 0. In the beginning the approaches' al-Available Online 10 October 2024 gorithms and error analysis are provided separately. Next, the methods are employed to calculate the $\mathcal{H}_{\infty}$ -norms of a numerical example pertaining to Keywords: an automotive gas turbine model, and the error limits are used to check the DAEs systems norms in the suitable range, respectively. Ultimately, every solution is com- $\mathcal{H}_{\infty}$ -norm pared individually with the problem's $\mathcal{H}_{\infty}$ -norm values, which are retrieved Bisection method from MATLAB. Extended-balanced singular

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# 1. Introduction

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The phenomenon of control means "making a system capable of acting as desired". It dates back to Ancient Egypt. The first known control tools are water clocks, Although it is not known when and by whom water clocks were first invented, the first example was found in tomb of Pharaoh Amenhotep I, in 1500s BC. These mechanisms, known to have been designed by Vitrivius and Ktesibos in 325 BC and called clepsydra (water thief) were used by the Greeks to adjust speaking times in assemblies and courts.

Control, in the modern sense, begins with Watt's steam engine, in 1789. Until the 1870s, hundreds of regulators (governors) were patented worldwide using Watt's principles. From then until today, major seminal works in the field of control were carried out by many famous scientists from various areas such that; Maxwell, Vyshnegradski, Routh, Lyapunov, Hurwitz, Sickels, McFarlane,

Farcot, Minorsky, Nyquist, Bode, Bellman, Pontryagyn, Kalman etc [1]. For more detail about historical development of control theory see [2].

One of the most powerful techniques of modern control is  $\mathcal{H}_{\infty}$  control.  $\mathcal{H}_{\infty}$  control is a very useful tool for large-scale multivariable problems to numerically measure the performance, sensitivity and durability of closed loop (feedback) system controllers. Its primary aim is to reduce modeling inaccuracies and account for unquantified disturbances, such as environmental factors, inner uncertainties, and noise, by transforming an optimization problem into a sensitivity problem involving the  $\mathcal{H}_{\infty}$ -norm. Here,  $\mathcal{H}_{\infty}$  refers to "the space encompassing all bounded analytic matrixvalued functions within the open right-half complex plane." This concept was initially introduced by Zames in 1981 [3] and has since found applications across numerous works utilizing various control theory techniques [4–9]. For more comprehensive information, please refer to [10].

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Boyd, Balakrishnan and Kamamba (1988) presented the Bisection algorithms, which is an important tool in control theory [11, 12]. In this field, the energy associated with each state of the system is characterized by Hankel singular values, whereas eigenvalues indicate the stability of a system. Making a link between the stability of the system and the energy of its states is the basic idea underlying the bisection method. This entails connecting the imaginary eigenvalues of the associated Hamiltonian matrix, designated as  $M_{\gamma}$ in Eq.(12), with the singular values of the transfer matrix evaluated along the imaginary axis. The technique is applied in numerous works [13, 14].

In high-level control problems which contain large number of variables and parameters, researches confront many difficulties and complexity. To cope with these adverse conditions, researchers try to create some alternative methods to convert these high-level problems into far smaller dimensional models which can be solved more easily, without losing structural characteristic of the original problems. These kinds of methods are called model order reductions [15–18]. One of the methods is balanced truncation approach. Balanced truncation approach means, to find appropriate balanced realization and truncate this realization preserving the structural characteristic of the original problems.

Let  $\mu > 0$  be a parameter, a dynamical system which contains some state component derivatives with  $\mu$  coefficients is called a singular perturbation model. Singular perturbation models are represented by following set of equations,

$$\dot{x}_1 = A_{11}x_1 + A_{12}x_2 + B_1u \tag{1}$$

$$\mu \dot{x}_2 = A_{21}x_1 + A_{22}x_2 + B_2 u \tag{2}$$

$$y = C_1 x_1 + C_2 x_2 + Du (3)$$

here  $x_1, x_2$  are called slow and fast variables, respectively, Eq.(1), Eq.(2) are called slow (powerful) and fast(weak) subsystems, respectively and  $\mu$  is called perturbation parameter.

Analysis of these system types is done by singular perturbation theory. Singular perturbation theory means to investigate behavior of solutions of the system Eq.(2) for an interval  $0 \le t \le T$ (or  $0 \le t < +\infty$ ). The basic idea of singular perturbation method is to protect the slow(lowfrequency) part (Eq.(1)) while neglecting the fast(high-frequency) (Eq.(1)). When considered from this point of view the method can be associated with a dominant mode state. In other words, it is process of examining solutions of the given system for  $\mu = 0$  [18,19].  $\mu$ -parameter may correspond to different concepts depending on the structure of the system. For example, it represents machine reactance or transients in voltage regulators in power systems, actuators in industrial control, enzymes in biochemical models and fast neutrons in nuclear reactor models.

The extended-balanced singular perturbation method represents a hybrid approach that combines the principles of both balanced truncation and singular perturbation methods. It begins by reducing the model order through the application of balanced truncation. Subsequently, the norm of the transfer function for the reduced model is determined using the singular perturbation method.

This paper organized into six sections. A number of basic definitions and notations which will be used next chapters are given in Section 2. In Section 3, general information about bisection method is told and algorithm of the method is given. In Section 4, extended-balanced singular perturbation method is told and its algorithm summarize as a table with the error bounds. A numerical example is solved by both methods and tolerances are computed in Section 5. Finally, in Section 6, the results are compared and discussed.

# 2. Preliminaries

Let's examine the linear dynamic system;

where  $A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, C \in \mathbb{R}^{p \times n}, D \in \mathbb{R}^{p \times m}$ . Transfer matrix (or function) of the system Eq. (4) is defined as;

$$G(s) = C(sI - A)^{-1}B + D$$
 (5)

Let  $\lambda_j(M), \sigma_j(M)$  denote the  $j^{\text{th}}$  eigenvalue and  $j^{\text{th}}$  singular value of a matrix M respectively, where  $\sigma_j(M) = \sqrt{\lambda_j(MM^T)}$ . A is stable if  $Re(\lambda_j(A)) < 0$  for all j. If A is stable  $H_{\infty}$ -norm of the transfer matrix G(s) is given as follows;

$$||G||_{\infty} = \sup_{\operatorname{Re} s > 0} \sigma_{\max}(G(s)) = \sup_{\omega \in \mathbb{R}} \sigma_{\max}(G(i\omega))$$
(6)

where  $\sup_{\omega \in \mathbb{R}}$  denotes least upper bound for all real frequencies  $\omega$ .

Let  $J_{2n \times 2n} = \begin{bmatrix} 0_n & I_n \\ -I_n & 0_n \end{bmatrix}$  be a skew-symmetric matrix where  $0_n, I_n$  are *n*-dimensional zero and

identity matrices, respectively.  $H_{2n\times 2n}$  is called a Hamiltonian matrix, if HJ is symmetric, such that  $(HJ)^T = HJ$ . The definition confirms that the distinctive block structure form of Hamiltonian matrices is as follows;

 $H = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & -H_{11}^T \end{bmatrix}, \text{ where } H_{12} \text{ and } H_{21} \text{ are symmetric. For the system Eq.(4) the matrices } W_{\mathcal{C}}(t) \text{ and } W_{\mathcal{O}}(t) \text{ are called controllable and observable Grammians, respectively, defined as follows;}$ 

$$W_{\mathcal{C}}(t) = \int_{0}^{t} e^{A\tau} B B^{T} e^{A^{T}\tau} d\tau$$
$$W_{\mathcal{O}}(t) = \int_{0}^{t} e^{A^{T}\tau} C^{T} C e^{A\tau} d\tau \qquad (7)$$

which satisfy the Lyapunov equations as follows;

$$A^{T}W_{\mathcal{O}} + W_{\mathcal{O}}A + C^{T}C = 0$$
  

$$AW_{\mathcal{C}} + W_{\mathcal{C}}A^{T} + BB^{T} = 0$$
(8)

and singular values of  $W_{\mathcal{C}}(t)W_{\mathcal{O}}(t)$  are called Hankel singular values of the system Eq.(4) which describes the energy of each state of the system Eq.(4) and are denoted as  $\sigma H_j$  for j = 1, 2, ...

Any positive definite matrix  ${\cal M}$  can be expressed in the form of

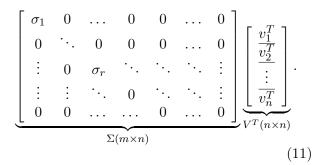
$$M = LL^T \tag{9}$$

where L is a lower triangular matrix. The expression Eq.(9) and the matrix L are called Cholesky factorization and Cholesky factor of M, respectively. Let  $M \in \mathbb{R}^{m \times n}$  and rank(M) = r =min(m, n), the expression

$$M = U\Sigma V^T \tag{10}$$

is called singular value decomposition of the matrix M. Here U and V are orthogonal matrices of type of  $m \times m$  and  $n \times n$ , respectively, that is,  $U^T U = I_m, V^T V = I_n$  and  $\Sigma$  is a half-diagonal matrix which contains singular values  $(\sigma_1, \ldots, \sigma_r)$ of the matrix M. Singular value decomposition can be formulated clearly as follows for a matrix M,

$$M = U\Sigma V^T = \underbrace{\left[\begin{array}{cccc} u_1 & | & u_2 & | & \cdots & | & u_m \end{array}\right]}_{u(m \times m)} \times$$



# 3. Bisection method

Let  $\gamma > 0$  related Hamiltonian matrix  $M_{\gamma}$  for system Eq. (4) is given as follows;

$$M_{\gamma} = \begin{bmatrix} A & 0 \\ 0 & -A^T \end{bmatrix} + \begin{bmatrix} B & 0 \\ 0 & -C^T \end{bmatrix} \times \begin{bmatrix} -D & \gamma I \\ \gamma I & -D^T \end{bmatrix}^{-1} \begin{bmatrix} C & 0 \\ 0 & B^T \end{bmatrix}$$
$$= \begin{bmatrix} A - BR^{-1}D^TC & -\gamma BR^{-1}B^T \\ \gamma C^TS^{-1}C & -A^T + C^TDR^{-1}B^T \end{bmatrix}$$
(12)

where  $R = D^T D - \gamma^2 I$  and  $S = D D^T - \gamma^2 I$ . For special case

$$D = 0, M_{\gamma} = \begin{bmatrix} A & \frac{1}{\gamma} B B^T \\ -\frac{1}{\gamma} C^T C & -A^T \end{bmatrix}.$$

Prior to initiating the bisection algorithm, it is essential to establish clear lower  $(\gamma_{lb})$  and upper  $(\gamma_b)$  bounds. While one option is to set  $\gamma_{lb} = 0$  and  $\gamma_{ub}$  to a sufficiently large value before proceeding with the bisection protocol, this approach can be time-consuming and inefficient. To streamline this process and determine suitable bounds, we can leverage Hankel singular values, as derived by Enns [20] and Glover [21], which are outlined below:

$$\gamma_{lb} = \max \left\{ \sigma_{\max}(D), \sqrt{Tr(W_{\mathcal{C}}W_{\mathcal{O}})/n} \right\}$$
$$\gamma_{ub} = \sigma_{\max}(D) + 2\sqrt{nTr(W_{\mathcal{C}}W_{\mathcal{O}})}$$
(13)

or alternative formulas;

$$\gamma_{lb} = \max \{ \sigma_{\max}(D), \sigma H_1 \}$$
  
$$\gamma_{ub} = \sigma_{\max}(D) + 2 \sum_{j=1}^n \sigma H_i$$
(14)

here,  $\sigma H_i$  s represents the Hankel singular values, while  $W_{\mathcal{O}}$  and  $W_{\mathcal{C}}$  stand for the observability and controllability Grammians of the system Eq.(4) Assuming A is stable and  $\varepsilon > 0$  is the error margin for system Eq.(4), the bisection algorithm is outlined as follows:

**Step 1.** Determine the lower and upper bounds for the bisection algorithm, where

$$\gamma_{lb} = \max \left\{ \sigma_{\max}(D), \sigma H_1 \right\}$$
$$\gamma_{ub} = \sigma_{\max}(D) + 2\sum_{j=1}^n \sigma H_j$$

**Step 2.** Set  $\gamma = (\gamma_{lb} + \gamma_{ub})/2$ If  $\gamma_{ub} - \gamma_{lb} < \frac{\varepsilon}{2}$ , end.

**Step 3.** Calculate  $M_{\gamma}$ .

**Step 4.** Check eigenvalues of  $M_{\gamma}$ . If there exists a purely imaginary eigenvalue set  $\gamma_{lb} = \gamma$ . Else set  $\gamma_{ub} = \gamma$ .

# 4. Extended balanced singular perturbation method

The extended balanced singular perturbation method, as introduced in the Introduction, combines the principles of both balanced truncation and singular perturbation methods, as described below.

Suppose we have an asymptotically stable, minimal realization of the system Eq.(4) as defined in equation Eq.(5). The algorithm for the balanced truncation approach is implemented using the following MATLAB commands:

**Step 1.** Find controllable and observable Grammians  $W_{\mathcal{C}}$  and  $W_{\mathcal{O}}$  of the given system through the Lyapunov equations with the MATLAB commands

**Step 2.** Find the Cholesky factors  $L_{\mathcal{C}}$  and  $L_{\mathcal{O}}$  of  $W_{\mathcal{C}}$  and  $W_{\mathcal{O}}$ , respectively, such that

$$W_{\mathcal{C}} = L_{\mathcal{C}} L_{\mathcal{C}}^T$$
$$W_{\mathcal{O}} = L_{\mathcal{O}} L_{\mathcal{C}}^T$$

with the MATLAB commands

$$Lc = chol(Wc, 'lower')$$
  
 $Lo = chol(Wo, 'lower')$ 

**Step 3.** Find the singular value decomposition of  $L_{\mathcal{O}}^T L_{\mathcal{C}}$  such that

$$L_{\mathcal{O}}^T L_{\mathcal{C}} = U \Sigma V^T$$

with the MATLAB command

$$[U, S, V] = svd(Lo' *Lc).$$

**Step 4.** Make the transformation  $T = L_{\mathcal{C}}V\Sigma^{-1/2}$ and obtain coefficient matrices of balanced system by similarity transformation as follows,  $\tilde{A} = T^{-1}AT, \quad \tilde{B} = T^{-1}B, \quad \tilde{C} = CT, \quad \tilde{D} = D$ where  $\tilde{G}(s) = \begin{bmatrix} \tilde{A} & | & \tilde{B} \\ -\bar{C} & | & \tilde{D} \end{bmatrix}$  and find controllable and observable Grammians of the balanced system  $\widetilde{W}_C$  and  $\widetilde{W}_0$  respectively which are given as below,

$$\widetilde{W}_{\mathcal{C}} = T^{-1} W_{\mathcal{C}} T^{-T}$$
$$\widetilde{W}_{\mathcal{O}} = T^T W_{\mathcal{O}} T$$

here  $\widetilde{W}_{\mathcal{C}} = \widetilde{W}_{\mathcal{O}} = \Sigma = diag (\sigma_1, \sigma_1, \dots, \sigma_n).$ Let  $\widetilde{G}(s) = \begin{bmatrix} \widetilde{A} & | & \widetilde{B} \\ - & - & - \\ \widetilde{C} & | & \widetilde{D} \end{bmatrix}$  be the balanced sys-

tem obtained by balanced truncation approach, the algorithm of singular perturbation method is given as follows;

**Step 1.** Separate the balanced system 
$$\tilde{G}(s) = \begin{bmatrix} \tilde{A} & \mid & \tilde{B} \\ - & - & - \\ \tilde{C} & \mid & \tilde{D} \end{bmatrix} \Leftrightarrow \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix}$$
 into two subsys-

tem as slow(powerful ) and fast(weak). Choose  $A_{11}$  as coefficient matrix of the slow part where  $A_{11}, \Sigma_1 \in \mathbb{R}^{r \times r}$ , for  $r \ll n$ . Rearrange the matrices  $\tilde{A}, \tilde{B}, \tilde{C}, \tilde{D}$  in block matrix form as seen below,

$$\tilde{A} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, \tilde{B} = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}$$
$$\tilde{C} = \begin{bmatrix} C_1 & C_2 \end{bmatrix}, \tilde{D} = D$$

add perturbation parameter  $\mu$  and rewrite  $\tilde{G}(s)$  as the followings,

$$\begin{bmatrix} \dot{x}_1 \\ \mu \dot{x}_2 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} u$$
$$y = \begin{bmatrix} C_1 & C_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + Du.$$

**Step 2.** Eliminate the fast(weak) part  $\mu = 0$  and find the system as;

$$\dot{x}_1 = A_{11}x_1 + A_{12}x_2 + B_1u$$
  

$$0 = A_{21}x_1 + A_{22}x_2 + B_2u$$
  

$$y = C_1x_1 + C_2x_2 + Du$$

and weak variable as,

$$x_2 = -A_{22} \,{}^{-1}A_{21}x_1 - A_{22} \,{}^{-1}B_2u$$

**Step 3.** Substitute  $x_2$  to the other equations to get the final version of the system which denoted by  $G_f(s)$  as is below

$$G_f(s) = \left[ \begin{array}{ccc} A_f & \mid & B_f \\ - & - & - \\ C_f & \mid & D_f \end{array} \right] =$$

	Balanced Truncation Approach Singular Perturbation Method			
Step 1.	Find Grammians of the original sys- Separate the balanced system $\tilde{G}(s)$			
	tem $(W_{\mathcal{C}}, W_O)$ into two parts as; strong and weak			
Step 2.	Find Cholesky factors of Grammi- Eliminate the weak part taking $\mu =$			
	ans $(L_{\mathcal{C}}, L_{\mathcal{O}})$ 0 and find weak variable $x_2$			
Step 3.	Find singular value decomposition Substitute $x_2$ in other equations, get			
	of $L_O^T L_C = U \Sigma V^T$ the final version of the system $G_f(s)$			
Step 4.	Make the transformation $T = \text{Obtain the } H_{\infty}\text{-norm of } \ G_f(s)\ _{\infty}$			
	$L_{\mathcal{C}}V\Sigma^{-1/2}$ and find the balanced			
	system $ ilde{G}(s)$			
Error Analysis	Compute actual and theoretical infinity error bounds and apply the er-			
	ror tolerance criterion which says actual bound must be less than or			
	equal to theoretical bound			

 Table 1. Algorithm of extended balanced singular perturbation method step by step.

$\begin{bmatrix} A_{11} - A_{12}A_{22} & ^{-1}A_{21} \end{bmatrix}$		$B_1 - A_{12}A_{22} \ ^{-1}B_2$
	—	
$C_1 - C_2 A_{22}^{-1} A_{21}$		$D - C_2 A_{22} {}^{-1} B_2$

**Step 4.** Obtain the  $H_{\infty}$ -norm of  $||G_f(s)||_{\infty}$  in MATLAB.

The algorithm of extended balanced singular perturbation method is summarized in Table 1 as follows.

To analyze the error tolerance first we define modelling error transfer function as follows;

$$E_r = [G(s) - G_f(s)]$$
 (15)

then, we have a criterion about sufficiency of error tolerance which is based on comparison of two error bounds called actual infinity error bound and theoretical infinity error bound defined in [22,23] given as below;

- Actual infinity error bound:  $||E_r||_{\infty} = ||[G(s) G_f(s)]||_{\infty}$
- Theoretical infinity error bound:  $2\sum_{i=r+1}^{n} \sigma_i$
- The criterion:

$$\|E_r\|_{\infty} \le 2\sum_{i=r+1}^n \sigma_i$$

#### 5. Application to a numerical example

**Example 1.** The system two-input, twelve-state, two-output model of an automobile gas turbine [24].

For more detail and examples see [25]. Consider the system Eq.(4) with the coefficient matrices given as follows:

When employing the bisection method for this problem, we obtain the values presented in Table 2. The first and the last columns in the table pertain to number of iteration that denoted as Itr briefly and verifying the presence of purely imaginary eigenvalues that denoted as Eig briefly, respectively.

Table 2.Related values of Example 2.

$\operatorname{Itr}$	$\gamma_{lb}$	${\gamma}_{ub}$	$\gamma$	$\operatorname{Eig}$
1	3.0368	36.4417	19.7397	no
2	3.0368	19.7397	11.3881	yes
3	11.3881	19.7397	15.5637	no
4	11.3881	15.5637	13.4759	yes
5	13.4759	15.5637	14.5198	no
6	13.4759	14.5198	13.9979	no
$\overline{7}$	13.4759	13.9979	13.7369	yes
8	13.7369	13.9979	13.8674	no
9	13.7369	13.8674	13.8022	no
10	13.7369	13.8022	13.7695	no
11	13.7369	13.7695	13.7532	no
12	13.7369	13.7532	13.7450	no
13	13.7369	13.7450	13.7410	no
14	13.7369	13.7410	13.7389	no
15	13.7369	13.7389	13.7379	yes
16	13.7379	13.7389	13.7384	yes
17	13.7384	13.7389	13.7387	yes
18	13.7387	13.7389	13.7388	no
19	13.7387	13.7388	13.7388	yes
20	13.7388	13.7388	13.7388	

After 20 iterations  $\gamma_{ub}$  and  $\gamma_{lb}$  are so close, the all next iterations will be automatically assigned the same value by MATLAB and error margin  $\varepsilon$  is also will be satisfied. Thus,  $\mathcal{H}_{\infty}$  norm of transfer function of the given problem found as  $\|G(s)\|_{\infty} \approx 13.7388$ . Now, if we apply balanced truncation approach algorithm step by step finally we get

$$\tilde{G}(s) = \begin{bmatrix} \tilde{A} & | \tilde{B} \\ -\frac{1}{\tilde{C}} & -\frac{1}{\tilde{D}} \end{bmatrix}$$
where;

and Hankel singular values of the original system as,

$$\sigma(G) = (7.1833 \quad 1.4904 \quad 0.9279 \quad 0.5876 \quad 0.4633$$
$$0.2368 \quad 0.1613 \quad 0.0936 \quad 0.0006 \quad 0 \quad 0)$$

-0.1647 0.01850.1116 -0.0528-0.46980.23340.0559-0.0336 0.0179-0.0049 -0.0001 0 -0.0071 -0.8293 -0.2913 0.3813 0.2261-0.0513 -0.7095-1.6433 0.0079 -0.0065 0.0008 -0.0003 0.3709 0 -0.0605 0.6599-0.13680.19091.9093 -0.6958 0.0074-0.0453 0.0129 0.0001 -0.0676 -0.2951-0.1328 -0.1111 0.01560.2976 0.34950.46410.0339 -0.0075 -0.0005 0.0001-0.4673 -0.3296 -1.3820-1.3904-5.88063.75741.4509-1.16500.4207-0.1141 -0.00180.00040.2332 0.0786 0.41070.53523.7468-2.6771-2.27601.6069-0.3983 0.1083 0.0016 -0.0004 $\tilde{A} =$ -0.0103 0.7485-0.3240 0.0251 -0.4105 1.6010 -1.2640 -2.6186 -0.0926 0.0100 0.0033 -0.0010 0.0416 1.6502-4.2162 -0.7122 0.3698 1.9050-1.8933 -11.6604 0.3158-0.15260.0113 -0.0035 -0.0144 -0.0545 0.0096 -0.0499 -0.3612 0.3313 0.18430.9343 -6.2677 3.6203 0.0367 -0.0080 -0.0032 -0.0197 0.0056-0.0128 -0.0838 0.07530.0693 0.3210-3.5719-13.7547-0.0809 0.0128-0.0002 0 -0.0002 -0.0005 -0.00420.0040 -0.00040.0010 -0.0948 -0.5578-0.24770.14400.07250.1343 0 -0.0001 0.0001 0.0001 0.0011 -0.0011 0.0005 0.0011 0.0177 -0.9059 Τ -0.4823 1.4882-0.5001 0.0220 -0.51640.2995-0.6184 -1.33070.02740.0129-0.0003 0.0002 $\tilde{B} =$ -1.4609 -0.0008 0.0002-0.5073-0.0613-0.3607-2.27651.08550.15950.6417-0.0796-0.0200-0.5368 1.49930.0399-0.3178-0.81390.37400.63741.32300.0181 -0.0010-0.0008 0.00021.4417 -0.4735 0.5023 0.0399 0.0823 -0.0238 -0.0001 0 -0.1721-2.18791.0621-0.6574 $\tilde{D} = 0$ 

It is seen clearly in the Figure 1 the first three Hankel singular values are much greater than the others so we choose r = 6 and apply extended balanced singular perturbation method. First separate the balanced system  $\tilde{G}(s)$  into two parts as slow(powerful) and fast(weak) and rewrite the system for perturbation parameter  $\mu = 0$  as is given below;

$$\dot{x}_1 = A_{11}x_1 + A_{12}x_2 + B_1u 
0 = A_{21}x_1 + A_{22}x_2 + B_2 
y = C_1x_1 + C_2x_2 + Du$$

-0.16470.0185 0.1116 -0.0528-0.46980.2334-0.0071-0.8293-0.29130.3813 0.2261-0.0513-0.06050.6599-0.13680.19091.9093-0.6958 $A_{11} =$ -0.0676-0.2951-0.1328-0.11110.01560.2976-0.3296-5.8806-0.4673-1.3820-139043.75740.23320.0786 0.41070.53523.7468-2.67710.0559-0.03360.0179-0.0049-0.00010 -0.7095-1.64330.0079-0.00650.0008-0.00030.00740.3709 -0.04530.0129 0.00010  $A_{12} =$ 0.4641 0.0339-0.0075-0.00050.0001 0.34951.4509-1.16500.4207-0.1141-0.00180.0004 -2.27601.6069-0.3983 0.10830.0016-0.0004-0.01030.7485-0.32400.0251-0.41051.60100.04161.6502-0.71220.36981.9050-1.8933-0.0144-0.05450.0096 -0.0499-0.36120.3313  $A_{21} =$ -0.0032-0.01970.0056-0.0128-0.08380.0753-0.00020 0.0002-0.0005-0.00420.0040 -0.00010 0.00010.00010.0011-0.0011

where;

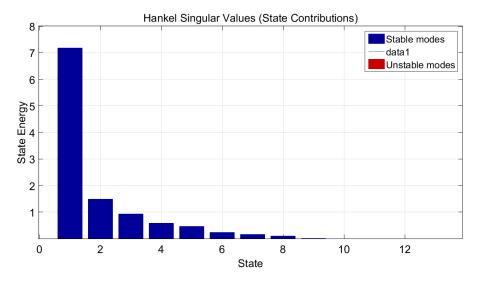


Figure 1. Hankel singular values of the original system.

$A_{22} =$	-4.2162 0.1843 0.0693	$\begin{array}{c} -2.6186 \\ -11.6604 \\ 0.9343 \\ 0.3210 \\ 0.0010 \\ 0.0011 \end{array}$	$\begin{array}{c} -0.0926\\ 0.3158\\ -6.2677\\ -3.5719\\ -0.0948\\ 0.0177\end{array}$	$\begin{array}{c} 0.0100 \\ -0.1526 \\ 3.6203 \\ -13.7547 \\ -0.5578 \\ 0.0725 \end{array}$	$\begin{array}{c} 0.0033\\ 0.0113\\ 0.0367\\ -0.0809\\ -0.2477\\ 0.1343\end{array}$	$\begin{array}{c} -0.0010 \\ -0.0035 \\ -0.0080 \\ 0.0128 \\ 0.1440 \\ -0.9059 \end{array} \right]$
$B_1 =$	0 500	$\begin{array}{rrrr} 2 & -0.50' \\ 1 & -0.062 \\ 0 & -0.360 \\ 4 & -2.270 \end{array}$	$\begin{array}{c c} 73 \\ 13 \\ 07 \\ 65 \end{array} = B$	$B_2 = \begin{vmatrix} -1 \\ 0 \\ 0 \\ -0 \end{vmatrix}$	3307 ).0274 - ).0129 -	$\begin{array}{c} 0.1595\\ 0.6417\\ -0.0796\\ -0.0200\\ -0.0008\\ 0.0002 \end{array} \right]$
$C_1 = \left[ \right]$	-0.5368 -1.4417	$1.4993 \\ -0.4735$	$0.0399 \\ 0.5023$	-0.3178 -0.1721		

 $C_2 = \left[ \begin{array}{cccc} 0.6374 & 1.3230 & 0.0181 & -0.0010 & -0.0008 & 0.0002 \\ 0.0399 & -0.6574 & 0.0823 & -0.0238 & -0.0001 & 0 \end{array} \right] \quad D = 0$ 

and from the second equation find weak variable as,  $x_2 = -A_{22}^{-1}A_{21}x_1 - A_{22}^{-1}B_2u$ . Continue from Step3 make necessary algebraic matrix operations and finally get,  $G_f(s) =$ 

$$\begin{bmatrix} A_f & | & B_f \\ -- & -- & -- \\ C_f & | & D_f \end{bmatrix} \text{ where;}$$

$$A_f = \begin{bmatrix} -0.1690 & 0.0951 & 0.0784 & -0.0663 & -0.6557 & 0.6759 \\ -0.0058 & -1.1996 & -0.1312 & 0.3503 & 0.2631 & -0.5240 \\ -0.0513 & 0.5609 & -0.0938 & 0.2259 & 2.3058 & -1.5693 \\ -0.0772 & -0.0122 & -0.2554 & -0.1296 & -0.3903 & 1.3889 \\ -0.5873 & 1.7458 & -2.2822 & -1.7701 & -11.0375 & 15.9797 \\ 0.4156 & -3.1167 & 1.7961 & 1.1096 & 11.5963 & -21.3316 \end{bmatrix}$$

$$B_f = \begin{bmatrix} -0.5472 & -1.4593 \\ 1.7922 & -0.6034 \\ -0.2146 & -0.3261 \\ -2.2766 & -2.2466 \\ 3.0081 & 1.0291 \end{bmatrix} C_f = \begin{bmatrix} -0.5419 & -1.4612 \\ 1.8765 & -0.2345 \\ -0.1233 & 0.3985 \\ -0.3049 & -0.2438 \\ -1.0190 & -3.0315 \\ 1.1786 & 2.9523 \end{bmatrix}$$

$$D_f = \begin{bmatrix} -0.3115 & 0.0807 \\ -0.2056 & -0.0223 \end{bmatrix}$$

Obtain the  $\mathcal{H}_{\infty}$ -norm in MATLAB as  $\|G_f(s)\|_{\infty} = 13.7413$  which is so close to the  $\mathcal{H}_{\infty}$ -norm of the original system  $\|G(s)\|_{\infty} = 13.7388$ . Let's now assess the error tolerance between the original system and the reduced-order balanced model using both actual and theoretical infinity error bounds, as outlined below.

$$||E_r||_{\infty} = ||[G(s) - G_f(s)]||_{\infty} = 0.3774$$

and for r = 6 and n = 12,

$$2\sum_{i=r+1}^{n} \sigma_i = 2(0.1613 + 0.0936 + 0.0006 + 0.0006 + 0.0006) + 0 + 0 + 0) = 0.5110$$

It is obvious that  $||E_r||_{\infty} \leq 2 \sum_{i=r+1}^n \sigma_i$  thus we can say that error tolerance is in a satisfied level.

#### 6. Conclusion

In this research, we applied both the bisection method and the extended-balanced singular perturbation method to analyze a linear dynamic system with the parameter D set to 0. Our goal was to compute the  $\mathcal{H}_{\infty}-$  norm of its transfer function. We conducted a numerical experiment using both methods and performed a detailed error analysis. The outcomes of our investigation revealed that the bisection method performed satisfactorily, with error tolerances falling within an acceptable range after a certain number of iterations. Similarly, the extended-balanced singular perturbation method demonstrated satisfactory performance, as the error tolerances met the criteria for investigating the accuracy of the reducedorder models. According to the  $\mathcal{H}_{\infty}$ -norms computed by methods, we conclude that bisection

method is a slightly accurate than extendedbalanced singular perturbation method. Utilizing bisection and extended balanced singular perturbation methods, the research not only provides detailed algorithms and error analysis but also demonstrates practical application through a numerical example involving an automotive gas turbine model, enhancing the precision and reliability of  $\mathcal{H}_{\infty}$ -norm computations in real-world systems.

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RESEARCH ARTICLE

# Fuzzy-PID and interpolation: a novel synergetic approach to process control

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#### ARTICLE INFO

# ABSTRACT

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This paper presents a novel approach for tuning a fuzzy-based proportional-integral-derivative (PID) controller to enhance the control performance of a chemical process control system. The proposed approach combines the advantages of fuzzy- PID and interpolation to achieve improved control performance. Properly tuned PID controllers can help maintain process stability, minimize deviations from setpoints, and ensure efficient operation in industrial systems. Fuzzy logic allows for the incorporation of expert knowledge and linguistic rules, enabling the controller to handle uncertain and imprecise process information. Fuzzy PID controllers combine fuzzy logic and conventional PID control to enhance control performance, particularly in systems with complex or nonlinear dynamic such as chemical plant. It dynamically adjusts the PID parameters—proportional gain (Kp), integral gain (Ki), and derivative gain (Kd)—based on error e(t) and change of error  $\Delta e(t)$ . Interpolation plays a crucial role in this context by filling in the gaps or handling situations not explicitly covered by the fuzzy rules. Comparative studies are conducted to evaluate the performance of the fuzzy PID controller against conventional PID controllers and other advanced control techniques. It is demonstrated that the synergy between fuzzy logic and interpolation not only enhances control performance but also offers a more intuitive and adaptable solution for addressing the complexities of modern chemical process control systems.

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# 1. Introduction

Process control systems should be designed to ensure the efficient and safe operation of chemical processes in industries such as oil refining, petrochemicals, pharmaceuticals, and food processing. These systems monitor and regulate process variables such as temperature, pressure, flow rate, level and concentration with the aim of achieving optimal process performance, product quality, and resource utilization. The complexity of chemical processes, often characterized by nonlinear dynamics, time delays, and interactions between various process variables, poses significant challenges. The primary objective of a chemical process control system is to maintain these variables within desired operating ranges, despite disturbances and uncertainties in the process environment. Traditionally, control systems in chemical processes have relied on classical control techniques such as Proportional-Integral-Derivative (PID) control. PID controllers are widely used owing to their inherent simplicity, ease of implementation, and familiarity among control engineers. А

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PID controller calculates a control action based on the error between the desired setpoint and the actual process variable, taking into account the proportional, integral, and derivative components. However, traditional PID control approaches have limitations when applied to complex chemical processes. These limitations include difficulty in handling nonlinearities, interactions, and time-varying dynamics, as well as challenges in tuning the controller parameters for optimal performance. Consequently, there is a need for advanced control strategies that can address these limitations and enhance the control performance of chemical process systems.

Several classical methods pertaining to PID control have been proposed to achieve desired controller performance. Ziegler and Nichols in 1942 [1], first introduced the method of The tuning method described PID tuning. by them is a heuristic approach that provides simple and practical technique for initial tuning but had limitations in terms of control performance and robustness. To overcome the limitations of the Ziegler-Nichols (Z-N) method, researchers focused on developing more sophisticated techniques. Passivity-based control strategy [2] offers a promising alternative for controlling generalized passive systems, providing stability, robustness, and adaptability to different system dynamics. Cohen and Coon's method [3] focuses on achieving better control performance by accounting for the time delay, which can significantly impact the system's response. Despite of some limitations, Z-N is one of the most widely used PID tuning method because of its simplicity. A modified Ziegler-Nichols method is proposed in [4] by refining the calculation of ultimate gain, ultimate period and tuning rules. An Internal Mode Control (IMC) based design was proposed in [5].

This seminal work introduced the concept of Internal Model Control (IMC) and provided a comprehensive framework for designing PID controllers based on this innovative control However, the paper mainly focused strategy. on linear systems, and the robustness analysis was limited to linear uncertainties. Skogestad and Postlethwait [6] proposed the modified IMC method, which aimed to achieve the desired closed-loop response by designing an internal model that mimics the process dynamics. The IMC method showed improved disturbance rejection and robustness compared to the Ziegler-Nichols method. A comprehensive reference guide that focuses on providing practical insights and guidelines for tuning proportional-integral-derivative (PID) controllers has been presented in [7]. Detailed review of various PID controller tuning method has been discussed in [8]. In order to reduce the time and knowledge of tuning process, Åström and Hägglund [9] proposed method that focuses on the automatic tuning of simple regulators, likely referring to control systems that use basic feedback control techniques like proportional, integral, and derivative (PID) control. The main emphasis of the paper is on achieving desired phase and amplitude margins for stability and performance of control systems. Author went further to explore more of autotuning method and presented an experimental comparison of various PID autotuners. The objective of this study is likely to evaluate the performance and effectiveness of different autotuning methods in real-world scenarios [10].

In addition to aforementioned methods for tuning PID controllers, there are numerous other. Some of the popular tuning methods are Model-based Tuning, 'Trial and error', Optimization Techniques etc. However, in many real-world scenarios, the system's behavior may be complex, uncertain, or difficult to model accurately. In such cases, expert knowledge from experienced operators or domain experts can be valuable in improving the control performance.

Fuzzy logic has been used to incorporate the expert knowledge for the PID controller tuning. Ucak. K introduced the concept of fuzzy and proposed a novel adaptive multi-input multi-output (MIMO) fuzzy PID controller for time delay systems, building upon prior work on single-input single-output (SISO) system. The study evaluates the controller's performance in stabilization, tracking, and disturbance rejection against classical PID controllers. Results demonstrate the effectiveness of the proposed adaptation mechanism, suggesting its successful application in delay systems [11]. An another article showing the usefulness of integrated fuzzy-PI/PID control has been authored by Demirtas and Papanikolopoulos [12]. In this, AC voltage controller capable of operating at different power factors presents a power factor correction (PFC) scheme using various controllers (PI, fuzzy logic PI, and fractional order PI).

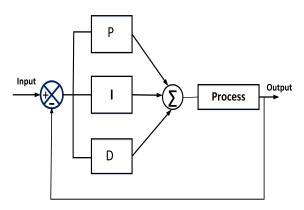


Figure 1. PID control system.

A single-phase boost converter is modeled in MATLAB/Simulink, and a filter is designed to minimize THD. The proposed model demonstrate the combination of fuzzy and PI controllers achieves the best power factor control. Tzafestas and Papanikopoulos [13] were among the first who introduced concept of Fuzzy-tuned PID controller design.

They suggested enhancing the performance of a closed-loop system by making adjustments to PID parameters. This was accomplished through a fuzzy matrix, encapsulating the operator's experiential insights within a concise rule base. In [14], [15] researchers introduced an auto-tuning algorithm for PID controller using Fuzzy logic. This algorithm aimed to dynamically adjust PID parameters in real-time, utilizing the generated error signal from the closed-loop system as input. An observer and error based adaptive proportional-integral-derivative (PID) controller has been introduced for type-2 fuzzy based system [16].

Numerous other scholars have also adopted a similar type of approach, introducing error to implement expert insights within the PID tuning process. The fuzzy tuned PID controller has some advantages over other tuning methods. Fuzzy logic-based tuning methods provide an effective means of adjusting the gains of a PID controller while minimizing overshoot, settling time, and steady-state error, particularly in nonlinear and complex systems. Contrary to other tuning methods, the fuzzy logic approach does not need an exact mathematical model of the system and can handle non-literariness and uncertainties in the process. The paper introduces a novel approach to controller tuning by combining both fuzzy logic and computational techniques to optimize the PID controller parameters. Fuzzy logic for rule-based decision-making, and interpolation techniques are combined in this work. This represents a unique approach, which has not been encountered in research arena.

A PID controller is a type of feedback control system commonly used in engineering and industrial processes (Figure 1). It continuously measures the difference between a desired set-point and the current value of a controlled variable, and adjusts an output signal to bring the two values closer together. The first term of PID provides an output proportional to the error signal, the integral term sums up the past errors to correct for any steady-state errors, and the derivative term predicts the future error based on the current rate of change. By merging all three parameters, a PID controller can achieve stable and accurate control of a wide range of systems, from simple temperature control to complex manufacturing processes.

In recent years, various tuning methods based upon fuzzy logic have been proposed for optimizing the performance of fuzzy logic Traditional approaches, such as controllers. heuristic tuning and optimization algorithms, often rely on iterative procedures and expert knowledge to define the fuzzy ranges. These methods, while effective, can be time-consuming and may not generalize well to different problem domains. In contrast, the proposed method leverages interpolation to set the fuzzy ranges. providing a unique and efficient alternative to conventional tuning techniques. This approach simplifies the tuning process by reducing the dependency on expert intervention. Moreover, it ensures controller parameters remain within specified bounds, a crucial consideration for safety and practicality in real-world applications. Α third-order reactor plant has been taken into consideration as the system. Aim of this work is to maintain the concentration of effluent in each at a certain desired level. Simulation has been done using MATLAB software to get the desired response of the system subjected to step input. The results were observed and compared with few existing relevant literature.

# 1.1. Tuning of PID controller

PID controller tuning refers to the process of adjusting the parameters of the controller (proportional gain, integral time constant, and derivative time constant) to achieve the desired performance of the control system. The process of tuning involves adjusting the parameters based on the response of the system to different inputs, and is done through many methods.

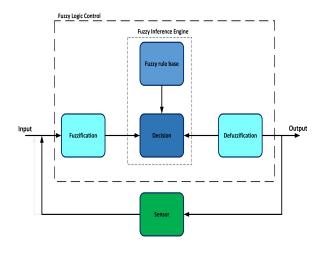


Figure 2. General Structure of Fuzzy Logic Control System

The importance of tuning a PID controller is rooted in its crucial role in ensuring the effective and efficient functioning of a control system. If the controller is not tuned correctly, the system may be unstable or oscillate, leading to inefficient operation or even damage to the system. On the other hand, a well-tuned PID controller can help maintain stable control of the process variable, reduce overshoot, improve settling time, and improve the overall performance of the system.

#### 1.2. Fuzzy-tuned PID controller

Fuzzy logic is mathematical tool to deal with uncertainty in the system. In traditional binary logic, propositions are either true or false, but in fuzzy logic, propositions can be partially true or partially false, and the degree of truth or falsity is expressed using a range of values between 0 Primary benefit of fuzzy logic is its and 1. knowledge, that is efficient to handle imperfect and ambiguous data. Fuzzy logic is appropriate for modeling complex systems that are difficult to describe using traditional mathematical models. It allows for the use of linguistic variables, which can be more intuitive and easier to understand than traditional mathematical models. A typical Fuzzy logic control structure is depicted in Figure 2.

It takes crisp value as inputs variables. After fuzzification, processing with Fuzzy Inference Engine (FIE) and defuzzification, again desired crisp output is obtained. Fuzzy knowledge base together with decision form FIE in the control structure. A fuzzy tuned PID controller is a type of proportional-integral-derivative (PID) controller that uses fuzzy logic to tune its parameters. PID controllers are widely used in control systems to maintain a desired set-point by adjusting the output as per the difference between the set-point and the measured process variable. However, the performance of a PID controller is highly dependent on its tuning parameters, which can be difficult to determine for complex systems. Fuzzy tuned PID controllers use fuzzy logic to determine the optimal tuning parameters for the PID controller based on the current state of the system. This approach can be more effective than traditional PID tuning methods because it takes into account the complexity and uncertainty of the system being controlled. Additionally, fuzzy tuned PID controllers can adapt to changing conditions in the system, making them more robust and effective in real-world applications.

# 2. System description

A chemical process control system typically involves monitoring and adjusting the variables in a chemical reaction to optimize the output. In such a control industry it is required commonly to maintain the concentration of solute in a solvent. In the proposed work, the n-numbers of cascaded tanks are arranged in series, with the first tank receiving the solvent and the solute as shown in Figure 3. The output of the first tank is fed into the second tank, where further mixing occurs. The output of second tank is then fed into the third tank, where further mixing occurs. This process continues up to nth tank of the system where final mixing occurs. The concentration of solute in the solvent in final tank is measured and the signal is sent to controller, which adjusts the flow rate of the solute feed to the fist tank in order to maintain the desired concentration.

# 2.1. Modeling of the system

In order to obtain simple mathematical model of the aforementioned system, volume-flow rate and corresponding volumes are assumed to be constant. Writing mass-balance equation for first two tank.

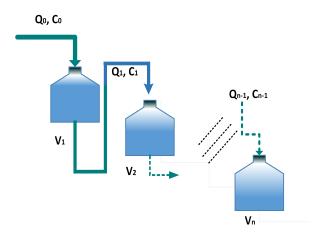


Figure 3. Cascaded 'n' number of tanks.

$$T_1 \frac{dC_1}{dt} = C_0 - C_1, \tag{1}$$

$$T_2 \frac{dC_2}{dt} = C_1 - C_2,$$
 (2)

where,  $T_1 = V_1/q0$  and  $T_2 = V_2/q0$ . In the above equation V, C and q0 represents volume, concentration and inlet flow rate of the both the tanks in proper unit with subscript number denoting the tank number. Transforming the above equations in Laplace domain yields.

$$\frac{C_1}{C_0} = \frac{1}{T_1 s + 1},\tag{3}$$

$$\frac{C_2}{C_1} = \frac{1}{T_2 s + 1}.$$
(4)

The effect of  $C_0$  on  $C_2$  can be computed as:

$$\frac{C_2}{C_0} = \frac{1}{T_1 s + 1} \times \frac{1}{T_2 s + 1}.$$
 (5)

For 'n' number of tanks in series, the generalized equation can be expressed as;

$$\frac{C_n}{C_0} = \frac{1}{(T_1 s + 1)(T_2 s + 1)\dots(T_n s + 1)}.$$
 (6)

Order of the system described by the equation (6) will vary with the value of 'n' or number of tanks. for the proposed work a 3-tank process control system has been considered, where, values of T1, T2 and T3 is assumed to be 1,3 and 5 respectively. Transfer function of the aforementioned system can be written as:

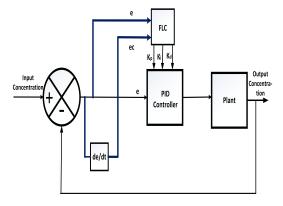
$$G(s) = \frac{1}{(S+1)} \times \frac{1}{(S+3)} \times \frac{1}{(S+5)}.$$
 (7)

Subsequently, rewritten as:

$$G(s) = \frac{1}{(S+1)(0.33S+1)(0.2S+1)}.$$
 (8)

### 2.2. Design of fuzzy tuned PID controller

The solute concentration in the solvent is measured continuously and the signal is sent back through feedback to a fuzzy PID (Proportional-Integral-Derivative) controller. The fuzzy PID controller uses a set of rules and linguistic variables to adjust the flow rate of the solute feed to the first tank, in order to maintain the desired solute concentration in the solvent. The controller takes into account factors the current concentration error the rate of change of the error. The proposed structure of Fuzzy-PID control has been shown in Figure 4.



**Figure 4.** Fuzzy-PID controller for a chemical mixing plant

The design process involves tuning of PID controller parameters with the help of Fuzzy logic controller, which takes 'error(e)' and 'rate of change of error(ec)' as inputs and provide Kp, Ki and Kd as output. Hence, there are total of five linguistic variables. For each of these variables total of seven fuzzy values (NL,NA,NT,ZE,PT,PA,PL) have been chosen. The range of the 'e' and 'ec' are between -3 and 3, whereas, by formulating a kind of interpolation, fuzzy values for Kp,Ki and Kd are kept between 0 and 1. Aim of performing interpolation is to keep the values of the variable within some range. In the following equations, interpolation has been applied to keep the value of parameters (Kp, Ki and Kd) between 0 to 1. As the result, parameters are scaled to a common range, enabling a consistent, normalized and controlled analysis.

The determination of these ranges involves the following two steps:

- Identification of Extreme Values: The maximum and minimum values of all the three parameters of controller are identified.
- Normalization Process Once the minimum and maximum values are identified, the values of controller parameter are normalized to the range [0, 1] using the following equations:

$$K_{p} = \frac{K_{p,0} - K_{p,\min}}{K_{p,\max} - K_{p,\min}}$$
(9)

$$K_{i} = \frac{K_{i,0} - K_{i,\min}}{K_{i,\max} - K_{i,\min}}$$
(10)

$$K_{d} = \frac{K_{d,0} - K_{d,\min}}{K_{d,\max} - K_{d,\min}}$$
(11)

 $K_{p,0}$ ,  $K_{i,0}$  and  $K_{d,0}$  are initially estimated values of  $K_p$ ,  $K_i$  and  $K_d$  respectively. Fuzzy rule base for the three PID parameters are shown in Table 1, 2 and 3.

**Table 1.** Rule base for proportional gain,  $K_p$ 

e/ec							
NL	PL	PL	PA	PA	PT	ZE	ZE
NA	PL	PL	PA	PT	PT	NT	NT
NT	PA	PA	PA	PT	ZE	NT	NT
ZE	PA	PA	PT	ZE	NT	NA	NA
PT	PT	PT	ZE	NT	NT	NA	NA
PA	PT	ZE			NA		
PL	$\mathbf{PT}$	ZE	NA	NA	NA	NL	NL

**Table 2.** Rule base for proportional gain,  $K_i$ 

e/ec							
NL	NL	NL	NA	NA	NT	ZE	ZE
NA	NL	NL	NA	NT	NT	ZE	ZE
NT	NL	NA	NT	NT	ZE	$\mathbf{PT}$	PT
ZE	NA	NA	NT	ZE	$\mathbf{PT}$	PA	PA
PT	NA	NT	ZE	PT	$\mathbf{PT}$	PA	PL
PA	ZE	ZE	PT	$\mathbf{PT}$	PA	PL	PL
PL	ZE	ZE	PT	PA	PA	PL	PL

**Table 3.** Rule base for proportional gain,  $K_d$ 

e/ec	NL	NA	NT	ZE	$\mathbf{PT}$	PA	$\mathbf{PL}$
NL	PT	NT	NL	NL	NL	NA	$\mathbf{PT}$
NA	PT	NT	NL	NA	NA	NT	ZE
NT	ZE	NT	NA	NA	NT	NT	ZE
ZE	ZE	NT	NT	NT	NT	NT	ZE
PT	ZE	ZE	ZE	ZE	ZE	ZE	ZE
PA	PL	NT	PT	$\mathbf{PT}$	PT	PT	PL
$\mathbf{PL}$	PL	PA	PA	PA	$\mathbf{PT}$	$\mathbf{PT}$	PL

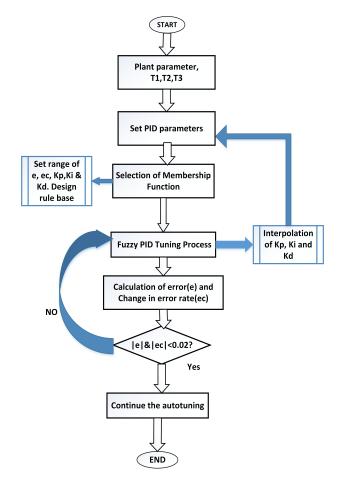
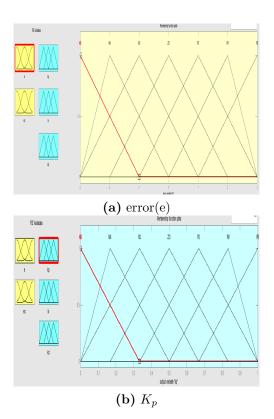


Figure 5. Flow chart of the control action.

### 2.3. FIS computational model and control action

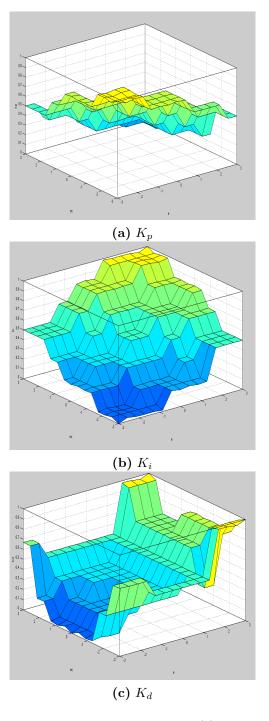
Entire scheme of control action has been shown in the form of flow chart in the Figure 5. A fuzzy inference engine (FIE) employs fuzzy logic to approximate human reasoning/experience. Two input "error(e)" and "rate of change of error(ec))" have been taken as input variables as well as  $K_p$ ,  $K_i$  and  $K_d$  as output. Triangular membership function has been chosen for both input and output variables. For the illustration purpose range of the membership function for 'e' and ' $K_p$ ' have been shown in the Figure 6.



**Figure 6.** Membership function plots with its range for (a)error(e) and (b) proportionality constant  $(K_p)$ 

Fuzzy logic uses linguistic variables, which are variable that take on values in a fuzzy set. On the basis of these variables linguistic rules (rule base) are made that plays a crucial role in the interpretation of fuzzy logic systems by defining the meaning of linguistic variables and interpreting the output in a way that is understandable to humans.

A number of such rules are made to provide the direction to controller for appropriate action. With seven assigned membership values to each variable, a total of 49 rules base have been proposed to completely describes the control action. These rules for PID coefficients ( $K_p$ ,  $K_i$ and  $K_d$ ) are summarized in the form

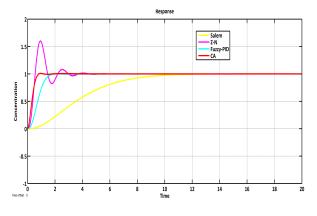


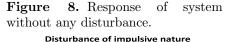
**Figure 7.** Surface view of (a)  $K_p$  (b) $K_i$  and (c)  $K_d$ 

of three tables. The variations of these with respect to inputs (e and ec) are shown as the form of surface view in Figure 7.

**Table 4.** Comparison in terms of fewperformance indicators of differentmethods.

Method	$T_r$	$T_s$	$%M_p$	ITAE
Salem	9	10	0.2	0.9405
Z-N	0.5	5	60	7.905
CA	0.8	1.6	2	50
Proposed	1.7	2	0.8	0.63





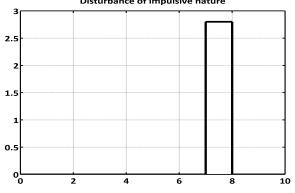


Figure 9. Disturbance to the system

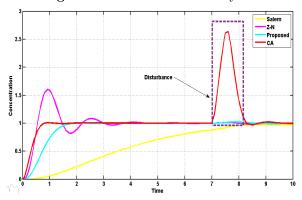


Figure 10. Response of system with some disturbance.

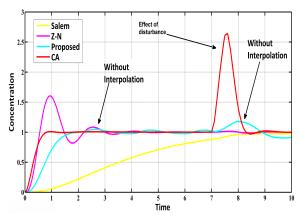


Figure 11. Response of system without using interpolation.

#### 3. Results and discussions

The proposed Fuzzy-PID process control system is designed to maintain the concentration of solute in the tanks. With the step input(concentration of solute), proposed system is analyzed considering two cases, first assuming no disturbance on the system, secondly taking disturbances into the account at seventh second in given test time. The function of the system is to track this step input. Again, in chemical process control systems, disturbances can occur due to fluctuations in feed composition, temperature variations, or unexpected reactions. These disturbance are usually of impulsive nature . In the proposed work, disturbance that is taken for account, is of periodic impulsive nature, whose amplitude and time period have been considered of 2.8 unit and 10 seconds respectively, while pulse width is 10 percent of time period as shown in Fig. 9. The fuzzy logic system continuously monitors the system's performance under such disturbances and adjusts the PID parameters accordingly. The interpolation mechanism allows for smooth adjustments, preventing abrupt changes that could destabilize the system. A total of four performance specification parameters have been considered analyzing the working of the system. A step input is applied to the proposed system and compared with Ziegler-Nicolas(Z-N) method [1], model-based design in [7] and computational approach (CA). response of the proposed system is shown in Figure 8. It can be observed that PID-tuning by Z-N method has highest overshoot and settle to steady state in approximately 5 second, when system is subjected to step input. Model based approach proposed by *Salem* [14] is quite sluggish as rise time of the response Computational approach(CA) is 9 seconds. [9] has somewhat satisfactory results in terms of rise time, settling time and maximum overshoot. However, CA has poor "disturbance rejection" capacity having Integral time absolute error(ITAE) nearly equal to 50, that result in spike( shown by the arrow) when subjected to disturbance of impulsive nature at 7th second as shown in Figure 10. Proposed system qualify in all the four performance specification parameter and shows satisfactory performance even at the onset of sudden disturbance. It has fast response, low settling time, low overshoot and good disturbance rejection capacity. Values of performance parameters of different methods are tabulated in Table 4. It is also worth mentioning the importance of interpolation technique in settling the system response specially under the

effect of disturbance which is occurring at the 7th second of operation. Without interpolation, disturbance try to hinder the tracking of desired value in the proposed method as shown in Fig. 11. Effect can also be seen at the 2.5 sec, when there is slight overshoot causing unsettling of system-response. Thus interpolation mechanism used in the self-tuning Fuzzy PID controller is achieving smooth the PID parameters. By interpolating between predefined range, the controller can fine-tune its responses to varying process conditions more effectively. Therefore. synergetic approach introduced in this work enhances the self-tuning Fuzzy PID controller by combining the strengths of fuzzy logic and This combination traditional PID control. provides a dual benefit: fuzzy logic handles the nonlinearity and uncertainty in the process, while the PID control ensures precise regulation. The Synergetic approach's particularly useful scenarios with high process variability, where it maintains control performance and robustness.

#### 4. Conclusions

In this a interpolation-enhanced study, Fuzzy-PID controller has been designed to control the concentration of a solute in a process control system. The proposed synergistic approach has been applied to a chemical process control system consisting of three tanks, aimed at maintaining a constant effluent concentration, has proven to be successful. This method has demonstrated the ability to attain the desired performance in the closed-loop system by dynamically adjusting the controller parameters,  $K_p$ ,  $K_i$  and  $K_d$ . Performance of Fuzzy-PID controller has been assessed for third order chemical process system. Aim of the controller function is to regulate the level of concentration of solute in the solution in three tanks. A comprehensive set of simulation and case studies have been conducted to illustrate the versatility and robustness of the fuzzy PID controller across a range of chemical processes. It has been observed that proposed system seems is working satisfactorily even in the case of sudden disturbance and it tries to maintain the level of solute at pre-defined values in all the tanks. The simulation results indicate that the suggested approach outperforms the conventional PID controller when it comes to handling disturbances and accurately following set-points. The fuzzy PID controller display improved performance in the presence of uncertainties and disturbances. The result was compared with few existing literature, proposed system seems to be working better among all. The Synergetic methods developed in this work have potential applications in various industrial domains where precise and adaptable process control is critical.

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RESEARCH ARTICLE

### Global mathematical analysis of a patchy epidemic model

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#### ARTICLE INFO

#### ABSTRACT

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AMS Classification 2010: 34K50; 60H30; 65C30; 92B05; 92D25 The dissemination of a disease within a homogeneous population can typically be modeled and managed in a uniform fashion. Conversely, in nonhomogeneous populations, it is essential to account for variations among subpopulations to achieve more precise predictive modeling and efficacious intervention strategies. In this study, we introduce and examine the comprehensive behavior of a deterministic two-patch epidemic model alongside its stochastic counterpart to assess disease dynamics between two heterogeneous populations inhabiting distinct regions. First, utilizing a specific Lyapunov function, we demonstrate that the disease-free equilibrium of the deterministic model is globally asymptotically stable. For the stochastic model, we establish that it is well-posed, meaning it possesses a unique positive solution with probability one. Subsequently, we ascertain the conditions necessary to ensure the total extinction of the disease across both regions. Furthermore, we explicitly determine a threshold condition under which the disease persists in both areas. Additionally, we discuss a scenario wherein the disease persists in one region while simultaneously becoming extinct in the other. The article concludes with a series of numerical simulations that corroborate the theoretical findings.

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#### 1. Introduction

Infectious diseases are defined as illnesses caused by pathogenic agents, transmitted from an infected person, animal, or contaminated inanimate object to a susceptible host [1]. They are the main cause death worldwide killing more people than all wars and natural disasters combined [2,3]. For instance, during the past three years, the world has been under enormous threat from the highly contagious coronavirus which first emerged in China and has spread rapidly to cover almost the entire globe leading to the death of more than six million people, according to the statistics of the World Health Organization [4]. In addition to the human casualties from the coronavirus, the economic and social disruption caused by this pandemic is devastating. Millions of people at risk of crossing the poverty line, thousands of companies face an existential threat and almost 50% of the global workforce, comprising 3.3 billion individuals, faces the threat of unemployment [5]. To understand how infectious diseases spread, the mathematical models are useful tools to describe and simulate concrete situations for anticipating their future behaviour. Most models for the transmission of infectious diseases descend from the classical SIR model of Kermack and McKendrick established in 1927 [6]. Such model is called a compartmental model where the population is divided into compartments of susceptible, infected, and recovered. A non-linear ordinary differential

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equations are used to model the dynamics between these compartments.

A major criticism for this model and the models that followed (for example [7–15]), is that the total population is assumed to be entirely homogenous and all individuals behave the same. Therefore, the model may not represent complex mobility and contact patterns for many real-world diseases. To overcome this inconvenience, Calvo et al. [16] have incorporated population heterogeneity to examine interactions between urban and rural populations on the dynamics of disease spreading by using a compartmental framework of susceptible–infected–susceptible dynamics with some level of immunity. The proposed model is as follows:

$$\begin{aligned} \frac{dS_1}{dt} &= \mu_1 N_1 + \beta_1 \frac{I_1}{N_1} S_1 - \mu_1 S_1 + \delta_{21} S_2 - \delta_{12} S_1, \\ \frac{dI_1}{dt} &= \beta_1 \frac{I_1}{N_1} S_1 - (\mu_1 + \gamma_1) I_1 + \rho_1 \frac{I_1}{N_1} R_1 + \delta_{21} I_2 - \delta_{12} I_1, \\ \frac{dR_1}{dt} &= \gamma_1 I_1 - \rho_1 \frac{I_1}{N_1} R_1 - \mu_1 R_1 + \delta_{21} R_2 - \delta_{12} R_1, \\ \frac{dS_2}{dt} &= \mu_2 N_2 + \beta_2 \frac{I_2}{N_2} S_2 - \mu_2 S_2 + \delta_{12} S_1 - \delta_{21} S_2, \\ \frac{dI_2}{dt} &= \beta_2 \frac{I_2}{N_2} S_2 - (\mu_2 + \gamma_2) I_2 + \rho_2 \frac{I_2}{N_2} R_2 + \delta_{12} I_1 - \delta_{21} I_2, \\ \frac{dR_2}{dt} &= \gamma_2 I_2 - \rho_2 \frac{I_2}{N_2} R_2 - \mu_2 R_2 + \delta_{12} R_1 - \delta_{21} R_2. \end{aligned}$$
(1)

The subscript 1 is used to denote the urban parameters and variables, and the subscript 2 for the rural parameters and variables. For  $i \in \{1, 2\}$ ,  $S_i, I_i, R_i$  and  $N_i$  denote the numbers of susceptible, infected, post-recovery susceptible individuals and the total population, respectively. The parameter  $\mu_i$  is the rate of birth and death.  $\beta_i$ is the infection transmission coefficient between susceptible and infected individuals. The postrecovery susceptible individuals are infected at rate  $\rho_i$ , while infected individuals become postrecovery susceptibles at rate  $\gamma_i$ . The motion between urban and rural populations is modeled by the function  $\delta_{ij}(t)$  which denotes the fraction of individuals who travel from patch  $i \in \{1, 2\}$  to patch  $j \in \{1, 2\}$  (with  $i \neq j$ ) at time t. To study the dynamics of system (1), the authors of [16]compute steady states, showing the local stability of the disease-free steady state, and identify conditions for the existence of the endemic steady states.

In the model above, infectious diseases can spread through interactions between the urban and rural populations. Therefore, infected individuals in urban area can infect rural population and the rural infected can transmit the disease to the urban dwellers. In this paper, we assume that there is no immunity. From this perspective, we propose another version of model (1) by introducing four infection transmission coefficients  $\beta_i$  (i = 1, 2, 3, 4), presented as follows:

$$\begin{cases} dx_1 = (A_1 - \beta_1 x_1 y_1 - \beta_3 x_1 y_2 - \mu_1 x_1) dt, \\ dy_1 = (\beta_1 x_1 y_1 + \beta_4 x_2 y_1 - \mu_1 y_1) dt, \\ dx_2 = (A_2 - \beta_2 x_2 y_2 - \beta_4 x_2 y_1 - \mu_2 x_2) dt, \\ dy_2 = (\beta_2 x_2 y_2 + \beta_3 x_1 y_2 - \mu_2 y_2) dt. \end{cases}$$

$$(2)$$

For the variables  $x_i$  and  $y_i$  (i = 1, 2), we use the subscript 1 to denote the urban variable and the subscript 2 for the rural one. All the other parameters appearing in model (2) are assumed to be constant positives. The symbols involved in the model are described in Table 1.

On the other hand, the spread of diseases is characterized by randomness due to the unpredictability of the natural behavior [17]. A lot of scholars have introduced the white noise into the deterministic models to reveal the effect of the evironmental fluctuations on the spread of diseases. For example, Cao et al. [18] considered a stochastic SEI epidemic model with saturation incidence and logistic growth. By constructing a suitable Lyapunov function, they established sufficient conditions for the existence and uniqueness of an ergodic stationary distribution of the solutions to the model. They also established sufficient conditions for the extinction of the disease. In [19], Pang et al. discussed the dynamics of a stochastic SIQS epidemic model and investigated the boundedness, extinction and the persistence of the stochastic system. Khan et al. [20] proposed a stochastic model to analyze the dynamics of the novel coronavirus disease. They studied the extinction and the persistence of the disease. For more details on the impact of environmental fluctuations on the spread of diseases and population dynamics, we refer the readers to [21-39].

Based on the aforementioned facts, we substitute  $\beta_i dt$  in model (2) by  $\beta_i dt + \sigma_i dB_i(t)$ , where  $B_i(t)$  are mutually independent standard Brownian motions and  $\sigma_i > 0$  are the intensities of their corresponding white noises, i = 1, 2, 3, 4. All these Brownian Motions are defined on a filtered probability space  $(\Omega, \mathcal{F}_{\Omega}, (\mathcal{F}_{\{t\}})_{t\geq 0}, \mathbb{P})$  endowed with a filtration that meets the usual criteria. Thus, we get a stochastic version of the deterministic model (2), defined as follows:

 $\begin{aligned} dx_1(t) &= (A_1 - \beta_1 x_1(t)y_1(t) - \beta_3 x_1(t)y_2(t) - \mu_1 x_1(t))dt - \sigma_1 x_1(t)y_1(t)dB_1(t) - \sigma_3 x_1(t)y_2(t)dB_3(t), \\ dy_1(t) &= (\beta_1 x_1(t)y_1(t) + \beta_4 x_2(t)y_1(t) - \mu_1 y_1(t))dt + \sigma_1 x_1(t)y_1(t)dB_1(t) + \sigma_4 x_2(t)y_1(t)dB_4(t), \\ dx_2(t) &= (A_2 - \beta_2 x_2(t)y_2(t) - \beta_4 x_2(t)y_1(t) - \mu_2 x_2(t))dt - \sigma_2 x_2(t)y_2(t)dB_2(t) - \sigma_4 x_2(t)y_1(t)dB_4(t), \\ dy_2(t) &= (\beta_2 x_2(t)y_2(t) + \beta_3 x_1(t)y_2(t) - \mu_2 y_2(t))dt + \sigma_2 x_2(t)y_2(t)dB_2(t) + \sigma_3 x_1(t)y_2(t)dB_3(t). \end{aligned}$ (3)

Here, we assume that the urban susceptibles contamined by the rural infected individuals stay in the rural infect compartment and rural susceptibles contamined by urban infected people stay in the urban infected class.

For convenience, the abbreviation "a.s." means "almost surely", while  $\langle f(t) \rangle = t^{-1} \int_0^t f(r) dr$  is the time average of a continuous function f. For two numbers *a* and *b*, the symbols  $a \wedge b$  and  $a \vee b$ stand for the minimum and the maximum of *a* and *b*, respectively.

The rest of the paper proceeds as follows. In the next section, we study the stability of the equilibrium state  $E = (\frac{A_1}{\mu_1}, 0, \frac{A_2}{\mu_2}, 0)$  for the deterministic model (2). Section 3 is devoted to verify if the stochastic model (3) has a unique positive solution with probability one. In section 4, the conditions ensuring the exponential extinction of the disease in both patches are established. Afterwards, we will carry out an analysis leading to defining a threshold for the disease to persist completely. There remains a case where the disease persists in one patch, and disappears in the other, which is the main theme of the section 6. The paper ends with the realization of numerical simulations using the software Matlab 2015b.

#### 2. Stability of the deterministic model

The aim of mathematical modeling of the spread of epidemics is to know the conditions under which the epidemic dies out. The deterministic model (2) has one free-disease equilibrium  $E = (\frac{A_1}{\mu_1}, 0, \frac{A_2}{\mu_2}, 0).$ 

The following theorem gives sufficient conditions for local and global asymptotic stability of the free-disease equilibrium E.

**Theorem 1.** If  $\left( \left( \beta_1 \frac{A_1}{\mu_1} + \beta_4 \frac{A_2}{\mu_2} - \mu_1 \right) \lor \left( \beta_3 \frac{A_1}{\mu_1} + \beta_2 \frac{A_2}{\mu_2} - \mu_2 \right) \right) < 0$ , then the equilibrium *E* is locally asymptotically stable.

**Proof.** The Jacobian matrix related to model (2) at the equilibrium E is

$$J(E) = \begin{pmatrix} -\mu_1 & -\beta_1 \frac{A_1}{\mu_1} & 0 & -\beta_3 \frac{A_1}{\mu_1} \\ 0 & \beta_1 \frac{A_1}{\mu_1} - \mu_1 + \beta_4 \frac{A_2}{\mu_2} & 0 & 0 \\ 0 & -\beta_4 \frac{A_2}{\mu_2} & -\mu_2 & -\beta_2 \frac{A_2}{\mu_2} \\ 0 & 0 & 0 & \beta_2 \frac{A_2}{\mu_2} - \mu_2 + \beta_3 \frac{A_1}{\mu_1} \end{pmatrix}$$

According to the Hurwitz criterion, if  $\left(\left(\beta_1 \frac{A_1}{\mu_1} + \beta_4 \frac{A_2}{\mu_2} - \mu_1\right) \lor \left(\beta_3 \frac{A_1}{\mu_1} + \beta_2 \frac{A_2}{\mu_2} - \mu_2\right)\right) < 0$ , then the eigenvalues of matrix J(E) are all negatives.

Thus, the equilibrium state E is locally asymptotically stable.

**Theorem 2.** If  $\left(\left((\beta_1 + \beta_4)\frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_1\right) \lor \left((\beta_2 + \beta_3)\frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_2\right)\right) < 0$ , then the equilibrium E is globally asymptotically stable.

**Proof.** Consider the Lyapunov function  $\mathcal{V}$  defined by

$$\mathcal{V}(x_1(t), y_1(t), x_2(t), y_2(t)) = \frac{1}{2}(y_1^2 + y_2^2).$$

The derivative of  $\mathcal{V}$  along the trajectories of solution of model (2) is as follows

$$\begin{split} \frac{d\mathcal{V}(x_1(t), y_1(t), x_2(t), y_2(t))}{dt} \\ &= y_1(t)(\beta_1 x_1(t) y_1(t) + \beta_4 x_2(t) y_1(t) - \mu_1 y_1(t)) \\ &+ y_2(t)(\beta_2 x_2(t) y_2(t) + \beta_3 x_1(t) y_2(t) \\ &- \mu_2 y_2(t)) \\ &= y_1^2(t)(\beta_1 x_1(t) + \beta_4 x_2(t) - \mu_1) \\ &+ y_2^2(t)(\beta_2 x_2(t) + \beta_3 x_1(t) - \mu_2) \\ &\leq y_1^2(t) \left( (\beta_1 + \beta_4) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_1 \right) \\ &+ y_2^2(t) \left( (\beta_2 + \beta_3) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_2 \right). \end{split}$$

Assuming that 
$$\left(\left((\beta_1 + \beta_4)\frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_1\right) \lor \left((\beta_2 + \beta_3)\frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_2\right)\right) < 0$$
, we get  

$$\frac{d\mathcal{V}(x_1(t), y_1(t), x_2(t), y_2(t))}{dt} < 0 \quad \text{for any } t \ge 0,$$

which means that E is globally asymptotically stable.  $\Box$ 

Table 1. Description	on of symbols in model (2	2).
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Parameter	Meaning
$x_i$	The number of susceptible individuals to the disease, where $i =$
	1, 2.
$y_i$	The number of infective members.
$A_i$	A constant input of new members into the population $i$ per unit
	time.
$\mu_i$	Natural death rate of $x_i$ and $y_i$ .
$\beta_1$	Transmission coefficient between $x_1$ and $y_1$ .
$\beta_2$	Transmission coefficient between $x_2$ and $y_2$ .
$\beta_3$	Transmission coefficient between $x_1$ and $y_2$ .
$\beta_4$	Transmission coefficient between $x_2$ and $y_1$ .

# 3. Well-posedeness of the stochastic model

**Lemma 1.** The set  $\Gamma = \left\{ (x_1(t), y_1(t), x_2(t), y_2(t)) \in \mathbb{R}^4_+ : N(t) = x_1(t) + y_1(t) + x_2(t) + y_2(t) \leq \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} \right\}$  is positively invariant for the stochastic model (3).

**Proof.** From system (3), we have

$$dN(t) = (A_1 + A_2 - \mu_1(x_1(t) + y_1(t))) - \mu_2(x_2(t) + y_2(t)))dt$$
(4)  
$$\leq (A_1 + A_2 - (\mu_1 \wedge \mu_2)N(t))dt.$$

Thus

$$N(t) \leq \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} + \left(N(0) - \frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right) e^{-(\mu_1 \wedge \mu_2)t}.$$
  
If  $N(0) \leq \frac{A_1 + A_2}{\mu_1 \wedge \mu_2}$ , then  $N(t) \leq \frac{A_1 + A_2}{\mu_1 \wedge \mu_2}$  for all  $t > 0.$ 

**Theorem 3.** For any  $(x_1(0), y_1(0), x_2(0), y_2(0)) \in \Gamma$ , the stochastic system (3) is mathematically well-posed in the sense that it has a unique solution  $(x_1(t), y_1(t), x_2(t), y_2(t)) \in \Gamma$  with probability one.

**Proof.** The coefficients of system (3) are locally Lipschitz continuous, for any given initial value  $(x_1(0), y_1(0), x_2(0), y_2(0))$ , then there is a unique local solution  $(x_1(t), y_1(t), x_2(t), y_2(t))$  on  $t \in [0, \tau_e)$ , where  $\tau_e$  is the explosion time.

Let  $k_0 > 0$  such that  $x_1(0), y_1(0), x_2(0), y_2(0) > k_0$ . For  $k \le k_0$ , we consider the stopping times

$$\begin{aligned} \tau_k &= \inf \left\{ t \in [0, \tau_e) : x_1(t) \le k \text{ or } y_1(t) \le k \\ \text{ or } x_2(t) \le k \text{ or } y_2(t) \le k \right\}, \\ \tau &= \lim_{k \to 0} \tau_k = \inf \left\{ t \in [0, \tau_e) : x_1(t) \le 0 \text{ or } y_1(t) \le 0 \\ \text{ or } x_2(t) \le 0 \text{ or } y_2(t) \le 0 \right\}. \end{aligned}$$

$$V(X(t)) = V((x_1(t), y_1(t), x_2(t), y_2(t)))$$
  
=  $4 \ln \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \ln(x_1(t)y_1(t)x_2(t)y_2(t)).$ 

Applying Itô formula on V, we obtain

$$\begin{split} dV &= -\frac{dx_1}{x_1} - \frac{dx_2}{x_2} - \frac{dy_1}{y_1} - \frac{dy_2}{y_2} + \left(\frac{1}{2}\sigma_1^2 y_1^2 + \frac{1}{2}\sigma_3^2 y_2^2\right) \\ &+ \frac{1}{2}\sigma_2^2 y_2^2 + \frac{1}{2}\sigma_4^2 y_1^2 + \frac{1}{2}\sigma_1^2 x_1^2 + \frac{1}{2}\sigma_4^2 x_2^2 + \frac{1}{2}\sigma_2^2 x_2^2 + \frac{1}{2}\sigma_3^2 x_1^2 \right) dt \\ \leq & \left[ -\frac{A_1}{x_1} + \beta_1 y_1 + \beta_3 y_2 + \mu_1 - \beta_1 x_1 - \beta_4 x_2 + \mu_1 - \frac{A_2}{x_2} \right. \\ &+ \beta_2 y_2 + \beta_4 y_1 + \mu_2 - \beta_2 x_2 - \beta_3 x_1 + \mu_2 + \left(\sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_4^2\right) \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 \right] dt + \sigma_1 (y_1 - x_1) dB_1 + \sigma_2 (y_2 - x_2) dB_2 \\ &+ \sigma_3 (y_2 - x_1) dB_3 + \sigma_4 (y_1 - x_2) dB_4 \\ \leq & \left[ 2\mu_1 + 2\mu_2 + \left(\beta_1 + \beta_2 + \beta_3 + \beta_4\right) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} + \left(\sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_3^2 + \sigma_3^2 + \sigma_3^2\right) \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 \right] dt + \sigma_1 (y_1 - x_1) dB_1 \\ &+ \sigma_2 (y_2 - x_2) dB_2 + \sigma_3 (y_2 - x_1) dB_3 + \sigma_4 (y_1 - x_2) dB_4. \end{split}$$

Integrating the both sides of the inequality above and then taking the expectation give

$$\mathbb{E}[V(X(t))] \le \lambda t + V(X(0)), \tag{5}$$

where

$$\lambda = 2\mu_1 + 2\mu_2 + \left(\beta_1 + \beta_2 + \beta_3 + \beta_4\right) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} + \left(\sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_4^2\right) \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2.$$

Using the stopping time  $\tau_k$ , one has

Let

It follows that

$$\mathbb{E}[V(X(t \wedge \tau_k))] = \mathbb{E}[V(X(t \wedge \tau_k)) \mathbb{I}_{(\tau_k \leq t)}] \\ + \mathbb{E}[V(X(t \wedge \tau_k)) \mathbb{I}_{(\tau_k > t)}] \\ \ge \mathbb{E}[V(X(\tau_k)) \mathbb{I}_{(\tau_k \leq t)}],$$

where  $\mathbb{I}_A$  is the characteristic function of A. Notice that there is some component of  $X(\tau_k)$  equals to k. Therefore

$$V(X(\tau_k)) \ge \ln\left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2} \frac{1}{k}\right).$$

As a result, we have

$$\mathbb{E}[V(X(t \wedge \tau_k))] \ge \ln\left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2} \frac{1}{k}\right) \times \mathbb{P}\left(\tau_k \le t\right)$$

Together with (5), we get

$$\mathbb{P}\Big(\tau_k \le t\Big) \le \frac{\lambda t + V(X(0))}{\ln\left(\frac{A_1 + A_2}{\mu_1 \land \mu_2} \frac{1}{k}\right)}.$$

If we let  $k \to 0$ , we obtain for all  $t \ge 0$ :  $\mathbb{P}(\tau \le t) = 0.$ 

Hence

$$\mathbb{P}\Big(\tau = \infty\Big) = 1.$$

As  $\tau_e \geq \tau$ , then  $\tau_e = \infty$  a.s. Finally, the solution is global.

#### 4. Decline of the disease

**Theorem 4.** Let  $(x_1(t), y_1(t), x_2(t), y_2(t))$  be the solution of system (3) with any initial value  $(x_1(0), y_1(0), x_2(0), y_2(0)) \in \Gamma$ .

(1) If 
$$\frac{\beta_1^2}{2\sigma_1^2} + \frac{\beta_4^2}{2\sigma_4^2} < \mu_1$$
, then  $\lim_{t \to \infty} y_1(t) = 0$  a.s

(2) If 
$$\frac{\beta_2^2}{2\sigma_2^2} + \frac{\beta_3^2}{2\sigma_3^2} < \mu_2$$
, then  $\lim_{t \to \infty} y_2(t) = 0$  a.s

**Proof.** 1. Applying Itô formula to system (3), we get

$$d\ln y_1(t) = \frac{1}{y_1(t)} dy_1(t) - \frac{1}{2} \frac{1}{y_1^2} (dy_1(t))^2$$
  
=  $\left(\beta_1 x_1(t) + \beta_4 x_2(t) - \mu_1 - \frac{\sigma_1^2}{2} x_1^2(t) - \frac{\sigma_1^2}{2} x_2^2(t)\right) dt + \sigma_1 x_1(t) dB_1(t)$   
+  $\sigma_4 x_2(t) dB_2(t).$ 

$$\begin{aligned} \frac{1}{t} \ln \frac{y_1(t)}{y_1(0)} &= \beta_1 \langle x_1(t) \rangle + \beta_4 \langle x_2(t) \rangle - \mu_1 - \frac{\sigma_1^2}{2} \langle x_1^2(t) \rangle \\ &- \frac{\sigma_4^2}{2} \langle x_2^2(t) \rangle + \frac{M_1(t)}{t} \\ &\leq \beta_1 \langle x_1(t) \rangle + \beta_4 \langle x_2(t) \rangle - \mu_1 - \frac{\sigma_1^2}{2} \langle x_1(t) \rangle^2 \\ &- \frac{\sigma_4^2}{2} \langle x_2(t) \rangle^2 + \frac{M_1(t)}{t} \\ &= -\frac{\sigma_1^2}{2} \langle x_1(t) \rangle^2 + \beta_1 \langle x_1(t) \rangle - \frac{\sigma_4^2}{2} \langle x_2(t) \rangle^2 \\ &+ \beta_4 \langle x_2(t) \rangle - \mu_1 + \frac{M_1(t)}{t} \\ &= -\frac{\sigma_1^2}{2} \left( \langle x_1(t) \rangle^2 - 2\frac{\beta_1}{\sigma_1^2} \langle x_1(t) \rangle \right) \\ &- \frac{\sigma_4^2}{2} \left( \langle x_2(t) \rangle^2 - 2\frac{\beta_4}{\sigma_4^2} \langle x_2(t) \rangle \right) - \mu_1 \\ &+ \frac{M_1(t)}{t} \\ &= -\frac{\sigma_1^2}{2} \left( \langle x_2(t) \rangle - \frac{\beta_1}{\sigma_1^2} \right)^2 + \frac{\beta_1^2}{2\sigma_1^2} \\ &- \frac{\sigma_4^2}{2} \left( \langle x_2(t) \rangle - \frac{\beta_4}{\sigma_4^2} \right)^2 + \frac{\beta_4^2}{2\sigma_4^2} - \mu_1 \\ &+ \frac{M_1(t)}{t} \end{aligned} \tag{6}$$
$$&\leq \frac{\beta_1^2}{2\sigma_1^2} + \frac{\beta_4^2}{2\sigma_4^2} - \mu_1 + \frac{M_1(t)}{t}, \end{aligned}$$

where

$$M_1(t) = \sigma_1 \int_0^t x_1(r) dB_1(r) + \sigma_4 \int_0^t x_2(r) dB_2(r).$$

Bearing in mind the strong law of large numbers for martingales, we obtain

$$\limsup_{t \to \infty} \frac{\ln y_1(t)}{t} \le \frac{\beta_1^2}{2\sigma_1^2} + \frac{\beta_4^2}{2\sigma_4^2} - \mu_1 \quad \text{a.s.}$$

$$\lim_{t \to \infty} y_1(t) = 0 \quad \text{a.s.}$$

2. Similarly, we get :  $\lim_{t\to\infty} y_2(t) = 0$  a.s., under the condition  $\frac{\beta_2^2}{2\sigma_2^2} + \frac{\beta_3^2}{2\sigma_3^2} < \mu_2$ .

This completes the proof of Theorem 4.

**Theorem 5.** Let  $(x_1(t), y_1(t), x_2(t), y_2(t))$  be the solution of system (3) with any initial value  $(x_1(0), y_1(0), x_2(0), y_2(0)) \in \Gamma$ .

$$\begin{array}{rcl} (1) \ If \ \frac{A_1+A_2}{\mu_1} &\leq \ \frac{\beta_1}{\sigma_1^2}, \ \frac{A_1+A_2}{\mu_2} &\leq \ \frac{\beta_4}{\sigma_4^2} \ and \\ \beta_1 \frac{A_1+A_2}{\mu_1} &+ \ \beta_4 \frac{A_1+A_2}{\mu_2} \ - \ \frac{\sigma_1^2}{2} \left(\frac{A_1+A_2}{\mu_1}\right)^2 \ - \\ & \frac{\sigma_4^2}{2} \left(\frac{A_1+A_2}{\mu_2}\right)^2 < \mu_1, \ then \\ & \lim_{t \to \infty} y_1(t) = 0 \quad a.s. \end{array}$$

(2) If 
$$\frac{A_1+A_2}{\mu_1} \leq \frac{\beta_3}{\sigma_3^2}$$
,  $\frac{A_1+A_2}{\mu_2} \leq \frac{\beta_2}{\sigma_2^2}$  and  
 $\beta_3 \frac{A_1+A_2}{\mu_1} + \beta_2 \frac{A_1+A_2}{\mu_2} - \frac{\sigma_3^2}{2} \left(\frac{A_1+A_2}{\mu_1}\right)^2 - \frac{\sigma_2^2}{2} \left(\frac{A_1+A_2}{\mu_2}\right)^2 < \mu_2$ , then  
 $\lim_{t \to \infty} y_2(t) = 0$  a.s.

Before giving the proof of Theorem 5, we will present the two following Lemmas.

**Lemma 2.** Let  $(x_1(t), y_1(t), x_2(t), y_2(t))$  be the solution of system (3). We have

$$\lim_{t \to \infty} \frac{x_1(t) + y_1(t) + x_2(t) + y_2(t)}{t} = 0 \quad a.s.$$

**Proof.** Let 
$$N(t) = x_1(t) + y_1(t) + x_2(t) + y_2(t)$$
.

From system (3), one has

$$dN(t) = (A_1 + A_2 - \mu_1 (x_1(t) + y_1(t))) - (\mu_2 (x_2(t) - y_2(t))) dt.$$
(7)

Then

$$(A_1 + A_2 - (\mu_1 \vee \mu_2)N(t)) dt \le dN(t) \le (A_1 + A_2 - (\mu_1 \wedge \mu_2)N(t)) dt.$$
(8)

Thus

$$\frac{A_1 + A_2}{\mu_1 \vee \mu_2} + \left( N(0) - \frac{A_1 + A_2}{\mu_1 \vee \mu_2} \right) e^{-(\mu_1 \vee \mu_2)t} \le N(t),$$
 and

$$N(t) \le \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} + \left(N(0) - \frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right) e^{-(\mu_1 \wedge \mu_2)t}.$$
  
Hence

$$\lim_{t \to \infty} \frac{x_1(t) + y_1(t) + x_2(t) + y_2(t)}{t} = 0 \quad \text{a.s}$$

The proof is complete.

**Lemma 3.** Let  $(x_1(t), y_1(t), x_2(t), y_2(t))$  be the solution of system (3). Then

$$\limsup_{t \to \infty} \langle x_1(t) \rangle \le \frac{A_1 + A_2}{\mu_1} \qquad a.s.,$$
$$\limsup_{t \to \infty} \langle x_2(t) \rangle \le \frac{A_1 + A_2}{\mu_2} \qquad a.s.$$

**Proof.** By (7), we obtain

$$\langle x_1(t) \rangle \le \frac{A_1 + A_2}{\mu_1} - \frac{\phi(t)}{\mu_1},$$
  
 $\langle x_2(t) \rangle \le \frac{A_1 + A_2}{\mu_2} - \frac{\phi(t)}{\mu_2},$ 

where

$$\phi(t) = \frac{x_1(t) + y_1(t) + x_2(t) + y_2(t)}{t} - \frac{x_1(0) + y_1(0) + x_2(0) + y_2(0)}{t}.$$

Bearing in mind Lemma 2, we get the seeked results.  $\hfill \Box$ 

Proof of Theorem 5. 1. By Lemma 3, there is  $T_1 > 0$  such that, for any  $t \ge T_1$ ,

$$\langle x_1(t) \rangle \le \frac{A_1 + A_2}{\mu_1}$$
 and  $\langle x_2(t) \rangle \le \frac{A_1 + A_2}{\mu_2}$ .

For all  $t \geq T_1$ , we assume that

$$\langle x_1(t)\rangle \le \frac{A_1 + A_2}{\mu_1} \le \frac{\beta_1}{\sigma_1^2},$$

and

$$\langle x_2(t)\rangle \leq \frac{A_1 + A_2}{\mu_2} \leq \frac{\beta_4}{\sigma_4^2}$$

Together with (6), we have

$$\begin{aligned} \frac{1}{t} \ln \frac{y_1(t)}{y_1(0)} &\leq -\frac{{\sigma_1}^2}{2} \Big(\frac{A_1 + A_2}{\mu_1} - \frac{\beta_1}{\sigma_1^2}\Big)^2 + \frac{\beta_1^2}{2\sigma_1^2} \\ &- \frac{\sigma_4^2}{2} \Big(\frac{A_1 + A_2}{\mu_2} - \frac{\beta_4}{\sigma_4^2}\Big)^2 + \frac{\beta_4^2}{2\,\sigma_4^2} - \mu_1 \\ &= \beta_1 \frac{A_1 + A_2}{\mu_1} + \beta_4 \frac{A_1 + A_2}{\mu_2} - \frac{\sigma_1^2}{2} \Big(\frac{A_1 + A_2}{\mu_1}\Big)^2 \\ &- \frac{\sigma_4^2}{2} \Big(\frac{A_1 + A_2}{\mu_2}\Big)^2 - \mu_1. \end{aligned}$$

370

Since

$$\begin{split} \beta_1 \frac{A_1 + A_2}{\mu_1} + \beta_4 \frac{A_1 + A_2}{\mu_2} - \frac{\sigma_1^2}{2} \Big( \frac{A_1 + A_2}{\mu_1} \Big)^2 \\ - \frac{\sigma_4^2}{2} \Big( \frac{A_1 + A_2}{\mu_2} \Big)^2 - \mu_1 < 0, \end{split}$$

then

 $\limsup_{t\to\infty} \frac{\ln y_1(t)}{t} < 0 \quad \text{ a.s.}$ 

Consequently

$$\lim_{t \to \infty} y_1(t) = 0 \quad \text{a.s}$$

2. Following the same method above, we get

$$\lim_{t \to \infty} y_2(t) = 0 \quad \text{a.s.}$$

#### 5. Disease prevalence

**Theorem 6.** Let  $(x_1(t), y_1(t), x_2(t), y_2(t))$  be the solution of system (3) with any initial value  $(x_1(0), y_1(0), x_2(0), y_2(0)) \in \Gamma$ .

**Proof.** 1. From (7), we have

$$(\mu_1 \lor \mu_2) \langle x_1(t) + x_2(t) \rangle \ge A_1 + A_2 - \mu_1 \langle y_1(t) \rangle$$
  
 $- \mu_2 \frac{A_1 + A_2}{\mu_1 \land \mu_2} - \phi(t).$ 

Then, one can get

$$\langle x_1(t) + x_2(t) \rangle \geq \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \frac{\mu_1}{\mu_1 \vee \mu_2} \langle y_1(t) \rangle - \frac{\mu_2}{\mu_1 \vee \mu_2} \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \frac{\phi(t)}{\mu_1 \vee \mu_2} \geq \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \langle y_1(t) \rangle - \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \frac{\phi(t)}{\mu_1 \vee \mu_2}.$$
(9)

On the other hand, one can have

$$\frac{1}{t} \ln \frac{y_1(t)}{y_1(0)} \ge (\beta_1 \wedge \beta_4) \langle x_1(t) + x_2(t) \rangle - \mu_1 - \frac{\sigma_1^2 + \sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 + \frac{M_1(t)}{t}.$$
(10)

Combining (9) and (10) yields

$$\frac{1}{t} \ln \frac{y_1(t)}{y_1(0)} \ge (\beta_1 \wedge \beta_4) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - (\beta_1 \wedge \beta_4) \langle y_1(t) \rangle - (\beta_1 \wedge \beta_4) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \frac{\beta_1 \wedge \beta_4}{\mu_1 \vee \mu_2} \phi(t) - \mu_1 - \frac{\sigma_1^2 + \sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 + \frac{M_1(t)}{t}.$$

As a consequence, we get

$$\begin{split} \liminf_{t \to \infty} \left( \beta_1 \wedge \beta_4 \right) \langle y_1(t) \rangle \geq & \left( \beta_1 \wedge \beta_4 \right) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} \\ & - \frac{\sigma_1^2 + \sigma_4^2}{2} \left( \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} \right)^2 \\ & - \left( \left( \beta_1 \wedge \beta_4 \right) + \mu_1 \right) \quad \text{a.s.} \end{split}$$

Immediately, under the condition stated in the first part of Theorem 6, we deduce that

$$\liminf_{t \to \infty} \langle y_1(t) \rangle > 0 \quad \text{a.s.}$$

2. Concerning the second part of Theorem 6, we get the desired result using the above method.

## 6. Simultaneous extinction and persistence

**Theorem 7.** Let  $(x_1(t), y_1(t), x_2(t), y_2(t))$  be the solution of system (3) with any initial value  $(x_1(0), y_1(0), x_2(0), y_2(0)) \in \Gamma$ .

- (1) If  $(\beta_2 \vee \beta_3) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} \frac{\sigma_2^2 + \sigma_3^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 > \mu_2$  and  $\lim_{t \to \infty} y_1(t) = 0$  a.s., then:  $\liminf_{t \to \infty} \langle y_2(t) \rangle > 0$  a.s.
- (2) If  $(\beta_1 \vee \beta_4) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} \frac{\sigma_1^2 + \sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 > \mu_1$  and  $\lim_{t \to \infty} y_2(t) = 0$  a.s., then:  $\liminf_{t \to \infty} \langle y_1(t) \rangle > 0$  a.s.

**Proof.** 1. In the case of the extinction of urban infected, we have:  $\lim_{t\to\infty} y_1(t) = 0$  a.s.

Then, for any  $\epsilon > 0$ , there exist  $T_2 > 0$  such that:  $y_1(t) \le \epsilon$  for all  $t \ge T_2$ .

Together with (7), one can get

$$\begin{split} \phi(t) &\geq A_1 + A_2 - (\mu_1 \lor \mu_2) \langle x_1(t) + x_2(t) \rangle \\ &- \mu_1 \langle y_1(t) \rangle - \mu_2 \langle y_2(t) \rangle \\ &= A_1 + A_2 - (\mu_1 \lor \mu_2) \langle x_1(t) + x_2(t) \rangle \\ &- \mu_1 \frac{1}{t} \int_0^{T_2} y_1(r) dr - \mu_1 \frac{1}{t} \int_{T_2}^t y_1(r) dr \\ &\mu_2 \langle y_2(t) \rangle \geq A_1 + A_2 - (\mu_1 \lor \mu_2) \langle x_1(t) + x_2(t) \rangle \\ &- \frac{T_2}{t} \mu_1 \sup_{r \in [0, T_2]} y_1(r) - \mu_1 (1 - \frac{T_2}{t}) \epsilon - \mu_1 \langle y_2(t) \rangle \end{split}$$

Then

372

$$\langle x_1(t) + x_2(t) \rangle \ge \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \frac{T_2}{t} \sup_{r \in [0, T_2]} y_1(r) - \epsilon - \langle y_2(t) \rangle - \frac{\phi(t)}{\mu_1 \vee \mu_2}.$$
 (11)

Now, we apply Itô formula on system (3) to obtain

$$\frac{1}{t}\ln\frac{y_2(t)}{y_2(0)} \ge (\beta_2 \wedge \beta_3)\langle x_1(t) + x_2(t)\rangle - \mu_2 \\ - \frac{\sigma_2^2 + \sigma_3^2}{2} \Big(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\Big)^2 + \frac{M_2(t)}{t},$$
(12)

where

$$M_2(t) = \sigma_2 \int_0^t x_2(r) dB_2(r) + \sigma_3 \int_0^t x_1(r) dB_3(r).$$

Injecting (11) on (12) gives

$$\frac{1}{t}\ln\frac{y_2(t)}{y_2(0)} \ge (\beta_2 \wedge \beta_3)\frac{A_1 + A_2}{\mu_1 \vee \mu_2}$$
$$- (\beta_2 \wedge \beta_3)\frac{1}{t}\sup_{r \in [0, T_2]} y_1(r)$$
$$- (\beta_2 \wedge \beta_3)\langle y_2(t) \rangle - (\beta_2 \wedge \beta_3)\epsilon$$
$$- \frac{\beta_2 \wedge \beta_3}{\mu_1 \vee \mu_2}\phi(t) - \mu_2$$
$$- \frac{\sigma_2^2 + \sigma_3^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 + \frac{M_2(t)}{t}.$$

According to Lemma 2, we can have

$$\liminf_{t \to \infty} (\beta_2 \wedge \beta_3) \langle y_2(t) \rangle \ge (\beta_2 \wedge \beta_3) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \mu_2$$
$$- \frac{\sigma_2^2 + \sigma_3^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 \quad \text{a.s.}$$

2. Similarly, we get

$$\liminf_{t \to \infty} (\beta_1 \wedge \beta_4) \langle y_1(t) \rangle \ge (\beta_1 \wedge \beta_4) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \mu_1 \\ - \frac{\sigma_1^2 + \sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 \quad \text{a.s.}$$

The proof is complete.

#### 7. Numerical results

• The main goal of this section is to perform a numerical verification of the results obtained in the previous sections. First of all, we choose the initial value as  $(x_1(0), y_1(0), x_2(0), y_2(0)) = (0.5, 0.7, 0.4, 0.9)$ . The other parameters values are summarized in Table 2 split into 8 tests.

#### 7.1. Deterministic stability

Based on the values of Test 0, we have

$$\left( \left( (\beta_1 + \beta_4) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_1 \right) \vee \left( (\beta_2 + \beta_3) \frac{A_1 + A_2}{\mu_1 \wedge \mu_2} - \mu_2 \right) \right) \\= -0.41477.$$

According to Theorem 2, the equilibrium E = (0.2308, 0, 0.1667, 0) is globally asymptotically stable which is depicted in Figure 1.

#### 7.2. Stochastic extinction of the epidemic

By considering the values of Test 1, we have the following calculation

$$\frac{\beta_1^2}{2\sigma_1^2} + \frac{\beta_4^2}{2\sigma_4^2} - \mu_1 = -0.0036,$$

and

$$\frac{\beta_2^2}{2\sigma_2^2} + \frac{\beta_3^2}{2\sigma_3^2} - \mu_2 = -0.1375.$$

From Figure 2, we observe that:  $\lim_{t\to\infty} y_1(t) = \lim_{t\to\infty} y_2(t) = 0$ , which conform to the Theorem 4. Second, we obtain for Test 2

$$\frac{A_1 + A_2}{\mu_1} - \frac{\beta_1}{\sigma_1^2} = -1.3626, \ \frac{A_1 + A_2}{\mu_2} - \frac{\beta_4}{\sigma_4^2} = -2.441$$

and

$$\beta_1 \frac{A_1 + A_2}{\mu_1} + \beta_4 \frac{A_1 + A_2}{\mu_2} - \frac{\sigma_1^2}{2} \left(\frac{A_1 + A_2}{\mu_1}\right)^2 - \frac{\sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_2}\right)^2 - \mu_1 = -0.017.$$

According to Theorem 5,  $y_1(t)$  converges exponentially to zero (see Figure 2).

Next, based on the parameters values for Test 3, the numerical values are

$$\frac{A_1 + A_2}{\mu_1} - \frac{\beta_3}{\sigma_3^2} = -0.9437, \ \frac{A_1 + A_2}{\mu_2} - \frac{\beta_2}{\sigma_2^2} = -2.2292$$

and

$$\beta_3 \frac{A_1 + A_2}{\mu_1} + \beta_2 \frac{A_1 + A_2}{\mu_2} \frac{\sigma_3^2}{2} \left(\frac{A_1 + A_2}{\mu_1}\right)^2 - \frac{\sigma_2^2}{2} \left(\frac{A_1 + A_2}{\mu_2}\right)^2 - \mu_2 = -0.0799.$$

From Figure 2, we see that  $y_2(t)$  tends to zero, which agrees with Theorem 5.

#### 7.3. Stochastic persistence of the epidemic

We choose values of Test 4 and Test 5 to get the following

$$(\beta_1 \wedge \beta_4) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \frac{\sigma_1^2 + \sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 - (\beta_1 \wedge \beta_4) - \mu_1 = 0.1589$$

and

$$(\beta_2 \wedge \beta_3) \frac{A_1 + A_2}{\mu_1 \vee \mu_2} - \frac{\sigma_2^2 + \sigma_3^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \wedge \mu_2}\right)^2 - (\beta_2 \wedge \beta_3) - \mu_2 = 0.1489.$$

By virtue of Theorem 6, the epidemic will be persistent in both urban and rural areas (see Figure 3).

### 7.4. Simultaneous extinction and persistence

**Case 1.** We have already considered that  $\lim_{t\to\infty} y_1(t) = 0$ . From values of Test 6, we obtain

$$(\beta_2 \lor \beta_3) \frac{A_1 + A_2}{\mu_1 \lor \mu_2} - \frac{\sigma_2^2 + \sigma_3^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \land \mu_2}\right)^2 - \mu_2 = 0.0631.$$

Therefore, Theorem 7 yields

$$\liminf_{t \to \infty} \left\langle y_2(t) \right\rangle > 0,$$

which is well confirmed by Figure 4.

**Case 2.** Based on the values of Test 7 and , we get that

$$\left(\beta_1 \lor \beta_4\right) \frac{A_1 + A_2}{\mu_1 \lor \mu_2} - \frac{\sigma_1^2 + \sigma_4^2}{2} \left(\frac{A_1 + A_2}{\mu_1 \land \mu_2}\right)^2 - \mu_1 = 0.0528.$$

2 If we consider  $\lim_{t\to\infty} y_2(t) = 0$ , then Theorem 7 implies that:  $\liminf_{t\to\infty} \langle y_1(t) \rangle > 0.$ 

Therefore, Figure 4 reflects perfectly the statement of Theorem 7.

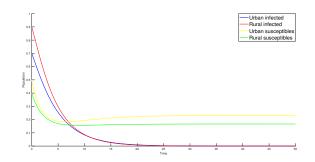


Figure 1. Computer simulation of  $x_1(t)$ ,  $x_2(t)$ ,  $y_1(t)$  and  $y_2(t)$  for model (2), corresponding to Test 0.

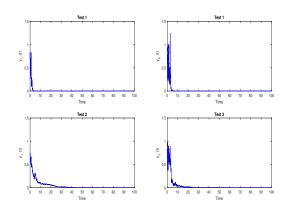
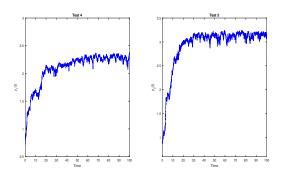


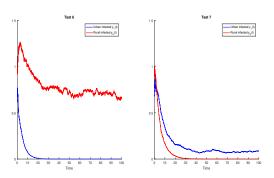
Figure 2. The paths of  $y_1(t)$  and  $y_2(t)$  for model (3), corresponding to Test 1, Test 2 and Test 3.

Parameters	Test 0	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7
$A_1$	0.06	0.3	0.06	0.04	0.1	0.1	0.06	0.04
$A_2$	0.05	0.25	0.05	0.035	0.1	0.2	0.05	0.035
$\mu_1$	0.26	0.1	0.26	0.2	0.08	0.08	0.26	0.2
$\mu_2$	0.3	0.2	0.1	0.2	0.09	0.09	0.1	0.2
$\beta_1$	0.14	0.2	0.14		0.5		0.14	0.6
$\beta_2$	0.1	0.15	0.1	0.15		0.5	0.5	0.15
$\beta_3$	0.2	0.2	0.2	0.211		0.4	0.4	0.211
$\beta_4$	0.08	0.3	0.211		0.4	_	0.211	0.7
$\sigma_1$		0.7	0.28		0.2	_	0.28	0.28
$\sigma_2$	_	0.6		0.24		0.2	0.2	0.24
$\sigma_3$		0.8		0.4		0.2	0.2	0.4
$\sigma_4$		0.9	0.244		0.2		0.244	0.244

 Table 2.
 Parameters values.



**Figure 3.** The paths of  $y_1(t)$  and  $y_2(t)$  for model (3), corresponding to Test 4 and Test 5.



**Figure 4.** The paths of  $y_1(t)$  and  $y_2(t)$  for model (3), corresponding to Test 6 and Test 7.

#### 8. Conclusion

In this paper, we elucidate the dynamics of disease transmission between two groups from distinct regions, operating under the assumption of comprehensive and unrestricted interaction. We consider both a deterministic two-patch epidemic model and its stochastic counterpart. For the deterministic model (2), we examine the global asymptotic stability of the equilibrium  $E = (\frac{A_1}{\mu_1}, 0, \frac{A_2}{\mu_2}, 0)$ . This result is illustrated in Figure 1. Regarding the stochastic version of model (2), we demonstrate the uniqueness of a positive solution for model (3). The thresholds that determine whether the disease will disappear are identified, as detailed in Theorems 4 and 5. Additionally, in Theorem 6, we establish conditions ensuring disease persistence. We also highlight a third scenario, distinct from those studied in sections 4 and 5, where the disease persists in one patch while simultaneously disappearing in the other. The accuracy of our theoretical findings is validated in the numerical simulation section.

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RESEARCH ARTICLE

# An Inverse recursive algorithm to retrieve the shape of the inaccessible dielectric objects

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#### ARTICLE INFO

#### ABSTRACT

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#### A regularized electromagnetic iterative inverse algorithm is formulated and implemented to reconstruct the shape of 2D dielectric objects using the far-field pattern of the scattered field data. To achieve this, an integral operator that maps the unknown boundary of the object onto the far-field pattern of the scattered field is defined and solved for the unknown boundary. The addressed inverse problem has an ill-posed nature and inherits nonlinearity. To overcome these, the proposed solution is linearized via Newton and regularized by Tikhonov in the sense of least squares. Besides, the dominance of the shadow region in the inverse-imaging process is exceeded by considering the superposition of multi-incoming plane waves, leading to less computational cost and a very fast inversion process. Comprehensive numerical analyses are carried out to ascertain the algorithm's feasibility, revealing that it is very efficient and promising.

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#### 1. Introduction

Inverse electromagnetic (EM) imaging methods that utilize scattered field data to reconstruct the shape of an unknown scatterer precisely are in significant demand across a wide variety of engineering fields, such as non-destructive testing, microwave imaging, and geophysical exploration, and so on [1-8]. Apart from its diverse applications, recovering objects from scattered fields poses an immense challenge due to its inherently nonlinear and ill-posed nature [9]. Recently, deep learning schemes and the corresponding applications have been of great interest among many engineering fields [10–12]. In addition to these, significant advancements in deep learning (DL) have led to substantial research investments in the field of inverse electromagnetic imaging problems [13-19]. In [14] and [15], the ill-posed problem is regularized considering Landweber iterations that are implemented in the regularized DL framework. [16] proposes two-step DL framework.

In the first step, the dielectric properties of the inaccessible object are recovered. The object's shape is then reconstructed using the outcomes of the first step. In the sense of rough surface imaging, [18] recovers the statistical parameters of the randomly formed rough surfaces. The shape of random rough surfaces are directly recovered in [17] and [19] for different scattering scenarios.

In addition to DL applications and with the notable exception of certain non-iterative inversion techniques such as Fourier method [20], reverse time migration (RTM)-based [21] approach, and equivalent source model [22], the vast majority of algorithms developed to address these issues are based on recursive applications of regularization and linearization techniques [23–30]. Generally, these are constructed with consideration for multiple incident illuminations to enhance the precision of reconstructions [24, 25, 29, 30]. Nevertheless, these undertakings incur additional

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computational expenses. Furthermore, many of these solutions address the inverse problem associated with perfectly electric conducting (PEC) and sound-soft boundary conditions acoustically. This is because conceptually and physically, the recovery of a penetrable scatterer presents a more difficult inverse problem than the inverse problems associated with impenetrable obstacles [31]. In this regard, [29] proposes a solution to recover the 2D profile of an acoustically sound-soft scatterer by using the far-field pattern. The method utilizes multi-incidence monochromatic incident fields for illumination and applies multi-frequency measurement for higher accuracy. It solves a linearized system with a huge number of unknowns. The same consequence is valid for the linearized iterative methodologies presented in [24] and [25], which offers multi-incidence illumination for rigorous reconstructions. The principal reason for illumination is to reduce (or eliminate) the effect of shadow regions. Namely, the information in the far-field data becomes blurred for a limited amount of illumination, so the lack of information becomes dominant and yields unsuccessful reconstructions as the problem is inherently ill-posed. Alternatively, a recursive linearized method that uses only single incident illumination is proposed in [32]. The method is applied to recover unknown non-penetrable acoustically sound-soft obstacles using the far-field measured field pattern. Later, it is expanded to reconstruct the shape of penetrable objects in [26]. Within this context, for penetrable and non-penetrable cases, the far-field measured field pattern is represented by the single layer potential form [9].

This paper proposes a regularized and linearized recursive inverse algorithm to recover unknown penetrable objects using the scattered field data measured in the far-field region. Unlike other multi-illuminated inversion algorithms, the proposed algorithm applies the superposition of the multi-incident illuminations. Thus, the unknown 2D scatterer is illuminated by multiple sources simultaneously, and the scattered field is collected only once due to these simultaneous illuminations. This allows a fast inverse algorithm to obtain robust and successful reconstructions with a reduced computational cost. The superposition of incident fields is first considered for reconstructing sound-soft obstacles in [33]. Furthermore, unlike the open literature, the inverse algorithm uses a combination of double and single-layer potentials to represent the far-field measured scattered field data.

The paper's outline is provided as follows: Section 2 presents the considered EM scattering scenario, and the following Section 3 briefly summarizes the direct problem. Section 4 presents the regularized recursive inverse-imaging solution, which utilizes the far-field measurements to recover the unknown surface profile in detail. In Section 5, an extensive numerical study was conducted using various scattering scenarios to illustrate the algorithm's efficiency and examine its validation restrictions. Final remarks are given in the Section 6.

#### 2. Geometry of the Problem

Fig. 1 represents the considered 2D scattering geometry. The unknown dielectric body is denoted as  $\Omega$  embedded in infinite free space medium with permittivity  $\varepsilon_0$  and permeability  $\mu_0$ . The body is a simple non-magnetic lossy object defined in terms of constitutive electromagnetic parameters, where its permittivity and conductivity are denoted with  $\varepsilon_1 = \varepsilon_0 \varepsilon_r$ , and  $\sigma$  (S/m), respectively. Accordingly, the body has a constant complex wave number  $k_1$  with  $Re\{k_1\} > 0$ and  $Im\{k_1\} \geq 0$ , precisely its square equals to  $k_1^2 = \omega^2 \varepsilon_1 \mu_0 + i \omega \mu_0 \sigma$ , where  $\omega$  is the radial operating frequency. The cross-section of the body constitutes the principle unknown of the problem, which is denoted with  $\partial\Omega$  and defined as:

$$\partial \Omega := \bigg\{ (\rho, \varphi) \, | \, \rho = r(\varphi) \bigg\}, \tag{1}$$

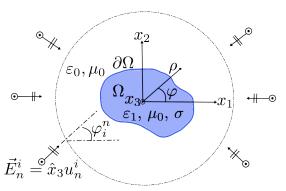


Figure 1. Geometry of the problem.

where  $(\rho, \varphi)$  are the cylindrical polar coordinates, such that  $\rho > 0$  and  $\varphi \in (0, 2\pi)$ . Within this context,  $\Omega$  has a star-like shape. As depicted, the 2D region is illuminated by a superposition of several monochromatic incident electric fields. The incident fields are TE polarized (transverse to wave propagation direction). The  $n^{th}$  incident is defined with a function  $u_n^i$ 

$$\vec{E}_n^i = \hat{x}_3 u_n^i,\tag{2}$$

where  $u_n^i$  is the monochromatic plane wave, precisely equals

$$u_n^i = u_n^i(r(\varphi), \varphi_i^n) := e^{ik_0 r(\varphi)\cos\left(\varphi - \varphi_i^n\right)}.$$
 (3)

Here,  $k_0 > 0$  is the wavenumber of the free space. The superposition of the incident fields enables to consider the summation of incident illuminations as a single unique field, *i.e.*,

$$u^{i} = \sum_{n=1}^{N} u_{n}^{i}(r(\varphi), \varphi_{i}^{n}).$$

$$\tag{4}$$

Regarding the incident illumination, both within the body and in the surrounding free space, the electric field vectors are in the  $\hat{x}_3$  direction. Consequently, the entire problem may be simplified to a scalar one. To do so, let  $u_0$  and  $u_1$  denote the total fields in free space and the dielectric body, respectively. Then, both of them satisfy the scalar wave equation

$$\left(\Delta + k_0^2\right) u_0 = 0 \text{ in } \mathbb{R}^2 \setminus \Omega,$$
$$\left(\Delta + k_1^2\right) u_1 = 0 \text{ in } \Omega.$$
(5)

Denote the derivative  $r'(\varphi) = \frac{dr(\varphi)}{d\varphi}$  and the outer normal vector of  $\partial\Omega$  as  $\hat{\nu}$ , which precisely equals

$$\hat{\nu} = \frac{\hat{\rho}r(\varphi) - \hat{\varphi}r'(\varphi)}{\sqrt{r(\varphi) + r'^2(\varphi)}}.$$
(6)

It follows that the fields and their derivatives with respect to the outward surface normal exhibit continuity on  $\partial \Omega$ . Namely, the boundary conditions imply the following:

$$u_0 = u_1, \tag{7a}$$

$$\psi_0 = \psi_1, \text{ on } \partial\Omega.$$
 (7b)

Noting that the fields  $\psi_m = \hat{\nu} \cdot \nabla u_m$   $(m = \{1, 2\})$ , where " $\nabla$ " denotes the gradient operator. Namely,  $\psi_0$  and  $\psi_1$  describe derivatives of  $u_0$  and  $u_1$  with respect to  $\nu$ , respectively. The scattered field, in this regard, is defined as the difference

$$u^s = u_0 - u^i, \tag{8}$$

which is an outgoing wave and fulfills the Sommerfield radiation condition

$$\lim_{\rho \to \infty} \sqrt{\rho} \left( \frac{\partial u^s}{\partial \rho} - ik_0 u^s \right) = 0, \ r \text{ in } \mathbb{R}^2 \setminus \Omega \quad (9)$$

in a uniform way in all directions. Furthermore, it is straightforward to demonstrate that  $u^s$  exhibits the subsequent asymptotic behavior:

$$u^{s}(\rho,\varphi) = \frac{e^{ik\rho}}{\sqrt{\rho}} u_{\infty}(\varphi) + \mathcal{O}\left(\frac{1}{\rho^{3/2}}\right), \ \rho \to \infty.$$
(10)

Here,  $u_{\infty}$  represents the scattered field measured far away from the source, namely the far-field pattern. It is worth noting that the field also depends on  $k_0$  and the incoming direction. However, the assumption is made by taking these quantities fixed so that  $u_{\infty}$  has only  $\varphi$  dependence. The fields defined in (7) represent the surface currents on the cross-section  $\partial \Omega$ . These are the unknowns of the direct scattering problem for which  $\partial \Omega$  and the constitutive parameters are known. Once the currents are obtained, one can take an opportunity to obtain the fields scattered anywhere in the first medium (in our particular case, in free space). The whole procedure constitutes the "direct EM scattering problem". In the inverse problem, conversely, the inputs and the outputs are reversed. That is, the main concern is to recover the unknown cross-section,  $\partial\Omega$ , utilizing the measured far-field pattern of the scattered field data, *i.e.*,  $u_{\infty}$ . To this aim, the integral representation of the scattered field data, described in the following subsection, is taken as a mapping operator into account, which maps  $\partial \Omega$  onto  $u_{\infty}$ . Hence, the problem turns into taking the inverse of the mapping operator. The following subsection describes the direct EM scattering problem applied to acquire the synthetic scattered field data utilized in the inverse problem.

#### 3. Direct EM Problem

As mentioned above, the forward scattering problem mainly considers obtaining the surface currents given in (7) within the knowledge of the 2D cross-section  $\partial\Omega$ . Using Green's theorem both in the free space and  $\Omega$ , one can easily obtain the integral representations of the surface currents  $u_0$ and  $\psi_0$  [34]

$$u_{0}(\boldsymbol{r}) = u^{i}(\boldsymbol{r}) + \int_{\partial\Omega} u_{0}(\boldsymbol{r'}) K_{0}(\boldsymbol{r};\boldsymbol{r'}) \, ds(\varphi') - \int_{\partial\Omega} \psi_{0}(\boldsymbol{r'}) G_{0}(\boldsymbol{r};\boldsymbol{r'}) \, ds(\varphi') u_{1}(\boldsymbol{r}) = -\int_{\partial\Omega} u_{1}(\boldsymbol{r'}) K_{1}(\boldsymbol{r};\boldsymbol{r'}) \, ds(\varphi') + \int_{\partial\Omega} \psi_{1}(\boldsymbol{r'}) G_{1}(\boldsymbol{r};\boldsymbol{r'}) \, ds(\varphi')$$
(11)

Here,  $G_m(\mathbf{r}; \mathbf{r'})$   $(m = \{0, 1\})$  is the fundamental solution of the scalar wave equation in 2D, *i.e.*,

$$G_m(\boldsymbol{r};\boldsymbol{r'}) = \frac{i}{4} H_0^{(1)}(k_m |\boldsymbol{r} - \boldsymbol{r'}|), \qquad (12)$$

where  $\mathbf{r} = \hat{x}_1 \rho \cos(\varphi) + \hat{x}_2 \rho \sin(\varphi)$  and  $\mathbf{r'} = \hat{x}_1 r(\varphi) \cos(\varphi') + \hat{x}_2 r(\varphi) \sin(\varphi')$  so that the argument of the Hankel-type function precisely

$$\left|\boldsymbol{r} - \boldsymbol{r'}\right| = \sqrt{\rho^2 + r^2 - 2\rho r \cos(\varphi - \varphi')}, \quad (13)$$

and the integrand is also

$$ds(\varphi) = \sqrt{r^2 + {r'}^2} d\varphi.$$
 (14)

Noting that  $r := r(\varphi)$  and  $r' := r'(\varphi)$ . Moreover,  $K_m = \partial G_m / \partial \nu$ . In regards to (8) and (11), the scattered field has an integral representation as a combination of single and double potential integral operators [9] as:

$$u^{s}(\boldsymbol{r}) = \int_{\partial\Omega} \left( u_{0}(\boldsymbol{r'}) K_{0}(\boldsymbol{r}; \boldsymbol{r'}) - \psi_{0}(\boldsymbol{r'}) G_{0}(\boldsymbol{r}; \boldsymbol{r'}) \right) ds(\varphi')$$
(15)

Now, by substituting (7) into (11) and considering the jump relations, the subsequent classical set of the boundary integral equations are obtained [35]:

$$u^{i}(\boldsymbol{r}) = \frac{1}{2}u_{0}(\boldsymbol{r}) - \int_{\partial\Omega} K_{0}(\boldsymbol{r};\boldsymbol{r'})u_{0}(\boldsymbol{r'}) ds(\varphi') + \int_{\partial\Omega} G_{0}(\boldsymbol{r};\boldsymbol{r'})\psi_{0}(\boldsymbol{r'}) ds(\varphi') 0 = -\frac{1}{2}u_{0}(\boldsymbol{r}) - \int_{\partial\Omega} K_{1}(\boldsymbol{r};\boldsymbol{r'})u_{0}(\boldsymbol{r'}) ds(\varphi') + \int_{\partial\Omega} G_{1}(\boldsymbol{r};\boldsymbol{r'})\psi_{0}(\boldsymbol{r'}) ds(\varphi').$$
(16)

Accordingly, one can find the unknown surface currents by the numerical solution of the integral equations such as the method of moments (MoM) [35] and then obtain the scattered field using the integral representation given in (15). It is worth noting that the recursive inverse algorithm described in Section 4 also needs to solve the direct problem for the reconstructed shape at each iteration step. Thus, an accurate solution for the direct scattering case, for which a numerical MoM solution is applied in this study, is essential. To verify the numerical solution of the direct problem, the following subsection is designed by considering scattering from an infinite-length cylinder, which has an analytical expression in terms of the Mie series.

### 3.1. Validation: Scattering by dielectric cylinder

Consider an infinitely long cylinder with a crosssection radius r = a located at the origin. Suppose it is a non-magnetic lossy dielectric with complex wavenumber  $k_1$  and embedded in free space with the wavenumber  $k_0$ . An incident plane wave with the angle of incidence  $\varphi_i$  illuminates the cylinder. The plane wave can be expressed with the infinite Bessel series by Jacobi-Anger identity [36]:

$$u^{i}(r,\varphi) = e^{ik_{0}r\cos(\varphi-\varphi_{i})}$$
$$= \sum_{n=-\infty}^{n=+\infty} i^{n}J_{n}(k_{0}r)e^{-in(\varphi-\varphi_{i})}$$
(17)

The fields inside and outside the cylinder are denoted  $u_0$  and  $u_1$ , respectively. They both satisfy the scalar Helmholtz equation regarding (5) and continuous on the boundary (r = a) as in (7). It is worth reminding that  $\hat{\nu} = \hat{\rho}$  for the circular cylinder. They have series representations

$$u_0(r,\varphi) = \sum_{n=-\infty}^{n=+\infty} \left( B_n J_n(k_0 r) + C_n H_n^{(1)}(k_0 r) \right) e^{-in\varphi}$$
$$u_1(r,\varphi) = \sum_{n=-\infty}^{n=+\infty} A_n J_n(k_1 r) e^{-in\varphi}, \tag{18}$$

where  $B_n = i^n e^{in\varphi_i}$  according to (17). Substituting (18) into (7) yields

$$B_n J_n(k_0 a) + C_n H_n^{(1)}(k_0 a) = A_n J_n(k_1 a)$$
  

$$B_n J_n'(k_0 a) + C_n H_n'^{(1)}(k_0 a) = \frac{k_1}{k_0} A_n J_n'(k_1 a).$$
(19)

Leading with  $\varsigma = k_1/k_0$ , the solution reads:

$$A_{n} = B_{n} \frac{H_{n}^{(1)}(k_{0}a)J_{n}'(k_{0}a) - H_{n}'^{(1)}(k_{0}a)J_{n}(k_{0}a)}{\varsigma H_{n}^{(1)}(k_{0}a)J_{n}'(k_{1}a) - H_{n}'^{(1)}(k_{0}a)J_{n}(k_{1}a)},$$
  

$$C_{n} = B_{n} \frac{J_{n}(k_{1}a)J_{n}'(k_{0}a) - \varsigma J_{n}(k_{0}a)J_{n}'(k_{1}a)}{\varsigma H_{n}^{(1)}(k_{0}a)J_{n}'(k_{1}a) - H_{n}'^{(1)}(k_{0}a)J_{n}(k_{1}a)}.$$
(20)

Accordingly, one can compute the total fields inside and outside the cylinder by substituting (20) into (18). In the context of the numerical MoMpoint matching solution, the whole cylinder sampled as follows: The circular cylinder with radius  $r(\varphi) = a$  has a circumference  $2\pi a$  with  $0 \leq \varphi < 2\pi \text{It}$  is divided into the number of Nequally spaced segments.  $n^{th}$  segment is denoted  $\varphi_n$  with its width is  $\Delta \varphi$ , precisely

$$\varphi_n = (n-1)\Delta\varphi$$
 with  $\Delta\varphi = \frac{2\pi}{N}$ . (21)

Here,  $n \in [1, N]$  and the sample number is settled as

$$N = 10 \left| \frac{k_1}{k_0} \right| 2\pi a \tag{22}$$

The unknown surface fields in (16) are expanded as linear combinations of the pulse-basis subdomain functions with some unknown coefficients positioned at each segment's center. Namely,

$$\begin{cases} u_0\\ \psi_0 \end{cases} \approx \sum_{n=1}^N \begin{cases} u_n\\ \psi_n \end{cases} f_n(\varphi),$$
 (23)

where the pulse basis function,

$$f_n(\varphi) = \begin{cases} 1 & (\varphi_n - \Delta \varphi/2) \le \varphi \le (\varphi_n + \Delta \varphi/2) \\ 0 & \text{elsewhere} \end{cases}$$
(24)

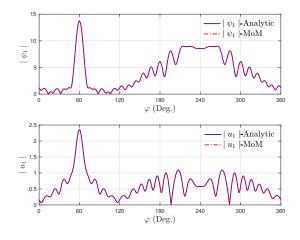
The length of each segment is sufficiently small so that the integrand doesn't vary significantly. Regarding point matching, the whole equation is weighted by Dirac-delta functions. Accordingly, one can obtain the matrix equation system.

$$\overline{Z}_{die}\,\overline{I}_{die} = \overline{V}_{die},\tag{25}$$

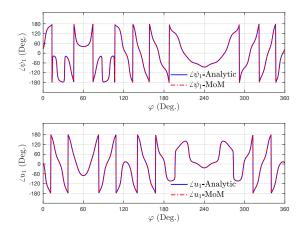
where  $\overline{I}_{die}$  and  $\overline{V}_{die}$  are vectors with size  $2N \times 1$ . The elements of the vectors and the impedance matrices are precisely given in the appendix. The numerical comparison of the analytic and MoM solutions for a dielectric cylinder is given in the following subsection.

### 3.2. Numerical comparisons for a dielectric cylinder

To validate MoM-point matching with the analytic Mie series solution, a dielectric lossy cylinder with radius r = 2m is considered. Outside of the cylinder is free space, and the dielectric parameters are  $\varepsilon_r = 4$  and  $\sigma = 5 \times 10^{-5}$ . In (18), n = 64 and in (22), N = 252. Operating frequency is 300 MHz, the angle of the incident plane wave illumination  $\varphi = 60^{\circ}$ . The following figures 2 and 3 show the modulus and the phase of the surface fields acquired by MoM and analytic series, respectively.



**Figure 2.** Modulus of the surface fields on dielectric cylinder



**Figure 3.** phase of the surface fields on dielectric cylinder

To compare the results quantitatively, an  $\ell_2$  normbased error is defined between the fields obtained from analytic and MoM solutions:

$$e(\%) = \frac{\|u_{\rm A} - u_{\rm MoM}\|_2}{\|u_{\rm A}\|_2} \times 100.$$
 (26)

Here,  $u_A$  and  $u_{MOM}$  denote the surface fields obtained by analytic and MoM solutions, respectively. The obtained surface fields with MoM solution in the figures 2 and 3 requires sampling N = 252. High agreements were achieved between the MoM and analytical solutions. The numerical errors obtained for this sampling number are below 2% for both  $u_0$  and  $\psi_0$ . As expected, increasing the number of samples in MoM improves the agreement between the two methods. Hence, the quantitative error decreases for a higher sampling number. The obtained errors for increased N values are shown in Fig. 4

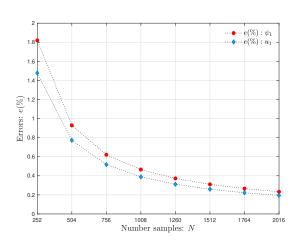


Figure 4. Errors vs. the number of samples in MoM

#### 4. Inverse Problem

The inverse problem addressing involves determining the boundary  $\partial\Omega$  of the scatterer  $\Omega$ , given the far-field pattern  $u_{\infty}$  for the superposition of the incident plane wave illuminations  $u^i$ . To define the far-field pattern precisely, it is necessary to consider the asymptotic behavior of the Hankel type functions for large argument, which equals [36]

$$H_0^{(1)}(\omega) = \sqrt{\frac{2}{\pi\omega}} e^{i\omega - \frac{\pi}{4}} \left( 1 + \mathcal{O}\left(\frac{1}{\omega}\right) \right), \, \omega \to \infty.$$
(27)

Within this context, assume that a point in the far field is described as  $\mathbf{r}_s := r_s(\hat{x}_1 \cos(\varphi_s) + \hat{x}_2 \sin(\varphi_s))$  and the cross-section is represented as in (1). Then, in accordance with Huygens' principle [37], the standard approximation for the 2D Green's function given in (12) and (13) have the phase term and the amplitude term as following

$$\tilde{G}(\boldsymbol{r};\boldsymbol{r_s}) = \gamma e^{ik_0 r_s} e^{-ik_0 r(\varphi) \cos(\varphi_s - \varphi)}, \qquad (28)$$

where the constant

$$\gamma = \frac{i}{4} \sqrt{\frac{2}{\pi k_0 r_s}} e^{-i\frac{\pi}{4}}.$$
(29)

That is, the modulus term of  $\tilde{G}$  is approximated as  $|\mathbf{r} - \mathbf{r}_s| \approx r_s$  and the phase term is  $|\mathbf{r} - \mathbf{r}_s| \approx$  $r_s - k_0(\mathbf{r}_s \cdot \mathbf{r})$ . It is naturally a good approximation for Green's functions and is conventionally applied to represent a far-field pattern of the scattered field. The reader may refer to [38] for the Huygens' principle in 3D and 2D scattering problems [39], for the details of the far-field expansion of 2D Green's function, and thus the far-field expansion of the Greens' function [34, 37]. In this context, one can easily define the derivative of the function with respect to the surface normal  $\hat{\nu}$  as

$$\frac{\partial \tilde{G}(\boldsymbol{r};\boldsymbol{r_s})}{\partial \nu} = \hat{\nu} \cdot \nabla \tilde{G}(\boldsymbol{r};\boldsymbol{r_s}) = -i\tilde{G}(\boldsymbol{r};\boldsymbol{r_s})\hat{k}_s \cdot \hat{\nu}.$$
(30)

Here,  $\hat{k}_s$  is the wavenumber vector in scattering direction with the angle  $\varphi_s$ , particularly equals to

$$\hat{k}_s = k_0 \bigg( \hat{x}_1 \cos(\varphi_s) + \hat{x}_2 \sin(\varphi_s) \bigg), \qquad (31)$$

which can be converted into polar coordinates:

$$\hat{k}_s = k_0 \bigg( \hat{\rho} \cos(\varphi_s - \varphi) + \hat{\varphi} \sin(\varphi_s - \varphi) \bigg). \quad (32)$$

Accordingly, the far-field scattered field has the integral representation as

$$u_{\infty}(\varphi) = \gamma \int_{\partial \Omega} \left( -i\hat{k}_s \cdot \hat{\nu} u_0(\varphi') + \psi_0(\varphi') \right) \\ e^{-ik_0 r(\varphi') \cos(\varphi_s - \varphi')} ds(\varphi').$$
(33)

Substituting (6) and (31) into (33) yields more precise expression for  $u_{\infty}$  as

$$u_{\infty}(\varphi) = -ik_{0}\gamma \int_{0}^{2\pi} \left\{ \left( r(\varphi')\cos(\varphi_{s} - \varphi') - r'(\varphi')\sin(\varphi_{s} - \varphi') \right) u_{0}(\varphi') + \psi_{0}(\varphi')\sqrt{r(\varphi')^{2} + r'(\varphi')^{2}} \right\}$$
$$e^{-ik_{0}r(\varphi')\cos(\varphi_{s} - \varphi')} d\varphi'.$$
(34)

To have a much more compact form of (34), the integral equation can be defined in an operator form  $\mathcal{D}$ . Thus, with the knowledge of the  $u_{\infty}$  and the surface fields, the inverse problem consists of solving the nonlinear and ill-posed equation

$$\mathcal{D}(r, u_0, \psi_0) = u_\infty,\tag{35}$$

for the unknown boundary  $\partial\Omega$  represented by  $r := r(\varphi)$ . To start with the inversion process, first, the operator is linearized via Newton's type iterations and then regularized by Tikhonov. Within the context of linearization, let  $r_0$  be the initially guessed shape, for which one can solve the direct problem to obtain the surface currents  $(u_{10}, \psi_{10})$  of the guessed shape. Accordingly, the linearization proceeds in the sense of Newton as

$$\mathcal{D}(r, u_0, \psi_0) \approx \mathcal{D}(r_0, u_{0_0}, \psi_{0_0}) + \mathcal{D}'(r_0; u_{0_0}, \psi_{0_0}) \delta r_0.$$
(36)

Here,  $\mathcal{D}'(r_0; u_{1_0}, \psi_{1_0})\delta r_0$  is the Frechet derivative of the surface with respect to r, and  $\delta r_0$  is the updated correlation function for which (36) has to be solved. For the regularization procedure, let  $\mathcal{D}'_0$ stand for the Frechet derivative for a short notation, and its ad-joint be denoted by  $\mathcal{D}'_0^{\dagger}$ . Then, by defining a regularization parameter  $0 < \tau < 1$ ,  $\delta r_0$  is the solution of

$$\tau \delta r_0 + \mathcal{D}_0^{\dagger} \mathcal{D}_0^{\prime} = \mathcal{D}_0^{\prime \dagger} \Delta u_{\infty}, \qquad (37)$$

where  $\Delta u_{\infty} = u_{\infty} - \mathcal{D}(r_0, u_{1_0}, \psi_{1_0})$ . Furthermore, one may also consider a scaling (tuning) parameter to have a much more robust  $\delta r_0$ . In this sense, the solution of (37) is written as

$$\delta r_0 = \alpha \left[ \tau \mathbf{I} + \mathcal{D}_0^{\dagger} \mathcal{D}_0^{\prime} \right]^{-1} \mathcal{D}_0^{\prime \dagger} \Delta u_{\infty}.$$
(38)

Here, **I** is the identity matrix, and  $0 < \alpha < 1$  is the scaling parameter. The reader may refer to [40] for the details of  $\alpha$  and  $\tau$ . For a predetermined threshold  $\xi$ , the procedure is repeated recursively until the stopping criteria  $\|\delta r_N\|_2 \leq \xi$ . Accordingly,  $n^{th}$  approximated boundary is updated by setting

$$r_{n+1} = r_n + \delta r_n. \tag{39}$$

Moreover, to have a more robust reconstruction, the solution is obtained via the least squares [41]. To this aim, the update correlation is expanded by the linear combination of some basis functions  $\Phi_q(\varphi), q = 1, \dots, Q$  as

$$\delta r(\varphi) = \sum_{q=1}^{Q} a_q \Phi_q(\varphi). \tag{40}$$

Hence, the problem turns into finding unknown coefficients of (40). For a set of grid points  $\varphi^1, \dots, \varphi^P$ , the unknown coefficients are determined by minimizing the sum of squares at  $n^{th}$  iteration, *i.e.*,

$$\sum_{p=1}^{P} \left| \mathcal{D}'(r_n, u_{0_n}, \psi_{0_n}) \sum_{q=1}^{Q} a_q \Phi_q(\varphi^p) - \Delta u_\infty \right|^2.$$
(41)

The whole procedure is summarized as follows:

- (i). Choose a closed curve for the initial guess  $\rho = r_0(\varphi)$
- (ii). Obtain the surface currents of the closed curve and thus the far-field pattern using (16) and (34), respectively.
- (iii). Solve (36) and (38) in the sense of least squares (40)-(41) for the updated correlation function  $\delta r_0$
- (iv). Obtain the new surface profile via (39)
- (v). Repeat (ii)-(iv) for n times (n > 1) such that  $r_{n+1} = r_n + \delta r_n$ .
- (vi). Break the loop, if  $\|\delta r_n\| \leq \xi$

Here, the crucial part of the whole framework is the Frechet derivative part, which is for a mapping from a domain of functions [42]. For the sake of simplicity, one may consider the Frechet derivative  $\mathcal{D}'(r_0; u_{1_0}, \psi_{1_0}) \delta r_0 := \mathcal{D}'_0$  as the superposition of two operators

$$\mathcal{D}_0' = \mathcal{F}_\mathcal{D}'(r_0; \psi_{1_0}) \delta r_0 + \mathcal{F}_\mathcal{N}'(r_0; u_{1_0}) \delta r_0 \qquad (42)$$

where the Frechet operators are:

$$\mathcal{F}_{\mathcal{D}}'(r_0;\psi_{1_0})\delta r_0 = -\gamma \int_0^{2\pi} ik \cos\left(\varphi_s - \varphi'\right) \\ e^{-ikr_0(\varphi')\cos(\varphi_s - \varphi')}\psi_{1_0}(\varphi') \\ \sqrt{r(\varphi')^2 + r'(\varphi')^2} \,\delta r_0 d\varphi', \quad (43)$$
$$\mathcal{F}_{\mathcal{L}}'(r_0;u_1)\delta r_0 = -\gamma \int_0^{2\pi} \left(ik \cos\left(\varphi_s - \varphi'\right)\right) d\varphi' = -\gamma \int_0^{2\pi} \left(ik \cos\left(\varphi_s - \varphi'\right)\right) d\varphi'$$

$$\begin{aligned} \Gamma_{\mathcal{N}}'(r_0; u_{1_0})\delta r_0 &= -\gamma \int_0^{\infty} \left( ik \cos(\varphi_s - \varphi') \\ &\kappa(r_0, \varphi', \varphi_s) u_{1_0}(\varphi') \\ &+ \frac{\partial \kappa(r_0, \varphi', \varphi_s)}{\partial r_0} u_{1_0}(\varphi') \right) \\ &e^{-ikr_0(\varphi')\cos(\varphi_s - \varphi')} \,\delta r_0 d\varphi', \ (44) \end{aligned}$$

and  $\kappa$  function

$$\kappa(r_0,\varphi,\varphi_s) = r_0 \cos(\varphi_s - \varphi) - r'_0 \sin(\varphi_s - \varphi)$$
(45)

is basically the result of  $k_s \cdot \hat{\nu}$ .

#### 5. Numerical results and discussion

The section is reserved to demonstrate the feasibility of the proposed inverse framework. For all considered scattering scenarios, the operating frequency is 300MHz so that the wavelength in freespace  $\lambda_0 = 1$ m. For all numerical examples, the predetermined threshold is  $\xi = 0.07$ . Except for one example, the far-field pattern is assumed to be known at 64 points equally distributed around the unit circle. For the expansion of the unknown updated correlation function with some basis functions,  $\Phi_q(\varphi) = e^{-iq\varphi}$ ,  $q = 0, \pm 1, \dots \pm Q$ . To verify the success of the reconstructions quantitatively, an  $\ell_2$ -norm based error is defined precisely

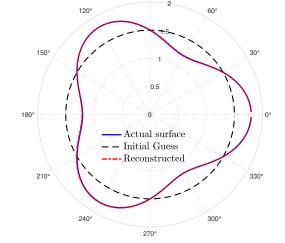
$$err(\%) = \frac{\|r(\varphi) - r_n(\varphi)\|}{\|r(\varphi)\|} \times 100, \qquad (46)$$

where  $r(\varphi)$  and  $r_n(\varphi)$  represent the actual and the reconstructed surfaces, respectively.

The first example aimed to put forth the effect of the penetrability of the object on the inverse algorithm. To this aim, a kite-like object is considered for reconstruction, considering both PEC and dielectric cases. The unknown kite-like surface is a radial function

$$r(\varphi) = 1.5(1 + 0.15\cos(3\varphi)).$$
(47)

For the dielectric case, the constitutive EM parameters are  $\varepsilon_1 = 4\varepsilon_0$  and  $\sigma = 10^{-5}$  (S/m). For both PEC and dielectric cases, the region is illuminated by 7 incident illuminations simultaneously, for which the angles of incidence are selected in the range:  $0^\circ$  :  $\Delta \varphi_i$  : 330° with the  $\Delta \varphi_i = 55^\circ$  angular increments. The reconstructions and the actual surface for PEC and Dielectric scenarios are shown in Fig. 5 and Fig. 6, respectively.



**Figure 5.** Reconstruction of the surface defined in (47) for PEC case.

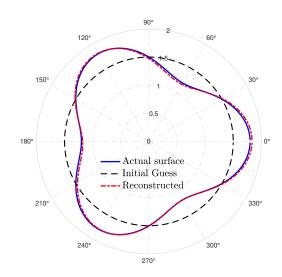


Figure 6. Reconstruction of the surface defined in (47) for Dielectric (penetrable) case.

It is worth noting that for the PEC case, the farfield pattern of the scattered field is represented with a single layer potential as shown in [32] in detail. Accordingly, for the Frechet derivative of the PEC case, (43) should be taken into consideration. As illustrated in the figure, a crosssection of an infinitely long cylinder with a radius  $1.5\lambda_1$  is considered as the initial guess for both cases. Moreover, both cases' stopping criteria are  $\|\delta r\| \leq \xi = 0.07$ . Accordingly, the needed 16 iteration is for the PEC case, and the 28 iteration is for the dielectric case. To visualize the expected decreasing tendency of the  $\|\delta r\|$  for each new iteration, Fig. 7 shows  $\|\delta r\|$  versus the number of iterations for the dielectric case.

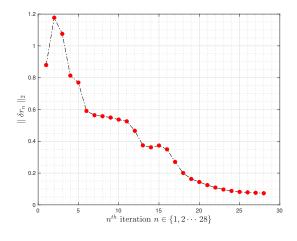


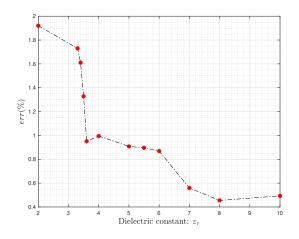
Figure 7.  $\|\delta r_n\|$  vs. iterations.

In addition, the reconstruction of PEC is better than the dielectric case qualitatively and quantitatively. This is mostly because the PEC case has no penetrated field to the second region. Hence, a more powerful scattered field contains more information for the scatterer, leading to better reconstructions. The quantitative errors for both cases are err(%) = 0.31% and err(%) = 1.37%, respectively, for PEC and dielectric cases.

The next analysis covers the algorithm's sensitivity to the constitutive parameters of the dielectric object, *i.e.*,  $\varepsilon_r$  and  $\sigma$ . Accordingly, the response of the algorithm is tested for higher and lower dielectric permittivity and conductivity values. In this regard, "4– leaf" shape boundary curve is assumed to be unknown, and it is reconstructed for different  $\varepsilon_r$  and  $\sigma$  values. The considered "leaf-shaped" radial function is defined as

$$r(\varphi) = 1.3(1 + 0.15\cos(4\varphi))$$
 (48)

First, the objective is to observe the dielectric dependency of the iterative inverse reconstruction algorithm. In order to notice the sensitivity to the dielectric permittivity, the algorithm is run for different  $\varepsilon_r$  values for a fixed conductivity  $\sigma = 10^{-5}$  (S/m). Within this context, the dielectric permittivity range is taken into account  $\varepsilon_r \in [2, 10]$ . Hence, the dielectric permittivities are defined in a wide range, from very penetrable cases to high levels. For all reconstructions, run for different  $\varepsilon_r$ , the circle with radius  $1.5\lambda_1$ is considered for the initial guess. The obtained quantitative errors of the reconstructions for different dielectric permittivity values are shown in Fig. 8.



**Figure 8.** Error: err(%) vs. dielectric constant:  $\varepsilon_r$ 

As shown, the bigger contrast between free space and the dielectric object yields better reconstructions quantitatively. It is worth noting that if  $\varepsilon_r < 2$ , it becomes impossible to obtain accurate reconstructions. Furthermore,  $\varepsilon_r > 10$  yields higher computational cost as the inversion algorithm needs a direct solver whose unknown is directly related to the dielectric permittivity  $\varepsilon_r$ . A similar analysis was also carried out to observe the conductivity sensitivity. To this aim,  $\varepsilon_r = 2$ is fixed and the conductivity varies in the range  $\sigma \in [5 \times 10^{-7}, 10^{-2}]$  (S/m). The algorithm's errors for different conductivity values are shown in Fig. 9

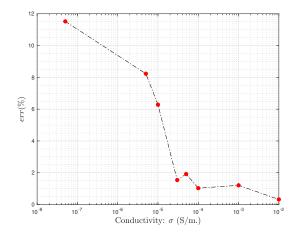


Figure 9. Error: err(%) vs. conductivity  $\sigma$  (S/m)

Accordingly, the higher conductivity yields better reconstructions such that for  $\sigma = 10^{-2}$ , the error err < 0.4%. However, such a high conductivity yields a huge loss, so the unknown object can almost turn into PEC rather than a penetrable object. Fig. 10 shows the worst and the best cases together to demonstrate reconstructions visually.

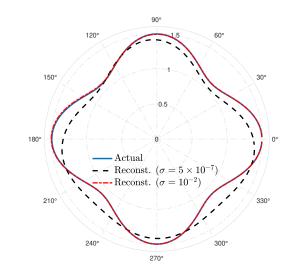


Figure 10. Reconstructions for the highest and the lowest conductivity values

Noting that the region is illuminated for 12 incident plane waves simultaneously where the angles of incidence are defined as  $0^{\circ} : \Delta \varphi_i : 330^{\circ}$  with the  $\Delta \varphi_i = 30^{\circ}$  angular increments. Again, the circle with the radius  $1.5\lambda_1$  is considered the initial guess. For all analyses conducted to obtain the sensitivity to the constitutive parameters, 19 exponential-type basis functions are applied in the sense of least squares.

The next analysis covers the algorithm's sensitivity against noise. For this purpose, a synthetic noise is added to the far-field pattern. The noisy scattered field is defined as  $\tilde{u}_{\infty} = u_{\infty} + n_{\ell} |u_{\infty}| e^{i2\pi r_d}$ , where  $n_{\ell}$  is the noise-level and  $r_d$  is the random number in the interval  $0 < r_d < 1$ . The bean-shaped object is considered for the noise analyses. It is defined as

$$r(\varphi) = 0.8 \frac{1 + 0.85 \cos(\varphi + \frac{\pi}{4}) + 0.05 \sin(2\varphi + \frac{\pi}{4})}{1 + 0.5 \cos(\varphi + \frac{\pi}{4})}$$
(49)

In regards to the scattering scenario,  $\varepsilon_r = 4$  and  $\sigma = 10^{-5}$  (S/m), and the number of 6 incident illuminations is applied simultaneously, where  $\varphi_i^n = \{0^\circ, 60^\circ, 120^\circ, 180^\circ, 240^\circ, 300^\circ\}$ . Fig. 11 shows the obtained quantitative errors for different noise levels.

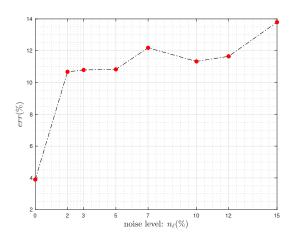
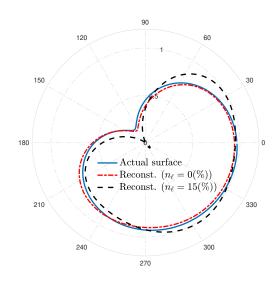


Figure 11. Error: err(%) vs. noise level:  $n_{\ell}(\%)$ 

Accordingly, the algorithm is sensitive to the noise such that  $n_{\ell}(\%) \leq 10\%$  for satisfactory reconstructions. The reconstructions for the noise-free case and with the highest noise level are shown in Fig. 12



**Figure 12.** Reconstruction of the bean-shaped object for the noise-free and the highest noise level

The following example investigates the sensitivity of the reconstructions to the amount of scattered field data. Let #MP denote the number of measurement points. It is worth to remind that, up to this example, #MP = 64. To this aim, a 5-leaf shape is reconstructed for different numbers of scattered field data. The inaccessible 5-leaf shape is defined as

$$r(\varphi) = 1.3(1 + 0.15\cos(5\varphi))$$
 (50)

For the sensitivity analysis to the number of scattered field data, the remaining parameters are kept constant such as the number of incident fields is 11, precisely defined in the range  $\varphi_i = 0^\circ$ :  $30^\circ: 300^\circ$ , the penetrable medium parameters are  $\varepsilon_r = 4$ ,  $\sigma = 10^{-5}$  S/m and the number of applied exponential basis functions are 27. The obtained error vs the amount of the measured field data is given in Fig. 13

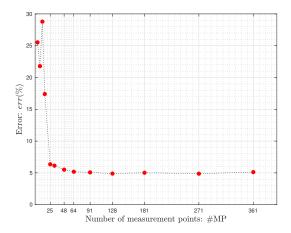


Figure 13. Error: err(%) vs. the number of measurement points: #MP

Accordingly, insufficient reconstructions observed for #MP < 25. For an accurate result,  $\#MP \ge$ 

25. As shown in Fig. 13, the error remains around 5% such that the differences between the reconstructions cannot be distinguished with the naked eye. To visualize this, the unsuccessful reconstructions obtained for #MP = 8, #MP = 16 and the satisfactory result of #MP = 32 are shown in Fig. 14

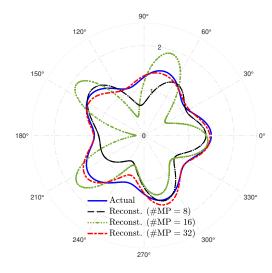


Figure 14. Reconstructions for different #MP values

The next analysis is carried out to emphasize the significance of multi-illumination. For this purpose, a potato-shaped curved object is considered. It is defined as a radial function

$$r(\varphi) = 4\sqrt{\left(\frac{1}{4} + \frac{3}{40}\cos(2\varphi)\right)^2 + \left(\frac{1}{4} + \frac{3}{100}\cos(3\varphi)\right)^2}$$
(51)

In the first case, the object is illuminated with a single incident plane wave with the angle of incidence  $\varphi_i = 0^\circ$ . The result is shown in Fig. 15

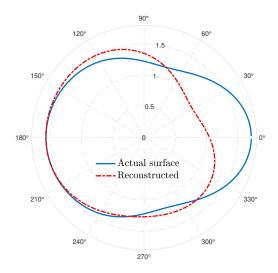


Figure 15. Reconstruction of the potato-shaped object with a single incident illumination

As illustrated, the reconstruction is unsatisfactory as the shadow region predominates inversion [24,33,43]. To overcome this, the same object is recovered for the superposition of 4 incident plane waves. The angles of incidence are  $\varphi_i^n = \{-30, 30, 150, 210\}$ , for  $n = \{1, 2, 3, 4\}$ . The satisfactory reconstruction for the multi-incidence is illustrated in Fig. 16

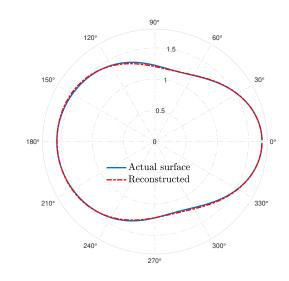
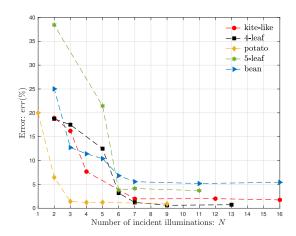


Figure 16. Reconstruction of the potato-shaped object with superposition of multi-incident illumination

Noting that, for both multi and singleillumination cases of potato shape objects,  $\varepsilon_r = 4$ and  $\sigma = 10^{-5}$  (S/m) and there are 13 exponential basis functions were utilized. Actually, the superposition of multi-incidence illumination is one of the essential factors for satisfactory reconstructions. To underline this, all 2D shapes reconstructed so far have been reconstructed again by considering different numbers of incident illumination in the following analysis. The error for different number of illuminations are shown in Fig. 17



**Figure 17.** Error: err(%) vs. number of multiincidence illumination: N

$r(\varphi)$	Angels of incidence: $\varphi_i^1: \Delta \varphi: \varphi_i^N$	increments: $\Delta \varphi$ (Deg.)	number of incident field in superposition: $N$
3-leaf 4-leaf 5-leaf potato	$\begin{array}{c} 0^\circ:\Delta\varphi:330^\circ\\ 0^\circ:\Delta\varphi:360^\circ\\ 0^\circ:\Delta\varphi:300^\circ\\ -30^\circ:\Delta\varphi:210^\circ\end{array}$	$ \{ 22, 30, 55, 110, 165, 330 \} \\ \{ 30, 45, 60, 72, 90, 180, 360 \} \\ \{ 20, 30, 45, 60, 75, 90, 150, 300 \} \\ \{ 30, 60, 80, 120, 240, \} $	$ \begin{array}{l} \{2,  3,  4,  7,  12,  16\} \\ \{2,  3,  5,  6,  7,  9,  13\} \\ \{2,  3,  4,  5,  6,  7,  11,  16\} \\ \{1,  2,  3,  4,  5,  9\} \text{ (Single illumination at } 0^\circ) \end{array} $

**Table 1.** Parameters for the superposition of themulti-incident illumination

As shown in Fig. 17, there are no satisfactory reconstructions for a single or double illumination. As expected, the error starts to decrease for increasing the number of illuminations, and after a specific number, it remains almost constant for each specific reconstruction. There is no certain value because it differs for every shapes. However, one can conclude that at least 2 incidence illumination should be considered even for a simple object (like the potato). The details of the analysis are given in Table 1. The table states the incident fields angles, given in (4), by defining  $\varphi_i^1 : \Delta \varphi : \varphi_i^N$ . Here,  $\varphi_i^1$  and  $\varphi_i^N$  are the initial and the final angles of the illumination, and  $\Delta \varphi$  denotes the increments.

The next example shows the reconstruction of a peanut-shaped object for the same constitutive EM parameters with different initial guessed surfaces. The object is defined with a radial function

$$r(\varphi) = 0.7 \sqrt{\left(0.2 \cos^2(\varphi) + \sin^2(\varphi)\right)}.$$
 (52)

Two incident illuminations were utilized with  $\varphi_i = \{90^\circ, 270^\circ\}$ . In this example, the reconstruction carried out for considering both a circular cylinder with a radius  $0.6\lambda_1$  and an ellipse defined as:

$$r_0(\varphi) = \frac{ab}{\sqrt{\left(a\cos^2(\varphi) + b\sin^2(\varphi)\right)}},$$
 (53)

where  $a = 0.6\lambda_1$  and  $b = 0.4\lambda_1$ . Since the elliptical initial guess is more similar to the actual peanut-shaped object, one may consider that using an elliptical cylinder as the initial guess would lead to a better reconstruction. However, both qualitatively and quantitatively, the difference between reconstructions is almost negligible. It is obtained err = 3.73% with the circular cylinder initial guess and err = 3.61% for the case of the elliptical cylinder. The only difference is that it requires 7 iterations for the elliptical case,

whereas it costs 11 for the circular initial guess. Thus, the method is stable and robust. Fig. 18 demonstrates the reconstruction, the elliptical initial guess, and the actual surface.

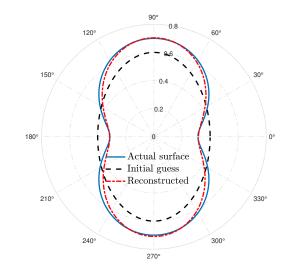


Figure 18. Reconstruction of the peanut-shaped object with the initial guess

For the peanut reconstruction cases,  $n_{\ell} = 2\%$  noise is applied for all the simulations, and 13 exponential functions are applied in the least square sense.

#### 6. Conclusion

A regularized and linearized iterative framework is presented to recover the shape of inaccessible 2-dimensional dielectric objects. The proposed framework utilizes the far-field pattern of the scattered field data for this aim. The inversion is done in accordance with the boundary integral representation of the far-field pattern considering the combination of the double and single-layer potentials. The problem is inherently ill-posed and nonlinear. Within this context, the Newton-type iterative linearization technique is applied, and it is regularized via Tikhonov in the sense of the least squares approach. To overcome the adverse effect of the shadow region on the imaging process, the superposition of the multi-incident wave is taken into account. Accordingly, robust and fast inversion is achieved with a very low computational cost. The feasibility of the proposed framework and its validation limits are asserted via various scattering scenarios.

The algorithm may be extended for threedimensional imaging problems in the acoustic case, as it still requires a scalar solution to the wave equations. However, the EM case must be reformulated, as the scattering problem needs a vectorial solution. The validation limits can be enlarged with hybrid approaches generated with deep learning techniques. All these issues are left as future works.

#### Appendix

 $\overline{I}_{die}$  and  $\overline{V}_{die}$  are vectors with size  $2N \times 1$  whose elements are precisely

$$\overline{I}_{die} = \left[ u_0 \, u_1 \cdots u_N \, \psi_0 \, \psi_1 \cdots \psi_N \right]^T, \qquad (A.1)$$

and tested incident fields with Dirac-delta function yields:

$$\overline{V}_{die} = \left[ u^{i}(\varphi_{1}) \ u^{i}(\varphi_{2}) \cdots u^{i}(\varphi_{N}) \underbrace{0 \ 0 \cdots 0}_{N} \right]^{T}.$$
(A.2)

Finally, the impedance matrix has a size of  $2N \times 2N$ , which is composed of 4 sub-matrices, each of which has a size  $N \times N$ :

$$\overline{Z}_{die} = \begin{bmatrix} \overline{Z^{1u}} & \overline{Z^{1\psi}} \\ \overline{Z^{2u}} & \overline{Z^{2\psi}} \end{bmatrix}.$$
 (A.3)

The elements of  $\overline{Z^{j\psi}}$   $(j = \{1, 2\})$  are  $N \times N$  are given as

$$Z_{mn}^{j\psi} = \Delta \varphi_n \begin{cases} G_j \left( \boldsymbol{r_m}; \boldsymbol{r_n} \right) & m \neq n \\ \frac{i}{4} \left[ 1 + i\frac{2}{\pi} \ln \left( \frac{\gamma k_0}{4e} \Delta \varphi_n \right) \right] & m = n. \end{cases}$$
(A.4)

Here,  $\gamma = 1.78107$ . The sub-matrix  $\overline{Z^{1u}}$  has the elements

$$Z_{mn}^{1u} = \Delta \varphi_n \begin{cases} -K_0 \left( \boldsymbol{r_m}; \boldsymbol{r_n} \right) & \text{ for } m \neq n \\ \frac{1}{2} & \text{ for } m = n. \end{cases}$$
(A.5)

 $\overline{Z^{2u}}$  has the same format with (A.5) taking the wavenumber  $k_1$  instead of  $k_0$  into account. Moreover, the diagonal elements of  $\overline{Z^{2u}} = -1/2$  in accordance with the (16).

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RESEARCH ARTICLE

### A local differential quadrature method for the generalized nonlinear Schrödinger (GNLS) equation

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ARTICLE INFO	ABSTRACT
Article History: Received 16 February 2024 Accepted 23 July 2024 Available Online 16 October 2024	A local differential quadrature method based on Fourier series expansion nu- merically solves the generalized nonlinear Schrödinger equation. For time inte- gration, a Runge-Kutta fourth-order method is used. Matrix stability analysis is used to examine the method's stability. Three test problems involving the
Keywords: Differential quadrature method Fourier series expansion Generalized nonlinear Schrödinger equation Solitary waves	motion of a single solitary wave, the interaction of two solitary waves, and a solution that blows up in finite time, respectively, demonstrate the accuracy and efficiency of the provided method. Finally, the numerical results obtained from the presented method are compared with the exact solution and those obtained in earlier works available in the literature.
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#### 1. Introduction

We consider the generalized nonlinear Schrödinger (GNLS) equation, given by

$$i\omega_t + \omega_{xx} + q_1|\omega|^2\omega + q_2|\omega|^4\omega + iq_3(|\omega|^2)_x\omega + iq_4|\omega|^2\omega_x = 0,$$
(1)

where  $i = \sqrt{-1}$ ,  $\omega$  is a complex-valued function of the spatial coordinate x and time t. The subscripts t and x denote differentiation with respect to time, t and space, x and  $q_1$ ,  $q_2$ ,  $q_3$ ,  $q_4$  are real parameters. Eq.(1) describes the modulation of a quasi-monochromatic wave train in a weakly nonlinear dispersive medium [1]. It also describes the behaviour of the Stokes wave near the state of modulation instability, which was independently proposed by Johnson [2], Kakutani and Michihiro [3]. The GNLS Eq.(1) takes some special forms [1] and these forms have found many applications [1, 4]. One of the special forms of Eq.(1) is the well known cubic nonlinear Schrödinger (CNLS) equation:

$$i\omega_t + \omega_{xx} + q_1 |\omega|^2 \omega = 0, \qquad (2)$$

which has found applications in nonlinear optics [5], plasma physics [6] and fluid dynamics [7]. Other special forms of Eq.(1) have applications including propagation of nonlinear Alfv $\hat{e}$ n waves [8] and the self-modulation of the complex amplitude of the solution to the Benjamin-Ono equation [9]. Under the condition that the initial condition  $\omega(\mathbf{x}, 0)$  vanishes for sufficiently large x, the CNLS Eq.(2) has analytic solution given by [6,10]. There are many papers about the numerical and analytical solutions of the CNLS equation. However, a few papers can be found in the past about the numerical and analytical solutions of the GNLS equation. Exact solution of the GNLS equation was obtained by using Gauss transformation by Pathria and Morris [1]. They also obtained the numerical solution of the GNLS equation using the pseudo-spectral split-step method. Different

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split-step pseudo-spectral methods were implemented for the numerical solution of the GNLS equation by Pathria and Morris [4]. Muslu and Erbay [11] used first, second and fourth-order versions of the split-step Fourier method to solve the GNLS equation numerically. The quintic B-spline collocation method was used to solve the GNLS equation by Irk and Dağ [12]. A meshfree method based on RBFs has been used to solve the GNLS equation by Uddin and Haq [13]. Bashan, Ali, et al. [14–16] used various methods based on the differential quadrature method to find the solution of the nonlinear Schödinger Equation. In literature, [17–19], many researchers have developed various types of differential quadrature methods (DQM) using different base functions.

Assuming that  $\omega$  and all its derivatives tend to zero rapidly as  $x \to \pm \infty$ , the solutions of the GNLS equation possess the following conservation laws [1,4]:

$$I_{1} = \int_{-\infty}^{\infty} |\omega|^{2} dx, \qquad (3)$$

$$I_{2} = \int_{-\infty}^{\infty} \left[ |\omega_{x}|^{2} - \frac{1}{2} (2q_{3} + q_{4})|\omega|^{2} Im(\omega \bar{\omega}_{x}) - \frac{1}{2} q_{1} |\omega|^{4} + \frac{1}{6} \{ q_{3} (2q_{3} + q_{4}) - 2q_{2} \} |\omega|^{6} \right] dx, \qquad (4)$$

and

$$I_3 = \int_{-\infty}^{\infty} \left[ 2Im(\omega\bar{\omega}_x) - q_3|\omega|^4 \right] dx, \tag{5}$$

which are the conservation of mass, energy and impulse respectively.

The differential quadrature method (DQM) was first introduced by Bellman et al. [20] in 1972 as a simple and versatile numerical technique for solving complex differential equations. This method approximates a function's derivative at a certain point through a weighted linear sum of the functional values at specific collocation points, whereby a key aspect is related to the computation of weighting coefficients. Many authors have used various test functions to formulate various DQ methods, like Legendre polynomials, Lagrange interpolating polynomials, spline functions, radial basis functions (RBF), Chebychev polynomials, etc. [20–26]. Shu proposed a better method for computing weighting coefficients [27]. Shu and Richards [28] used Lagrange interpolating polynomials, which have no limitation on the choice of grid points. This leads to the polynomial-based differential quadrature (PDQ) method. They also obtained a recurrence formula to compute the weighting coefficients for higher-order derivatives. When using Fourier series expansion, we call it the Fourier-based differential quadrature (FDQ) method.

The main advantage of DQM is their high accuracy. In general, DQMs are global in nature [29], which means that they approximate a function and its derivative at a point by using the functional values at all collocation points in the domain. The number of collocation points in the given domain must be large enough to achieve high accuracy approximation. However, it was found that DQM is inefficient when the number of collocation points is larger [30] because of instability. In this regard, Zong and Lam [31] introduced a localized DQ method to keep a balance between stability and accuracy. It has been demonstrated that accuracy and stability can be balanced by approximating the derivative of a function at a position using a weighted sum of functional values at the points in its neighbourhood rather than all collocation points. Therefore, we proposed an efficient numerical approach based on the local differential quadrature method using Fourier series expansion to solve the GNLS Eq.(1).

The paper is organized as follows: Section 2 briefly introduces DQM and the local Fourierbased differential quadrature (L-FDQ) method. The L-FDQ method is implemented in section 3 to solve the GNLS equation. In section 4, we discuss the matrix stability analysis of the proposed method. Section 5 reports the numerical results of the GNLS equation for some test problems. In section 6, we draw a brief conclusion about the presented method.

### 2. Differential quadrature method (DQM)

DQM is an approximation to the derivative of a function at any grid point using the weighted linear sum of all functional values at certain collocation points in the given domain of definition. We consider an arbitrarily distributed N grid points  $x_1 < x_2 < \cdots < x_N$  on the real axis. Then, according to DQ discretization, the  $n^{th}$  order derivatives of U(x,t) w.r.t. the spatial coordinate x at a point  $x_i$  is given by

$$U^{(n)}(x_i, t) = \sum_{j=1}^{N} w_{i,j}^{(n)} U(x_j, t), \qquad (6)$$

where  $w_{i,j}^{(n)}$  represents the weighting coefficients, i, j = 1, ..., N and n = 1, ..., N - 1.

# 2.1. Fourier-based differential quadrature (FDQ)

For Fourier-based differential quadrature (FDQ), we consider an arbitrary function defined on the interval [a, b]. Two typical sets of base functions are used to compute the weighting coefficients. These sets of base functions are:

$$1, \cos\left(\frac{\pi x}{b-a}\right), \sin\left(\frac{\pi x}{b-a}\right), \dots,$$

$$\cos\left(\frac{(N-1)\pi x}{2(b-a)}\right), \sin\left(\frac{(N-1)\pi x}{2(b-a)}\right),$$
(7)

and

$$g_j(x) = \frac{G(x)}{\sin\left(\frac{\pi(x-x_j)}{2(b-a)}\right)G^{(1)}(x_j)}, \quad x \in [a, b],$$

$$i = 1, 2, \dots, N$$
(8)

where

$$G(x) = \prod_{k=1}^{N} \sin\left(\frac{\pi(x-x_k)}{2(b-a)}\right),$$
$$G^{(1)}(x_j) = \prod_{k=1, k \neq j}^{N} \sin\left(\frac{\pi(x_j-x_k)}{2(b-a)}\right), \ x \in [a,b],$$
$$j = 1, \dots, N.$$

Using these sets of base functions given in Eq.(7) and Eq.(8), the weighting coefficients for the first and second-order derivatives as evaluated by Shu [29] are as follows:

$$w_{i,j}^{(1)} = \frac{\pi}{2(b-a)} \frac{G^{(1)}(x_i)}{\sin\left(\frac{\pi(x_i-x_j)}{2(b-a)}\right) G^{(1)}(x_j)}, \ i \neq j,$$

$$w_{i,j}^{(2)} = w_{i,j}^{(1)} \left(2w_{i,i}^{(1)} - \frac{\pi}{(b-a)} \cot\left(\frac{\pi(x_i-x_j)}{2(b-a)}\right)\right),$$

$$i \neq j,$$

$$w_{i,i}^{(n)} = -\sum_{j=1, j \neq i}^{N} w_{i,j}^{(n)}, \ n = 1, 2$$
(9)

where i, j = 1, 2, ..., N. We used equally spaced grid points in the space direction to approximate the derivative of the unknown function.

# 2.2. Local Fourier-based differential quadrature (L-FDQ)

We consider a partition  $a = x_1 < x_2 < \cdots < x_i < \cdots < x_N = b$  of the domain [a,b]. Following the method adopted by Shu [27], we consider a location  $x_i$  (i = 1, 2, ..., N) and for each i, consider a stencil  $S_i = \{x_{i-K_1}, x_{i-K_1+1}, ..., x_{i-1}, x_i, x_{i+1}, ..., x_{i+K_2}\}$  containing K + 1 ( $K = K_1 + K_2$ ) grid points. For the left boundary point  $x_1, K_1 = 0, K_2 = K$ , while for the right boundary point  $x_N, K_1 = K, K_2 = 0$ . Then using the K + 1 grid points  $x_{i-K_1}, x_{i-K_1+1}, ..., x_{i-1}, x_i, x_{i+1}, ..., x_{i+K_2}$  the n<sup>th</sup> order partial derivative of the function U(x, t) with respect to x at  $x_i$  is given by

$$U_x^{(n)}(x_i, t) = \sum_{j=-K_1}^{K_2} w_{i,i+j}^{(n)} U(x_{i+j}, t)$$
(10)

where , the L-FDQ weighting coefficients for the first and second-order derivatives in Eq.(9) are given by

$$w_{i,i+j}^{(1)} = \frac{\pi}{2(b-a)} \frac{G^{(1)}(x_i)}{\sin\left(\frac{\pi(x_i - x_{i+j})}{2(b-a)}\right) G^{(1)}(x_{i+j})},$$
  
for  $j \neq 0, j = -K_1, \dots, K_2$   
(11)

where

$$G^{(1)}(x_i) = \prod_{\substack{k=K_1\\k\neq 0}}^{K_2} \sin\left(\frac{\pi(x_i - x_{i+k})}{2(b-a)}\right) \text{ and}$$
$$G^{(1)}(x_{i+j}) = \prod_{\substack{k=-K_1\\k\neq j}}^{K_2} \sin\left(\frac{\pi(x_{i+j} - x_{i+k})}{2(b-a)}\right),$$

and

$$w_{i,i+j}^{(2)} = w_{i,i+j}^{(1)} \left( 2w_{i,i}^{(1)} - \frac{\pi}{b-a} \cot\left(\frac{\pi(x_i - x_{i+j})}{2(b-a)}\right) \right)$$
$$j \neq 0, j = -K_1, \dots, K_2$$
(12)

For the diagonal coefficients  $w_{i,i}^{(n)}$ , we have

$$w_{i,i}^{(n)} = -\sum_{\substack{k=-K_1,\\k\neq 0}}^{K_2} w_{i,i+k}^{(n)} \quad ; \ n = 1, 2.$$
(13)

Once the weighting coefficients are computed, then we make the following differentiation matrices,  $\mathbf{W}^{(1)} = \left(w_{i,j}^{(1)}\right)_{N \times N}$  and  $\mathbf{W}^{(2)} = \left(w_{i,j}^{(2)}\right)_{N \times N}$ to approximate the first and second-order spatial derivatives of U(x,t) in the domain [a,b]. These differentiation matrices are banded.

# 3. Implementation of L-FDQ

The GNLS Eq.(1) is examined in this part, with the following initial and boundary conditions applied across the interval [a, b]:

$$\omega(x,0) = f(x), x \in [a,b]$$
(14)

$$\omega(a,t) = \omega(b,t) = 0, t \in (0,T].$$
(15)

Taking  $\omega(x,t) = u(x,t) + iv(x,t)$ , where  $i = \sqrt{-1}$  the GNLS Eq.(1) with the initial and boundary conditions (14) and (15) are transformed into the following coupled initial-boundary value problem (IBVP):

PDEs:

$$u_{t} = -v_{xx} - [q_{1}(u^{2} + v^{2}) + q_{2}(u^{2} + v^{2})^{2}]v - [2q_{3}u^{2} + q_{4}(u^{2} + v^{2})]u_{x} - 2q_{3}uvv_{x} v_{t} = u_{xx} + [q_{1}(u^{2} + v^{2}) + q_{2}(u^{2} + v^{2})^{2}]u - [2q_{3}v^{2} + q_{4}(u^{2} + v^{2})]v_{x} - 2q_{3}uvu_{x}$$
(16)

ICs: 
$$u(x,0) = f_u(x), v(x,0) = f_v(x), x \in [a,b]$$
(17)

BCs : 
$$u(a,t) = u(b,t) = 0, v(a,t) = v(b,t) = 0,$$
  
 $t \in (0,T].$   
(18)

To solve the system (16) with ICs (17) and BCs (18) at the collocation points  $\{x_1, x_2, \ldots, x_N\}$  with uniform step size  $h = x_{i+1} - x_i$ , for  $i = 1, 2, \ldots, N-1$  we define the following:

$$\mathbf{U}(t) = [u_1(t), u_2(t), \dots, u_N(t)]^T,$$
$$\mathbf{V}(t) = [v_1(t), v_2(t), \dots, v_N(t)]^T,$$

where  $u_i(t) = u(x_i, t), v_i(t) = v(x_i, t)$  for all i = 1, 2, ..., N.

Using these definitions and the differentiation matrices  $\mathbf{W}^{(1)}$  and  $\mathbf{W}^{(2)}$  as defined in section 3, the system of PDEs (16) reduces to the following system of ordinary differential equations (ODEs), which can be written in the following matrix form:

$$\mathbf{U}'(t) = -\mathbf{W}^{(2)} \cdot \mathbf{V}(t) - \left[q_1 \left(\mathbf{U}^2(t) + \mathbf{V}^2(t)\right) + q_2 \left(\mathbf{U}^2(t) + \mathbf{V}^2(t)\right)^2\right] * \mathbf{V}(t) \\
- \left[2q_3\mathbf{U}^2(t) + q_4 \left(\mathbf{U}^2(t) + \mathbf{V}^2(t)\right)\right] * \left(\mathbf{W}^{(1)} \cdot \mathbf{U}(t)\right) - 2q_3\mathbf{U}(t) * \mathbf{V}(t) * \left(\mathbf{W}^{(1)} \cdot \mathbf{V}(t)\right) \\
\mathbf{V}'(t) = \mathbf{W}^{(2)} \cdot \mathbf{U}(t) + \left[q_1 \left(\mathbf{U}^2(t) + \mathbf{V}^2(t)\right) + q_2 \left(\mathbf{U}^2(t) + \mathbf{V}^2(t)\right)^2\right] * \mathbf{U}(t) \\
- \left[2q_3\mathbf{V}^2(t) + q_4 \left(\mathbf{U}^2(t) + \mathbf{V}^2(t)\right)\right] * \left(\mathbf{W}^{(1)} \cdot \mathbf{V}(t)\right) - 2q_3\mathbf{U}(t) * \mathbf{V}(t) * \left(\mathbf{W}^{(1)} \cdot \mathbf{U}(t)\right) \\$$
(19)

where " $\cdot$ " indicates the multiplication of two matrices and  $\mathbf{U}(t) * \mathbf{V}(t)$ ,  $\mathbf{U}^2(t) = \mathbf{U}(t) * \mathbf{U}(t)$  denote the component by component multiplication of two matrices.

Using the corresponding ICs and BCs (17) and (18), we solve the above system of ODEs (19) by the usual RK4 method.

# 4. Stability analysis

The method's stability is analyzed using the matrix stability analysis as suggested in literature [30,32]. After linearization of the system of ODEs (19), the resulting system can be written in the following matrix form:

$$\mathbf{X}'(t) = \mathbf{A} \cdot \mathbf{X}(t) \tag{20}$$

(since, both the system of ODEs and the BCs are homogeneous) or

$$\begin{bmatrix} \mathbf{U}'(t) \\ \mathbf{V}'(t) \end{bmatrix}$$

$$= \begin{bmatrix} -\alpha \mathbf{W}^{(1)} & -\beta \mathbf{I} - \gamma \mathbf{W}^{(1)} - \mathbf{W}^{(2)} \\ \beta \mathbf{I} - \gamma \mathbf{W}^{(1)} + \mathbf{W}^{(2)} & -\alpha \mathbf{W}^{(1)} \end{bmatrix} \begin{bmatrix} \mathbf{U}(t) \\ \mathbf{V}(t) \end{bmatrix}$$

where **I** is the identity matrix of order  $N \times N$ ,  $\mathbf{W}^{(1)}$  and  $\mathbf{W}^{(2)}$  are the weighting coefficient matrices for first and second order derivatives respectively, as defined in section-3. Also, we have taken  $\alpha = 2q_3\bar{u}^2 + q_4(\bar{u}^2 + \bar{v}^2)$ ,  $\beta = q_1(\bar{u}^2 + \bar{v}^2) + q_2(\bar{u}^2 + \bar{v}^2)^2$  and  $\gamma = 2q_3\bar{u}\bar{v}$ , where  $\bar{u} = ||\mathbf{U}||_{\infty}$ and  $\bar{v} = ||\mathbf{V}||_{\infty}$ .

The stability region for the complex eigenvalues is shown in Figure 1 [33].

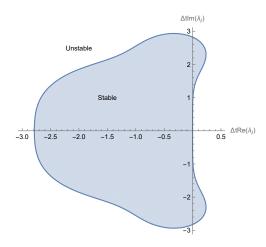


Figure 1. Stability region for complex eigenvalues.

The stability of the numerical integration of the system (20) is related to the stability of the numerical scheme for solving it. If the system of ODEs in (20) is not stable, then the stable numerical scheme for temporal discretization may not generate the converged solution.

The stability of (20) depends on the eigenvalues of the coefficient matrix **A** since its exact solution can be found using the eigenvalues. Let  $\lambda_i$  be the eigenvalues of the coefficient matrix **A**, then the stable solution of  $\mathbf{X}(t)$  as  $t \to \infty$  requires:

- (1) if all the eigenvalues are real  $-2.78 < \Delta t \ \lambda_i < 0$
- (2) if eigenvalues are imaginary,  $-2\sqrt{2} < \Delta t \ \lambda_i < 2\sqrt{2}$
- (3) if eigenvalues are complex  $\Delta t \lambda_i$  should be in the region shown in Figure 1

At the end of section 5, we will calculate the eigenvalues of the coefficient matrix **A** and we will see that our scheme is stable with the proper choice of the time step  $\Delta t$ .

## 5. Numerical experiment

The accuracy and effectiveness of the present method are demonstrated by taking three test problems. The accuracy of the method is measured by using  $L_{\infty}$ - error norm, which is defined as

$$L_{\infty} = \left\| |\omega|_{exct} - |\omega|_{approx} \right\|_{\infty}$$
$$= \max_{1 \le i \le N} \left| |\omega(i)|_{exct} - |\omega(i)|_{approx} \right|$$

#### 5.1. Single solitary wave solution

The exact solitary wave solution of the GNLS Eq.(1) for the parameters  $q_1 = 0.5$ ,  $q_2 = -1.75$ ,  $q_3 = -1.0$  and  $q_4 = -2.0$  is given by [1,4]:

$$\omega(x,t) = \frac{2e^{i\phi(x,t)}}{\sqrt{4+3\sinh^2(x-2t-x_0)}},$$
(21)

where 
$$\phi(x,t) = 2 \tanh^{-1} \left[ \frac{1}{2} \tanh(x - 2t - x_0) \right] + x - x_0.$$

The modulus of the above solution represents a single solitary wave initially located at  $x_0$ , moving to the right with constant speed 2. The exact values of the three conserved quantities  $I_1$ ,  $I_2$  and  $I_3$  as given in Eq.(3)-Eq.(5), for this problem can be found as:

$$I_{1} = 2 \log 3 \approx 2.19722, I_{2} = -1.5 + 3.875 \log 3 \approx 2.75712, I_{3} = 4 - 9 \log 3 \approx -5.88751.$$
(22)

Table 1.  $L_{\infty}$ - errors and conserved quantities for different stencil sizes K, for a single solitary wave motion, when h = 0.1,  $\Delta t = 0.001$  over the domain  $-20 \le x \le 30$ .

K	$I_1$	$I_2$	$I_3$	$L_{\infty}$
2	2.19724	2.75715	-5.88743	$2.40377 \times 10^{-2}$
4	2.19712	2.75701	-5.88717	$1.26695 \times 10^{-3}$
6	2.19712	2.75701	-5.88717	$1.07408 \times 10^{-4}$
8	2.19712	2.75701	-5.88717	$9.39029 \times 10^{-6}$
10	2.19712	2.75701	-5.88717	$4.23275 \times 10^{-6}$
12	2.19712	2.75701	-5.88717	$9.42336 \times 10^{-6}$

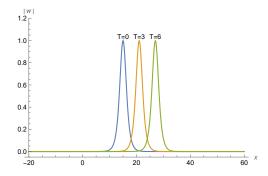
Using the initial condition obtained from (21) and imposing the boundary conditions (18), the GNLS equation is simulated by the proposed method for different stencils over the solution domain [-20, 30]. The  $L_{\infty}-$  error and the three conserved quantities for different stencil sizes K are reported in Table 1. From Table 1, we observe that  $L_{\infty}-$  error decreases when K, the size of the stencil increases from K = 2 to K = 10, however  $L_{\infty}-$  increase when K reached 12.

Table 2. Comparison of  $L_{\infty}$ - error at T = 3, for a single solitary wave motion, with  $x_0 = 15$ , N = 513, K = 18 and  $-20 \le x \le 60$ .

$\Delta t$	Present Method	Collocation [12]	First Order [11]	Second Order [11]
0.010	$2.75032 \times 10^{-5}$	$3.0 \times 10^{-4}$	$3.1 \times 10^{-3}$	$3.0 \times 10^{-5}$
0.005	$5.65732 \times 10^{-6}$	$3.1 \times 10^{-5}$	$1.6 \times 10^{-3}$	$2.0 \times 10^{-5}$
0.001	$3.86334 \times 10^{-7}$	$2.1 \times 10^{-6}$	$3.1 \times 10^{-4}$	$8.0 \times 10^{-7}$

**Table 3.**  $L_{\infty}$  – error norms and Rate of Convergence (ROC) for various numbers of grid points for K = 6, K = 8 and K = 10 with  $\Delta t = 0.001$  at T = 5.

N	K = 6		K = 8		K = 10	
	Error	ROC	Error	ROC	Error	ROC
201	$1.83495 \times 10^{-2}$	—	$1.01788 \times 10^{-2}$	_	$6.13463 \times 10^{-3}$	-
301	$1.98217 \times 10^{-3}$	5.5111	$4.52132 \times 10^{-4}$	7.71185	$1.13554 \times 10^{-4}$	9.87958
401	$3.91842 \times 10^{-4}$	5.65132	$5.23908 \times 10^{-5}$	7.51345	$7.34062 \times 10^{-6}$	9.548



**Figure 2.** Motion of a single solitary wave at different time levels.

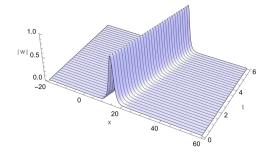


Figure 3. Space time graph of a single solitary wave for GNLS equation  $(N = 513, K = 18, \Delta t = 0.001)$ 

In order to compare our result with [11, 12], we choose  $x_0 = 15$ , N = 513 over the space interval [-20, 60] with time step size,  $\Delta t = 0.001$ . This comparison is reported in Table 2. Figure 2 and 3 represent the space-time graph of the numerical solution of single solitary wave up to time T = 6.

The absolute error distribution at time T = 6 for this case is shown in Figure 4.

The numerical rate of convergence (ROC) is calculated by using the formula [33],

$$ROC \approx \frac{\ln\left(\frac{E(N_2)}{E(N_1)}\right)}{\ln\left(\frac{N_1}{N_2}\right)}$$

where  $E(N_i)$  is the  $L_{\infty}$  – error norm when using  $N_i$  grid points.

The  $L_{\infty}$ - error norm and numerical rate of convergence analysis for various number of grid points are shown in Table 3. From the table it is evident that the rate of convergence (ROC) depends on the value of K.

#### 5.2. Interaction of two solitons

In this test problem, we consider the interaction of two solitons for the GNLS equation, in which the coefficients are taken as  $q_1 = 1$ ,  $q_2 = 1$ ,  $q_3 = -2$ and  $q_4 = 0$ . With these coefficients, we take the initial conditions as given by [1, 4]:

$$\omega(x,0) = \omega_1(x,0) + \omega_2(x,0), \qquad (23)$$

where

$$\omega_1(x,0) = \frac{1}{\sqrt{2}} \operatorname{sech}\left[\frac{1}{2}(x-15)\right]$$
$$e^{i\left[\frac{1}{4}(x-15) + \tanh\left\{\frac{1}{2}(x-15)\right\}\right]}$$

and

$$\omega_2(x,0) = \frac{1}{2\sqrt{2}} \operatorname{sech} \left[ \frac{1}{4} (x-35) \right]$$
$$e^{i \left[ -\frac{1}{2} (x-35) + \frac{1}{2} \tanh\{\frac{1}{4} (x-35)\}\right]}$$

**Table 4.** Conserved quantities at different time levels, for interaction of two solitons over the space interval [-50, 100] with N = 501 and  $\Delta t = 0.001$  with stencil size K = 14.

ſ	T	$I_1$	$I_2$	$I_3$
ſ	0	3.00145	0.18974	$-1.02223 \times 10^{-4}$
	5	3.00139	0.18977	$-1.02687 \times 10^{-4}$
	10	3.00141	0.18986	$-1.02482 \times 10^{-4}$
	15	3.00154	0.18968	$-1.02161 \times 10^{-4}$
	20	3.00142	0.18975	$-1.02403 \times 10^{-4}$

The exact values of the conserved quantities for this problem are  $I_1 = 3.0$ ,  $I_2 = \frac{3}{16}$  and  $I_3 = 0.0$ . The initial condition defined in Eq.(23), represents two solitons, one initially located at  $x_1 = 15$ , moving to the right with speed  $\frac{1}{2}$  and having amplitude  $\frac{1}{\sqrt{2}}$  and another initially located at  $x_2 = 35$  moving to the left with unit speed and having amplitude  $\frac{1}{2\sqrt{2}}$ . We have simulated this problem with the present method. These two solitons interact, and after the interaction, they retain their shapes and speeds, which has been shown in Figure 5. In Table 4, the conserved quantities  $I_1$ ,  $I_2$  and  $I_3$  at different time levels are reported. From the table, we see that the variations of these conserved quantities from the exact values are negligible.

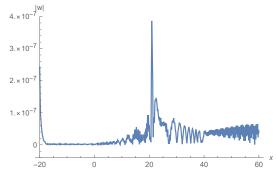


Figure 4. Error distribution of a single solitary wave for GNLS equation at t=6,  $(N = 513, K = 18, \Delta t = 0.001)$ .

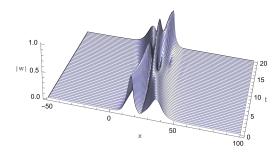


Figure 5. Interaction of two solitons  $(N = 501, K = 14, \Delta t = 0.001).$ 

# 5.3. Blow-up

In [1], it has been reported that for specific values of the coefficients and for certain initial conditions, the solutions of the GNLS equation have finite time blow-up. To see this experience, we take  $q_1 = -2$ ,  $q_2 = 20$  and  $q_3 = q_4 = 0$  and the Gaussian function  $\omega(x, 0) = e^{-x^2}$  as the initial condition, the numerical simulation has been conducted by our method. The exact values of the conserved quantities for this problem are found to be  $I_1 = \sqrt{\pi/2} \approx 1.5331$ ,  $I_2 = \sqrt{\pi}(9\sqrt{2} + 9 - 20\sqrt{6})/18 \approx -2.68447$  and  $I_3 = 0$ .

**Table 5.** Conserved quantities at different time levels for case of finite time blow-up ( $N = 151, -7.5 \le x \le 7.5, \Delta t = 10^{-4}$  and K = 6).

T	$I_1$	$I_2$	$I_3$
0.00	1.25330	-2.68419	0.0
0.02	1.25329	-2.68414	$-4.40186 \times 10^{-17}$
0.06	1.25107	-2.34227	$-1.13798 \times 10^{-15}$
0.07	1.15379	-2.07551	$-6.16625 \times 10^{-14}$
0.08	1.24722	-2.63257	$3.98570  imes 10^{-14}$
0.10	1.25129	-2.88368	$5.09393 \times 10^{-14}$
0.15	1.10587	-2.23570	$-6.12399 \times 10^{-12}$
0.20	1.24751	-3.39736	$1.97811  imes 10^{-11}$

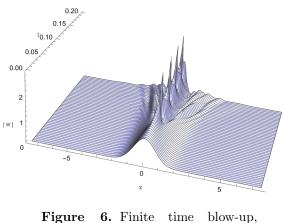


Figure 6. Finite time blow-up, with initial condition  $\omega(x,0) = e^{-x^2}(-7.5 \le x \le 7.5, N = 151, \Delta t = 0.0001, K = 12).$ 

The conserved quantities for this problem have been reported in Table 5, and from the table, we see that the variation of the conserved quantity is more in  $I_2$ . Figure 6 shows the space-time graph of this test problem. According to [1], it has been shown that the exact solution  $\omega(x, t)$  for this problem will blow up in finite time, and an upper bound on the blow-up time is  $t \approx 1.7$ . However, from Figure 6, we observed that the blow-up is evident at t = 0.07, and this result is consistent with the result obtained using the quintic bspline collocation method in [12]. Also, the graph shows that the blow-up is well occurring at about t = 0.07, 0.11, 0.15 and 0.20.

As a part of the stability analysis, we have calculated the eigenvalues of the coefficient matrix, **A** as defined in Eq.(20). We take  $\bar{u} = \bar{v} = 1$ , so that  $\alpha = 2q_3 + 2q_4$ ,  $\beta = 2q_1 + 4q_2$  and  $\gamma = 2q_3$ . The maximum absolute values of the eigenvalues of the coefficient matrix **A** for a single solitary wave motion is determined to be 248.273 (N = 513). Therefore, for maintaining stability the maximum value of  $\Delta t$  is given by  $\Delta t < \frac{2\sqrt{2}}{248.273} = 0.0113924$ . However, we take smaller values of  $\Delta t$  in order to get more accurate results. The distribution of eigenvalues for this case is shown in Figure 7. The figure shows that more eigenvalues are distributed near the imaginary axis.

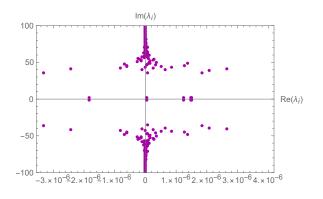


Figure 7 Distribution of eigenvalues for the coefficient matrix,  $\mathbf{A}$  (N = 513, K = 12).

# 6. Conclusion

In this study, we have examined the numerical solution of the GNLS equation by means of the L-FDQ method. The GNLS equation is discretized in space using differentiation matrices obtained from the L-FDQ method, and the resulting system of ordinary differential equations in time t is solved by the usual RK4 method. By the present method, the motion of a single solitary wave has been investigated, and the results obtained are compared with the exact solution and some other results obtained in earlier works. It has also been studied how two solitons interact, and it has been found that after the encounter, the solitons maintained their identities. The finite time blow-up problem has also been tackled by the suggested approach, which is consistent with the previous findings. Further, this study found that the finite time blow-up is repeating.

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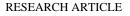
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# Modeling the dependency structure between quality characteristics in multi-stage manufacturing processes with copula functions

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# ABSTRACT

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# 1. Introduction

Today, production and service processes generally consist of many serial or parallel stages in which products are completed by passing from one to the other. In a multi-stage manufacturing process, it is not clear from which stage and which variables characterizing the process arise the variability in quality characteristics. The key to reducing quality variability in a product is understanding how, much of this variability occurs at each stage of the process and how much is transmitted to other stages.

The most important problem in the multi-stage manufacturing process is how to define the process in the context of interactions within and between stages and time dynamics. In past research, multistage processes have been described with statistical models such as the linear regression model. Conversely, for more effective monitoring and control of the process, engineering knowledge must also be combined with statistics in modeling and analysis of the multi-stage process. In this context; Many articles can be found in the sources that describe the multi-stage manufacturing process in a linear state-space model structure based on production engineering knowledge. A complex system, such as a multistage manufacturing process, may have many inputs and outputs. These inputs and outputs can be complexly interrelated. The hierarchical structure of the data obtained can be explained by multi-level

This study is about multi-stage manufacturing processes and their control by statistical process control modeling. There are two kinds of dependence structures in a multi-stage manufacturing process: one is the dependence between the stages of the process, and the other is the dependence between the concerned quality characteristics. This study employs state-space models to demonstrate the dependency structure between the process stages and uses the Kalman filter method to estimate the states of the processes. In this setup, copula modeling is proposed to determine the dependence structure between the quality characteristics of interest. A simulation study is conducted to assess the model's accuracy. As a result, it was found that the model gives highly accurate predictions according to the mean absolute percentage error (MAPE) criteria (<10%).



dynamic models. An example of this is a two-level linear state-space model.

In this study, in addition to a dynamic modeling approach such as the state-space model of the dependency between stages in multi-stage manufacturing processes, it is proposed to use copula modeling to reveal the internal dependencies of the quality characteristics of interest at each stage. In order to present the practical implications of the proposed model, the process was simulated and the applicability of the model was discussed.

The following sections of the study are organized as follows: In the second section, studies on statistical process control (SPC) methods used for modeling multi-stage manufacturing processes and monitoring these processes will be discussed. In the third section, modeling of multi-stage manufacturing processes with state-space models will be explained. Additionally, this chapter will include the proposal of the Kalman filter method for the statistical estimation of the state variables of the process equations put forward by statespace models. In the fourth chapter, the statistical dependence of quality characteristics and the explanation of dependence with copula functions will be highlighted, and multi-stage manufacturing process modeling under dependence will be presented. Multistage manufacturing processes under dependency The example and process simulation of SPC approaches

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will be presented in the fifth chapter. In the sixth chapter, the results of the study and some determinations about future studies as extensions of these will be stated.

#### 2. Literature review

In order to identify out-of-control situations in multistage manufacturing processes, SPC methods have been applied to the quality measurements of the product in the final stage of the process. Generally, Shewart, CUSUM, EWMA control charts for univariate quality measurements of the final product; It has been suggested to use Hotelling's  $T^2$  control chart for multivariate quality measurements [1]. Since these control charts were applied to a single stage of the process, they were insufficient to determine the stage that was the source of variability. In another study, quality measurements obtained from each stage of the process were evaluated separately [2]. In this study, where simultaneous confidence intervals were established for the average of each of the quality variables, it was examined whether the quality measurements of interest were within the confidence intervals in terms of the defined quality levels, and it was stated that the explanatory power of the method decreased as the size of the problem increased.

Statistical process control tools used to monitor multistage manufacturing processes have a wide place in the literature. These tools can be examined under three headings: multivariate control charts, control charts based on regression modeling, and methods based on engineering-based models.

In many production processes, it may be necessary to simultaneously monitor and control one or more interrelated quality characteristics. Independent examination of quality characteristics causes loss of information to be obtained from the process. The concept of multivariate quality control originated in Hotelling's work in 1947 [3]. In this study, he applied his proposed method to bombardment viewfinder data used in World War II. The most well-known multivariate process monitoring and control method used to monitor the mean vector of the process is Hotelling's  $T^2$  control chart, which is similar to the univariate Shewhart's  $\bar{x}$  chart. Applied to multi-stage manufacturing processes, Hotelling's  $T^2$  chart indicates when the entire process is out of control, but does not indicate which stage is out of control. Alternatively, quality metrics at each stage can be tracked with  $T^2$ cards. In this case, the effect of the quality output of the previous stage on the quality measurements at a certain stage will be ignored. As a result, it is difficult to interpret an out-of-control situation in a multi-stage manufacturing process with a  $T^2$  chart [1]. Following this pioneering work by Hotelling, control methods for many related variables have been proposed [4]. Nowadays, the issue of multivariate quality control (or process monitoring) has maintained its importance as many quality characteristics of products manufactured with automatic inspection methods can be measured at the same time. For example; Chemical and semiconductor manufacturers try to keep the process under control by constantly updating their databases for hundreds of important variables in their manufacturing processes.

It was thought that quality measurements in multi-stage manufacturing processes are affected by the output of the previous stage and the regression analysis technique was introduced [5]. This method is based on establishing univariate control cards for the residuals obtained from the multivariate regression line established on other variables for each quality variable [6]. Regression models can give misleading results when quality measurements from different stages are strongly correlated with each other. This problem in regression analysis can be partially reduced by the cause-selection method and is effective in identifying out-of-control stages [7]. A compilation of causeselection method studies was compiled by Wade and Woodall [8]. Nowadays, the use and applications of cause-selection schemes for multi-stage processes are also found in Shu and Tsung's article [9].

The hierarchical structure of data obtained from the multistage manufacturing process suggests a two-level model: At the first level, quality measurements are fitted to the system input and quality information. At the second level, the change in quality measurements is modeled as a function of measurements obtained from earlier stages of the process. An example of this situation is the state-space model.

Quality measurements for the *k*th stage of a production process consisting of *N* stages are formulated as a linear state-space model as in Eq. (1) and Eq. (2) [10].

$$x_k = A_{k-1} x_{k-1} + v_k \tag{1}$$

$$y_k = C_k x_k + w_k \quad \{k\} \subset \{1, 2, \dots, N\}$$
(2)

In Eq. (1),  $x_k$  shows unobservable product quality information such as dimensional deviations of products at the *k*th stage.  $v_k$  indicates the cause of variability and unmodelable errors (process noise).  $A_{k-1}x_{k-1}$  shows the transformation of quality information from the (k - 1)th stage to the *k*th stage. In Eq. (2),  $w_k$  is the measurement error of the product, and  $C_k$  is the matrix used to relate  $x_k$  with quality measurements  $(y_k)$ .

 $A_{k-1}$  and  $C_k$  are constant matrices obtained from engineering knowledge, laws of physics and process/product design information and known at the kth stage of the process. For univariate cases,  $v_k \sim N(0, \sigma_{v_k}^2)$  and  $w_k \sim N(0, \sigma_{w_k}^2)$  with its variance depending on the stage index k and the initial state  $x_0 \sim N(a_0, \tau^2)$ . Various methods have been researched to monitor whether the process is out of control, and fixture errors, machine errors and thermal errors in the process are seen as process out of control or process errors.

A multistage manufacturing process can have many inputs and outputs. These inputs and outputs can be

intricately related to each other. There are many articles explaining multi-stage manufacturing processes with state-space models based on process management expertise. Lawless et al. [11] and Agrawal et al. [12] revealed quality variability in multi-stage manufacturing processes with AR(1) type models in the form of state-space models. Part assembly process [12] and sheet metal assembly [13] are examples of modeling proposals in the form of state-space model. Detailed descriptions of state-space models can be found in [10] and [14]. There are many studies in the literature on error detection, error prevention and corrective methods in multi-stage manufacturing operations. Tsung et al.'s study compiled past studies on multi-stage manufacturing and service operations and provided ideas for future research [15].

Today, modeling for monitoring and control of multistage manufacturing processes, which have become more complex with developing technology, is a complex issue that still maintains its importance. Statespace models are a modeling method that has a wide place in the literature and includes the physics rules surrounding engineering and production structures suitable for the structure of multi-stage manufacturing processes. In a dynamic system represented by a statespace model, the state of the system can be predicted from the input and output information together with the previous information of the model. Estimation of the state of the system from a series of noisy measurements obtained from a dynamic system can be made with the Kalman filter.

In this study, it is suggested to model the dependency structure between quality characteristics with copula and combine it with Kalman filter. Some studies in which copulas, Kalman filter and/or state space models are used together are given in Table 1.

Authors	Methods/Models	Examples/Application Area
Lindsey [16].	Kalman filter and copulas	The application to autoimmunity in multiple sclerosis data
Junker, Szimayer and Wagner [17	Kalman filter based on copula functions	Nonlinear cross-sectional dependence in the term structure of US-Treasury yields and points out risk management implications
Hafner and Manner [18]	A multivariate stochastic volatility models with Gaussian copula	The application to two bivariate stock index series
Goto [19]	State space model to describe the target system's behaviour	A simulation study conducted to show the effectiveness of the developed controller
Creal and Tsay [20]	Gaussian, Student's t, grouped Student's t, and generalized hyperbolic copulas with time-varying correlations matrices	Modeling an unbalanced, 200-dimensional panel consisting of credit default swaps and equities for 100 US corporations
Alpay and Hayat [21]	Copula and Data Envolopment Analysis (DEA)	The application to simulated and real hospital data
Zhang and Choudhry [22]	Four generalized autoregressive conditional heteroscedasticity (GARCH) models and the Kalman filter method	Empirically forecasting the daily betas of a few European banks during the pre-global financial crisis period and the crisis period
Fernández, García and González-López [23]	Copula and the multivariate Markov chain	Spike prediction in neuronal data
Smith and Maneesoonthorn [24]	Construction of copulas from the inversion of nonlinear state space models	Forecasting of quarterly U.S. broad inflation and electricity inflation
Wang, Meng, Liui Fu and Cau [25]	The Unscented Kalman Filter (UKF), copula and the worst case analysis	A two-stage dynamic attack strategy using global network information
Xu, Liang, Li and Wang [26]	Characterization of the dependence among all components by a copula function	Investigation of the optimal condition-based maintenance policy under periodic inspection for a <i>K</i> -out-of- <i>N</i> : G system
Kreuzer, Dalla Valle and Czado [27]	Non-linear non-Gaussian state space model	Estimation of airborne pollutant concentrations
Ly, Sriboonchitta, Tang and Wong [28]	A hybrid of ARMA-GARCH, static and dynamic copulas and dynamic state space models	Investigation of dependence and integration among the European electricity markets
Wang, Xu, Trajcevski, Zhang, Zhong and Zhou [29]	A non-linear neural state space model based on copula-augmented mechanism	Electricity forecasting
Kreuzer, Dalla Valle and Czado [30]	Multivariate nonlinear non-Gaussian state space models	The application to atmospheric pollutant measurement data

Table 1. Some selected studies on copulas, Kalman filter and state space models.

The rest of the study is organized as follows. In the third section of the study, state-space models will be discussed. In the fourth section, the copulas proposed to model the dependency structure between quality characteristics will be explained in detail. Application of the proposed approach by a simulation study is given in the fifth section. The last section includes the conclusions of the study, and the future studies.

#### 3. Multi-stage manufacturing processes and statespace models

Dynamic systems, such as multistage manufacturing processes, can be more generally represented in the form of state-space models by the equations shown in Eq. (3) and Eq. (4).

$$x_k = A_{k-1}x_{k-1} + B_k u_k + D_k \varepsilon_k \tag{3}$$

$$y_k = C_k x_k + H_k \eta_k \tag{4}$$

Similar to Eq. (1) and Eq. (2),  $x_k$  is the state and  $y_k$  is the measurement or observation vectors (k = 1, ..., N). The vectors  $\varepsilon_k$  and  $\eta_k$  express the noise in the state and the observations, and the vector  $u_k$  represents the effects of managerial inputs at the *k*th stage in the process in Eq. (3) and Eq. (4).

Estimation of the state vector  $x_k$ , k = 1, ..., N in statespace models and other related analyzes can be done within the framework of three main approaches [31]. These are Bayesian, Fisher and unknown-bounded approaches. In the Bayesian approach, the error terms  $\varepsilon_k$  and  $\eta_k$  in the equations are stochastic, and the initial state vector  $x_0$  is a random variable. In the Fisher approach, the measurement equation term  $\eta_k$  has a stochastic feature,  $\varepsilon_k$  can be stochastic or completely unknown, and  $x_0$  can be random. Within the framework of the unknown – bounded approach,  $\varepsilon_k$ ,  $\eta_k$  and  $x_0$  are unknown but are limited from above to the values of the ellipsoids expressing the variance-covariance quantities [32].

When  $A_{k-1}$ ,  $B_k$  and  $C_k$  matrices are accepted as known matrices in state-space models, the model estimation problem is solved by using the observation values  $y_1, y_2, ..., y_{k_1}$  obtained up to time  $k_1$  and estimating  $x_{k_2}$ at time  $k_2$ . When  $k_1 = k_2$ , the estimation problem becomes a filtering process, for which Kalman filter (KF) or weighted least squares (WLS) methods can be used. Estimation equations that can be applied within the framework of the Bayesian model approach are known as Kalman filters in the literature [33].

The Bayesian model approach is the most widely used state-space modeling approach and can offer flexible perspectives on the dependence and independence of the vectors  $\varepsilon_k$ ,  $\eta_k$  and  $x_0$  within and among themselves in the time dimension. In this sense, the issues of determining the prior and posterior probability distributions for the random variables in the state-space model and the expected value and covariance functions are needed in estimation process.

Control effects that can be applied in a dynamic stochastic process are represented by the sequence  $\{u_k\}$  in state-space models. While control effects, state vectors should be a function of  $x_k$ 's, in the absence of a complete and direct observation of the situations, measurement or observation values must be considered as a function of  $y_k$ 's and determined by the opinion of system experts;  $u_k = \omega_0 (y_0, y_1, \dots, y_k)$ . In the literature, it is also recommended to impose a constraint such as  $|u_k| \le 1$  for  $u_k$ 's [34].

The Kalman filter and its calculation equations are explained in detail in the next section. In the weighted least squares method, the aim is to estimate the state vector with the deviation of  $x_k$ , which minimizes the quantity in Eq. (5), where the covariance matrix of the variable  $\eta_k$  is  $R_k > 0$ .

$$J(x_k) = (y_k - C_k x_k)' R_k^{-1} (y_k - C_k x_k)$$
(5)

In Eq. (5), the  $R_k^{-1}$  matrix is a positive definite matrix and must be determined in the context of the inputs, states and outputs of the dynamic system of interest. For  $x_k$  estimation that gives the smallest value of  $J(x_k)$ . The solution in Eq. (6) is found for the  $x_k$ estimation that gives the smallest value of  $J(x_k)$ .

$$\hat{c}_k = (C_k R_k^{-1} C_k)^{-1} C_k R_k^{-1} y_k$$
(6)

Estimation of  $x_k$  in the context of the weighted least squares method for the state-space model in Eq. (5) and Eq. (6);  $P_0$  is the covariance matrix for the initial state vector  $x_0$ , and  $Q_k$  is the covariance matrix for the vector  $\varepsilon_k$ , and Equation 7 is obtained by reaching its minimum value under the  $x_k = A_{k-1}x_{k-1} + B_ku_k + D_ke_k$ constraint.

$$J(x_{k}, \varepsilon_{0}, \varepsilon_{1}, ..., \varepsilon_{k-1})$$

$$= \sum_{k=1}^{N} (y_{k} - C_{k} x_{k})' R_{k}^{-1} (y_{k} - C_{k} x_{k})$$

$$+ \sum_{k=0}^{n-1} \varepsilon_{k} Q_{k}^{-1} \varepsilon_{k} + x_{0}' P_{0}^{-1} x_{0}$$
(7)

In Eq. (7),  $R_k$ ,  $Q_k$  and  $P_0$  matrices are positive definite and determined based on expert knowledge about the dynamic system of interest [10].

#### 3.1. State estimation with filtering: Kalman filter

The state of the system may not be directly measurable. In a dynamic system represented by a state-space model, the state of the system can be estimated by using the model's information obtained at previous times and its output information. Kalman filter, which was first introduced by Kalman in 1960, is an effective analysis algorithm that estimates the state of the system from a series of measurements obtained from a dynamic system that may contain error (noise), and updates the estimate as observations are made [35]. The Kalman filter combines measurement data, a priori information about the system, and indirectly measuring state values to make the desired predictions by minimizing the error statistically. Therefore, it gives better results than most other filters for statistical estimation purposes. Within the framework of the Bayesian approach, by conditioning the real data information provided by measuring devices, the spread of conditional probability densities for the features to be estimated can be filtered. Kalman filter helps the purpose of predictive analysis of a system that can be expressed with a linear model, where measurement errors are white noise and normally distributed, by providing conditional probability distribution [36].

For the dynamic and stochastic multi-stage production system represented by the state-space model equations Eq. (3) and Eq. (4), a series of prediction and filtering processes are required in line with the estimation of the state vector  $x_k$  at stage k. The difference equations needed for this purpose within the scope of the Bayesian approach are known as Kalman or Kalman-Bucy equations. There are various approaches and generalizations in determining the equations in question, and it is possible to consider equivalent criteria that form the basis for all of them. Minimizing the expected value of prediction error squares is one of these criteria [37].

# **3.1.1.** Minimization of expected value of squared error criteria method

In order to make state estimation with the Kalman filter, explanations about the variables and coefficients in the state-space model equations Eq. (3) and Eq. (4) are given below:

 $x_k \in \mathbb{R}^n$ : System state vector.

 $y_k \in \mathbb{R}^m$ : System observation vector.

 $A_k: n \times n$  dimensional system transition matrix.

 $B_k: n \times n$  dimensional system input matrix.

 $C_k: m \times n$  dimensional observation transition matrix.

 $u_k$ : Vector expressing the effect of managerial inputs at time (stage) k.

 $D_k: n \times n$  dimensional system noise matrix.

 $H_k: m \times n$  dimensional observation noise matrix.

It is assumed that the matrices  $A_k$ ,  $B_k$ ,  $C_k$ ,  $D_k$  and  $H_k$  are known at all times k = 0, 1, 2, ... The zero-mean white noise processes  $\varepsilon_k \in \mathbb{R}^n$  and  $\eta_k \in \mathbb{R}^m$  are assumed to satisfy the following assumptions for each k, j value in Eqs. (8)-(17).

$$E[\varepsilon_k] = 0 \tag{8}$$

$$E[\eta_k] = 0 \tag{9}$$

$$E[\varepsilon_k \varepsilon_j'] = Q_k \delta_{kj} \tag{10}$$

$$E[\eta_k \eta'_j] = R_k \delta_{kj} \tag{11}$$

$$\delta_{kj} = \begin{cases} 1, & k = j \\ 0, & k \neq j \end{cases}$$
(12)

$$E[\varepsilon_k \eta'_j] = 0 \tag{13}$$

$$E[x_0] = \bar{x}_0 \tag{14}$$

$$E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)'] = P_0 \qquad (15)$$

$$E[x_0\varepsilon_i'] = 0 \tag{16}$$

$$E[x_0\eta_j'] = 0 \tag{17}$$

 Table 2. Discrete time Kalman filter equations based on minimization of mean squared errors [38].

System dynamic model:

In addition to all given assumptions, it is assumed that the matrices  $Q_k$  and  $R_k$  are known. It is aimed to obtain  $\hat{x}_{k|m}$  by using observations  $\{y_1, y_2, ..., y_m\}$  for the best estimation of the  $x_k$  vector. In this direction, It is possible to use the covariance matrix  $(P_{k|m})$  of the estimation error  $(x_k - \hat{x}_{k|m})$ . When k = m, the estimation is called as filtering. Considering that the observations are not error-free, the assumption of  $R_k >$ 0 will be a realistic and necessary assumption. Let the vector  $Y_k = [y_1, ..., y_k]'$  represent the observations obtained until time (stage) k. If  $\vartheta_{k|m}$  is the estimation error of  $\hat{x}_{k|m}$  using  $Y_k$ , the covariance matrix of this error is expressed as  $P_{k|m} = E[\vartheta_{k|m}\vartheta'_{k|m}]$ , with  $E[\hat{x}_{k|m}] = E(x_k)$ . The estimation of vector  $x_k$  is done in two stages with various calculation steps. In Table 2, discrete time Kalman filter equations are summarized according to the method of minimizing the expected value of error squares by showing the filter system relationship.

On the other hand,  $\eta_k$  in the system equation Eq. (4) may become unobtainable. The solution to this problem requires adding additional state equations to the system equation. Bryson and Johanson proposed the first general solution to the problem in question [39]. To solve the problem, Brown and Hwang suggest removing exactly known state variables from the system equations and estimating the remaining ones by filtering [34]. This recommendation requires the separation of system state variables from other exactly known system variables by linear transformation. Simon summarized adequate explanations and methods of Kalman filter application approaches by considering the dependence as linear dependence and correlation for the cases where the random vectors  $\eta_k$  and  $\varepsilon_k$  are dependent within and between themselves [40].

#### 4. Modeling multi-stage manufacturing processes under the dependency between quality characteristics

In this section, a method is proposed by including copula functions in the approach of modeling and evaluating multi-stage manufacturing processes with state-space models under dependency. It has been suggested to use copula modeling to reveal the internal dependencies of the quality features within the state vector at each stage. With copula models, the stochastic relationship between quality characteristics can be determined by revealing the dependency structure without the need for common distributions of quality characteristics. In this context; Statistical properties such as marginal distributions, covariance, conditional probability distributions (and therefore regression function determination) of quality features that are random variables can be expressed.

#### 4.1. Copula functions

Copula functions are statistical tools used to model dependency. Copulas are functions that combine multivariate distributions with their univariate marginal distributions. Let *F* be the m-dimensional cumulative distribution function and  $F_1, F_2, ..., F_m$  be the

cumulative distribution functions of one-dimensional marginals. In this case, the m-dimensional copula function is defined as in Eq. (18).

$$F(y_1, y_2, ..., y_m) = C(F_1(y_1), F_2(y_2), ..., F_m(y_m); \theta)$$
(18)

 $\theta$  in Eq. (18) is called the dependency parameter and the marginal distributions of each of the quality characteristics express the relationship. The most basic theoretical determination about copula functions is put forward by the Scalar theorem.

**Theorem 1.** (*Sklar's Theorem*) The m-dimensional copula is a function C defined from the m-dimensional interval  $[0,1]^m$  to the unit interval [0,1] and satisfies the following conditions [41].

- $C(1, ..., 1, a_n, 1, ..., 1) = a_n, \forall n \le m \text{ and } a_n \in [0, 1].$
- If  $a_n = 0$  for any  $n \le m$ ,  $C(a_1, \dots, a_m) = 0$ .
- *C* is *m*-increasing.

In other words, the *m*-copula is an *m*-dimensional distribution function with m univariate marginals, each of which is uniformly distributed in the range (0,1).

There are many copula functions belonging to different copula families in the literature. When its application areas are investigated, it is seen that it has widespread use in finance, actuarial, time series and risk analysis. In this study, the focus is on the Gaussian (normal) copula, which belongs to the elliptic copula family and has many useful features.

**Definition 1.** (Gaussian Copula) Consider random variables  $Z_1, Z_2, ..., Z_k$  with correlation coefficients  $\rho_{ij} = \rho(Z_i, Z_j)$  with multivariate normal probability distribution. Let the joint cumulative distribution function of the random variables  $Z_1, Z_2, ..., Z_k$  be  $\Phi_G(z_1, z_2, ..., z_k)$ . In this case, the multivariate Gaussian (Normal) copula is defined in Eq. (19) [42].

$$(u_1, \dots, u_k) = \Phi_G \left( \Phi^{-1}(u_1), \dots, \Phi^{-1}(u_k) \right)$$
(19)

The two-variable Gaussian (Normal) copula is in the form of Eq. (20).

$$C(u_1, u_2; \theta) = \Phi_G(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta)$$
  
= 
$$\int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi (1 - \theta^2)^{1/2}}$$
  
× 
$$\left\{ \frac{-(s^2 - 2\theta st + t^2)}{2(1 - \theta^2)} \right\} ds dt \quad (20)$$

In Eq. (20),  $\Phi$  denotes the cumulative distribution function for the standard normal random variable and  $\Phi_G(u_1, u_2)$  denotes the standard bivariate normal distribution with the correlation parameter  $\theta$ , which takes values in the range of (-1,1). This copula function was proposed by Lee in 1983 [43]. The density function of the two-variable Gaussian copula is also in the form in Eq. (21).

$$c(u_1, u_2; \theta) = \frac{1}{\sqrt{1 - \theta^2}} \exp\left[\frac{-(u_1^2 - 2\theta u_1 u_2 + u_2^2)}{2(1 - \theta^2)}\right] \\ \times \exp\left(\frac{u_1^2 + u_2^2}{2}\right)$$
(21)

According to the scalar theorem, the bivariate probability distribution of the random vector  $X = (X_1, X_2)'$  can be determined by the non-normal (any distribution) marginal distributions of the vector and the Gaussian copula [44].

In order to determine the probability distribution of a random vector  $X = (X_1, X_2)'$ , it is necessary to determine the marginal distribution of each  $X_i$  and find the dependency structure between  $X_i$ . In order to determine the dependency structure between random variables, it is necessary to mention the measures and some special dependency structures included in the copula functions. There is a relationship between copula functions expressing dependence and dependence measurements, especially for two-variable cases. Dependency can be measured by many methods. The Pearson correlation coefficient is one of them; it is sensitive to outliers and does not change under strictly increasing linear transformations. The expression of the Pearson correlation coefficient in terms of copulas is shown in Eq. (22) [45].

$$\rho_{P}(X,Y) = \frac{1}{\sigma_{X}\sigma_{Y}} \int_{0}^{1} \int_{0}^{1} [C(u_{1},u_{2}) - u_{1}u_{2}] dF_{X}^{-1}(u_{1}) dF_{Y}^{-1}(u_{2}), \qquad u_{i} \in [0,1]$$
(22)

#### 4.2. Integration of state-space model with copula modeling

In this section, the state vector of quality characteristics under dependency is estimated by combining the statespace model, Kalman filtering and copula functions for multi-stage manufacturing processes. Therefore, a unique approach has been introduced to monitor quality in a multi-stage manufacturing process.

#### 4.2.1. Prediction error

Considering the general state-space model representation of a multi-stage manufacturing process with Eq. (3) and Eq. (4), the Kalman filter method for estimating the state vector  $x_k$  is introduced in Section 3.1. In the prediction phase of the estimation, it was seen that the uncertainty in the state vector  $\hat{x}_{k|k-1}$  is a function of the estimation of  $\hat{x}_{k-1|k-1}$  and the covariance  $Q_k$  of  $\varepsilon_k$ . In the next step, the prediction error components for vector  $x_k$  are; The statistical inference prediction error for  $x_k$  is  $x_k - \hat{x}_{k|k-1}$  and the prediction error for the observation vector  $y_k$  is  $\eta_k$ . Therefore, as expressed in Table 2, the conditional variance of the prediction error given in Eq. (23) should be evaluated as a function of the uncertainties or errors related to  $\hat{x}_{k|k-1}$  and  $R_k$ .

$$P_{k}(w) = C_{k}P_{k|k-1}C'_{k} + H_{k}R_{k}H'_{k}$$
(23)

According to the information obtained up to stage or time k-1, based on the conditional probability distribution of  $x_k$  to  $y_k - \hat{y}_{k|k-1}$ , the final estimation  $\hat{x}_{k|k}$  and its covariance  $P_{k|k-1}$  are obtained. Assuming that the joint probability distribution  $X = x_k$  and Y = $y_k - \hat{y}_{k|k-1}$  is a normal distribution given in Eq. (24), the conditional probability distribution X given that Y is  $N(\mu_{X|y}, \Sigma_{XX|y})$  with parameters  $\mu_{X|y} = \mu_X +$  $\Sigma_{XY}\Sigma_{YY}^{-1}(Y - \mu_Y)$  and  $\Sigma_{XX|y} = \Sigma_{XX} - \Sigma_{XY}\Sigma_{YY}^{-1}\Sigma_{YX}$ .

$$\begin{bmatrix} \begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix}, \begin{pmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{pmatrix} \end{bmatrix}$$
(24)

In Eq. (24),  $\mu_X = \hat{x}_{k|k-1}$ ,  $\Sigma_{XX} = P_{k|k-1}$ ,  $\Sigma_{XY} =$  $P_{k|k-1}C'_k$  and  $\Sigma_{YY} = P_k(w)$  (as in Eq. (23)) are some definitions. It is seen that by using these definitions, the expressions  $\hat{x}_{k|k}$  ve  $P_{k|k}$  which are the final estimates in the second stage of the Kalman filter, will be reached (see Table 2). The importance of the conditional variance  $P_k(w)$  of the prediction error in the estimation of  $x_k$  can be revealed from another perspective. For example; assuming that  $x_0, \varepsilon_k$  and  $\eta_k$  are random variables whose joint distribution is the normal distribution, the probability distribution of the random  $y_k$  conditional on the information vector  $\{y_1, y_2, \dots, y_{k-1}\}$ is normal distribution  $N[y_{k|k-1}, P_k(w)]$ , the estimates of  $x_k$  depend on the parameters of the distribution, conditional expected value and conditional variance-covariance  $y_{k|k-1}$  and  $P_k(w)$ , respectively. The estimation of the model parameters of interest can be achieved by maximizing the function given in Eq. (25), which expresses the loglikelihood in the context of all observation values. (1.)

$$L_{C}^{(\kappa)}(whole) = \ln \mathcal{L}$$
  
=  $-\frac{1}{2}\sum_{k} \ln[2\pi|P_{k}(w)|] - \frac{1}{2}\sum_{k} w_{k}'[P_{k}(w)]^{-1}w_{k}$   
=  $\sum_{k=1}^{N} L_{C}^{(k)}$  (25)

In the filtering stage, equations that express the estimates  $\hat{x}_{k|k}$  and  $P_{k|k}$  emerge. This was mentioned in Section 3.1, where the error quantities  $y_k - \hat{y}_{k|k-1} = w_k$ , and the variance expression of these error quantities  $P_k(w)$  are highlighted and discussed in state vector estimation. It has been emphasized more clearly that it constitutes the necessary essential element. Maximazing the likelihood function specified in Eq. (25) is equivalent to minimizing the quantity in Eq. (26), especially under the assumption of a normal distribution in general.

$$J = E[y_k - C_k \hat{x}_{k|k-1}][y_k - C_k \hat{x}_{k|k-1}]'$$
(26)

The assumptions and definitions for an illustrative example of this when the state vector  $x_k$  is a twoelement random vector with two quality characteristics are as follows:

410

- x<sub>k</sub> is a 2×1 dimensional state vector and y<sub>k</sub> is a 2×1 dimensional measurement vector.
- The quality characteristics in the measurement vector have marginal distributions  $y_{k1} \sim F_{k1}(.)$  and  $y_{k2} \sim F_{k2}(.)$ , respectively, and it is assumed that the internal dependency structure between them is modeled with an appropriate copula. The cumulative joint probability distribution of random variables  $y_{k1}$ and  $y_{k2}$  can be determined through copula functions as  $F_{k12}(y_{k1}, y_{k2})$ .
- $E(y_{ki}) = \mu_{ki}$ ,  $Var(y_{k1}) = \sigma_{ki}^2$ ,  $E(y_{ki}^2) = \sigma_{ki}^2 + \mu_{ki}^2$ , k = 1, 2, ..., N; i = 1, 2.
- $Cov(y_{k1}, y_{k2}) = \sigma_{k12}, \quad E(y_{k1}y_{k2}) = \sigma_{k12} + \mu_{k1}\mu_{k2}, \quad k = 1, 2, \dots, N.$
- It is assumed that the  $2 \times 2$  dimensional matrices  $A_k$ ,  $B_k$  and  $C_k$  are known.

• 
$$y_k = \begin{bmatrix} y_{k1} \\ y_{k2} \end{bmatrix}$$
,  $\hat{x}_{k|k-1} = \begin{bmatrix} \hat{x}_{k1} \\ \hat{x}_{k2} \end{bmatrix}$ ,  $\hat{x}_{k-1|k-1} = \begin{bmatrix} \hat{x}_{k1} \\ \hat{x}_{k2} \end{bmatrix}$ ,  $\hat{x}_{k-1|k-1} = \begin{bmatrix} \hat{x}_{k-1} \\ \hat{x}_{k-1} \end{bmatrix}$ ,  $u_k = \begin{bmatrix} u_{k1} \\ u_{k2} \end{bmatrix}$ ,  $k = 1, 2, ..., N$ .  
•  $B_k = \begin{bmatrix} b_{11}^{(k)} & b_{12}^{(k)} \\ b_{21}^{(k)} & b_{22}^{(k)} \end{bmatrix}$ ,  $A_{k-1} = \begin{bmatrix} a_{11}^{(k-1)} & a_{12}^{(k-1)} \\ a_{21}^{(k-1)} & a_{22}^{(k-1)} \end{bmatrix}$ ,  $C_k = \begin{bmatrix} c_{11}^{(k)} & c_{12}^{(k)} \\ c_{21}^{(k)} & c_{22}^{(k)} \end{bmatrix}$ ,  $k = 1, 2, ..., N$ .

If Eq. (26) is rewritten according to the definitions, the matrix in Eq. (27) is obtained.

$$J = E[y_k - C_k \hat{x}_{k|k-1}][y_k - C_k \hat{x}_{k|k-1}]'$$
$$= E\begin{bmatrix} N & L\\ L & M \end{bmatrix}$$
(27)

The expansion of the matrix elements in Eq. (27) is given in Eqs. (28)-(30).

$$N = \left(y_{k1} - c_{11}^{(k)}\hat{x}_{k1} - c_{12}^{(k)}\hat{x}_{k2}\right)^2$$
(28)

$$M = \left(y_{k2} - c_{21}^{(k)}\hat{x}_{k1} - c_{22}^{(k)}\hat{x}_{k2}\right)^2$$
(29)  
$$L = \left(y_{k1} - c_{k1}^{(k)}\hat{x}_{k1} - c_{k2}^{(k)}\hat{x}_{k2}\right)$$

$$\times \left( y_{k2} - c_{21}^{(k)} \hat{x}_{k1} - c_{22}^{(k)} \hat{x}_{k2} \right)$$
(30)

When the elements of matrix J are considered separately, the expected values in Eqs. (31)-(33) are obtained.

$$E(N) = \sigma_{k1}^{2} + \mu_{k1}^{2} - 2(c_{11}^{(k)}\hat{x}_{k1} + c_{12}^{(k)}\hat{x}_{k2})\mu_{k1} + (c_{11}^{(k)}\hat{x}_{k1} + c_{12}^{(k)}\hat{x}_{k2})^{2}$$
(31)

$$E(M) = \sigma_{k2}^{2} + \mu_{k2}^{2} - 2(c_{21}^{(k)}\hat{x}_{k1} + c_{22}^{(k)}\hat{x}_{k2})\mu_{k1} + (c_{21}^{(k)}\hat{x}_{k1} + c_{22}^{(k)}\hat{x}_{k2})^{2}$$
(32)

$$E(L) = \sigma_{k12} + \mu_{k1}\mu_{k2} - (c_{21}^{(k)}\hat{x}_{k1} + c_{22}^{(k)}\hat{x}_{k2})\mu_{k1} - (c_{11}^{(k)}\hat{x}_{k1} + c_{12}^{(k)}\hat{x}_{k2})\mu_{k2} + (c_{11}^{(k)}\hat{x}_{k1} + c_{12}^{(k)}\hat{x}_{k2}) \times (c_{21}^{(k)}\hat{x}_{k1} + c_{22}^{(k)}\hat{x}_{k2})$$
(33)

If the system transition matrix  $C_k$  is optimized (minimum), the partial derivatives of the expected values according to the elements of the  $C_k$  matrix are equal to zero. Then, the values in Eq. (34) and Eq. (35) for  $c_{11}^{(k)}$  and  $c_{12}^{(k)}$  are obtained.

$$c_{11}^{(k)} = \frac{\mu_{k1} - c_{12}^{(k)} \hat{x}_{k2}}{\hat{x}_{k1}}$$
(34)

$$c_{12}^{(k)} = \frac{\mu_{k1} - c_{11}^{(k)} \hat{x}_{k1}}{\hat{x}_{k2}}$$
(35)

It is necessary to test that the expressions in Eq. (34) and Eq. (35) are the values that minimize E(N). The values found for this are the values that make the second derivatives of E(N) with respect to  $c_{11}^{(k)}$  and  $c_{12}^{(k)}$  greater than zero,  $(\partial^2 E(N)/\partial (c_{11}^{(k)})^2 = 2\hat{x}_{k1}^2 > 0$ and  $\partial^2 E(N)/\partial (c_{12}^{(k)})^2 = 2\hat{x}_{k2}^2 > 0$ , will be the values that minimize E(N). Similarly, if the partial derivatives according to  $c_{21}^{(k)}$  and  $c_{22}^{(k)}$  in E(M) are taken and set equal to zero, the expressions in Eq. (36) and Eq. (37) are obtained.

$$c_{21}^{(k)} = \frac{\mu_{k2} - c_{22}^{(k)} \hat{x}_{k2}}{\hat{x}_{k1}}$$
(36)

$$c_{22}^{(k)} = \frac{\mu_{k2} - c_{21}^{(k)} \hat{x}_{k1}}{\hat{x}_{k2}}$$
(37)

Since,  $\partial^2 E(M) / \partial (c_{21}^{(k)})^2 = 2\hat{x}_{k1}^2 > 0$  and  $\partial^2 E(M) / \partial (c_{22}^{(k)})^2 = 2\hat{x}_{k2}^2 > 0$ , the values in Eq. (36) and Eq. (37) are the values that minimize E(M). If these values are substituted in E(L), the result will be as in Eq. (38) for k=1,2,...,N.

$$E(L) = E(Y_{k1}Y_{k2}) - \mu_{k1}\mu_{k2} = Cov(Y_{k1}, Y_{k2})$$
  
=  $\sigma_{k12}$ ,  $k = 1, ..., N$  (38)

In conclusion, the dependency between quality characteristics at any stage k is a phenomenon that affects the quality values of the production process. In the derivation made above, it is seen that the variance and covariance values directly affect the values symbolizing the quality status of the system, under the assumptions about the moments of the Y variables, which express the observable values of the X variables, which are the quality characteristics. Considering that variance and covariance values are quantities that determine correlation values; The conclusion is that the dependence, which can be expressed in general and specifically in the context of Gaussian copulas, is effective in the Kalman filter state estimation equations.

To state this more clearly, let us consider the Pearson correlation measure  $\rho_P = (y_{k1}, y_{k2}) = \sigma_{k12}(\sigma_{k1}\sigma_{k2})^{-1}$  in the context of observations for a two-element state vector. Pearson correlation measure can be expressed as a function of the copula function C(.,.) and the marginal distributions  $F_1$  and  $F_2$ , as shown in Eq. (22), in the form in Eq. (39).

$$\rho_P(y_{k1}, y_{k2}) = (\sigma_{k1}\sigma_{k2})^{-1} \int_0^1 \int_0^1 [C(u_1, u_2) - u_1 u_2] dF_1^{-1}(u_1) F_2^{-1}(u_2),$$
$$u_i \in [0, 1], \quad i = 1, 2 \quad (39)$$

By expressing the covariance  $\sigma_{k12}$  given in Eq. (38) in terms of copula, using Eq. (22), the adequacy of combining copula functions in the estimation of state-space models through the Kalman filter is demonstrated with Eq. (40).

$$\sigma_{k12} = (\sigma_{k1}\sigma_{k2})\rho_P(y_{k1}, y_{k2})$$
  
=  $\int_0^1 \int_0^1 [C(u_1, u_2) - u_1 u_2] dF_1^{-1}(u_1)F_2^{-1}(u_2)$  (40)

#### 4.2.2. Copula likelihood functions

Considering the copula functions and Sklar's Theorem, the joint probability distribution function for the elements of the observation vector  $y_k$ , which takes continuous values, will be in the form in Eq. (41) with the expression of the copula function.

$$F_{k12}(y_{k1}, y_{k2}; \gamma, \theta) = C(F_{k1}(y_{k1}; \gamma), F_{k2}(y_{k2}, \gamma); \theta)$$
(41)

In Eq. (41), the vector  $\gamma$  represents the probability distribution parameters except the dependence parameter  $\theta$  between  $y_{k1}$  and  $y_{k2}$ . It is not necessary for  $\theta$  parameter to express only correlation. If the distribution function in Eq. (41) is differentiated according to  $(y_{k1}, y_{k2})$ , the joint probability density function in Eq. (42) is obtained k = 1, 2, ..., N.

$$f_{k12}(y_{k1}, y_{k2}; \gamma, \theta) = c(F_{k1}(y_{k1}; \gamma_1), F_{k2}(y_{k2}; \gamma_2); \theta)$$
$$\times f_{k1}(y_{k1}; \gamma_1) f_{k2}(y_{k2}; \gamma_2)$$
(42)

 $c(...;\theta)$  in Eq. (42) is the copula density function corresponding to  $C(...;\theta)$ . Assuming that there are *n* observations that can be expressed as  $(y_{k11},...,y_{k1n})$  and  $(y_{k21},...,y_{k2n})$  for each of the  $y_k$ vector elements  $y_{k1}$  and  $y_{k2}$  at any stage or time *k*, the copula log-likelihood function, For k =1,2,...,N, the expression in Eq. (43) is obtained.

$$\mathcal{L}_{c}^{(k)} = \sum_{i=1}^{n} \ln f_{k12}(y_{1k}, y_{2k}; \gamma, \theta)$$
  
=  $\sum_{i=1}^{n} \ln c(F_{k1}(y_{k1}; \gamma_{1}), F_{k2}(y_{k2}; \gamma_{2}); \theta)$   
+  $\sum_{i=1}^{n} \ln f_{k1}(y_{k1}; \gamma_{1}) + \sum_{i=1}^{n} \ln f_{k2}(y_{2}; \gamma_{2})$  (43)

The difference between the expression in Eq. (43) and the ordinary log-likelihood function is that the sum of the log copula density functions is included in the equation. In the observation vector given in Eq. (3) where  $H_k = I_k$ ,  $\eta_{k1} = y_{k1} - c_{11}^{(k)} x_{k1} - c_{12}^{(k)} x_{k2}$  and  $\eta_{k2} = y_{k2} - c_{21}^{(k)} x_{k1} - c_{22}^{(k)} x_{k2}$  are defined as in the covariance matrix  $R_k$  in Eq. (44) for  $y_k = (y_{k1}, y_{k2})'$ with  $\eta_k = (\eta_{k1}, \eta_{k2})' \sim N(0, R_k)$ , k = 1, 2, ..., N.

$$R_{k} = \begin{bmatrix} Var(\eta_{k1}) & Cov(\eta_{k1}, \eta_{k2}) \\ Cov(\eta_{k1}, \eta_{k2}) & Var(\eta_{k2}) \end{bmatrix}$$
$$= \begin{bmatrix} \sigma_{\eta_{k1}}^{2} & \rho_{k}\sigma_{\eta_{k1}}\sigma_{\eta_{k2}} \\ \rho_{k}\sigma_{\eta_{k1}}\sigma_{\eta_{k2}} & \sigma_{\eta_{k2}}^{2} \end{bmatrix}$$
(44)

When the marginal density functions and joint probability density functions are given in Eq. (45), Eq. (46) and Eq. (47), respectively, the corresponding Gaussian (normal) copula density function expression can be calculated only with the help of the marginal distribution functions as in Eq. (48).

$$f_{k1}(y_{k1}; x_{k1}, x_{k2}, c_{11}^{(k)}, c_{12}^{(k)}) = \frac{1}{\sqrt{2\pi\sigma_{\eta_{k1}}^2}} \exp\left\{-\frac{(y_{k1} - c_{11}^{(k)}x_{k1} - c_{12}^{(k)}x_{k2})^2}{2\sigma_{\eta_{k1}}^2}\right\} (45)$$
$$f_{k2}(y_{k2}; x_{k1}, x_{k2}, c_{21}^{(k)}, c_{22}^{(k)})$$

$$=\frac{1}{\sqrt{2\pi\sigma_{\eta_{k_2}}^2}}\exp\left\{-\frac{\left(y_{k_2}-c_{21}^{(k)}x_{k_1}-c_{22}^{(k)}x_{k_2}\right)^2}{2\sigma_{\eta_{k_2}}^2}\right\}(46)$$

$$f_{k12}(y_k; x_k, C_k, R_k) = \frac{1}{2\pi\sqrt{|R_k|}} \times \exp\left\{-\frac{1}{2}(y_k - C_k x_k)' R_k^{-1}(y_k - C_k x_k)\right\}$$
(47)

$$c(F_{k1}(y_{k1}; x_{k1}, \gamma_{1k}), F_{k2}(y_{k2}; x_{k2}, \gamma_{2k}); \theta) = \frac{1}{\sigma_{\eta_{k1}}^2 \sigma_{\eta_{k2}}^2 - \rho_k^2} \exp\left\{-\frac{(\eta_{k1}^2 - 2\rho_k \eta_{k1} \eta_{k2} + \eta_{k2}^2)}{2(1 - \rho_k^2)}\right\} \times \exp\left(\frac{\eta_{k1}^2 + \eta_{k2}^2}{2}\right)$$
(48)

As seen from the copula log-likelihood function obtained in Eq. (43), the value size of the copula log-likelihood function is determined by the dependency parameter values when other parameters are given. Under normal distribution, the dependence parameter  $\theta$  is the parameter expressed in terms of moment factors and corresponding to the Pearson correlation.

#### 4.2.3. Copula functions and Kalman filter

In order to define the stochastic dependency structure between the quality characteristics of a product in multi-stage manufacturing processes with copula functions, it is sufficient to know the marginal probability distributions of the characteristics. By analyzing the representation of multi-stage manufacturing processes with the state-space models approach under dependency, it is possible to make Kalman filter estimations better trackable and interpretable on the basis of copula likelihood functions. To better express this, it would be useful to express the combination of Kalman filter estimation steps with copula functions, as shown in Table A1 in Appendix.

For the explicit expression of the copula log-likelihood functions  $L_c(prediction)$  and  $L_c(whole)$  in Table A1, it is necessary to know or predict the likelihood distribution models for the state-space model state vector  $x_k$  and therefore the observation vector  $y_k$ . In the predictions made for the Kalman filter method state-space model, normal distribution is assumed for the relevant model variables, and it is stated by many researchers that the predictions are efficient under these conditions [42].

For this reason, it is necessary to determine copula density functions and copula log-likelihood functions under certain distributions by using Eq. (43) to express the  $L_c(prediction)$  and  $L_c(whole)$  functions in Table A1.

For example; when the joint probability distribution of  $x_0$ ,  $e_k$  and  $\eta_k$  is a normal distribution, the  $L_c(prediction)$  and  $L_c(whole)$  functions for the  $y_k$  observation vector will be as in Eq. (49) and Eq. (50).

$$L_{c}(prediction) = \sum_{i=1}^{n} \ln f_{k12}(y_{1k}, y_{2k}; \gamma, \theta)$$
  
=  $\sum_{i=1}^{n} \ln c(F_{k1}(y_{k1}; \gamma_{1}), F_{k2}(y_{k2}; \gamma_{2}); \theta)$   
+  $\sum_{i=1}^{n} \ln f_{k1}(y_{k1}; \gamma_{1}) + \sum_{i=1}^{n} \ln f_{k2}(y_{2}; \gamma_{2})$  (49)

$$L_c(whole) = \sum_{i=1}^{N} L_c(prediction)$$
(50)

The copula density function in Eq. (49) is defined in Eq. (48). On the other hand,  $\gamma_1$  and  $\gamma_2$  in the expressions  $f_{k1}(y_{k1};\gamma_1)$  and  $f_{k2}(y_{k2};\gamma_2)$  defined in Eq. (45) and Eq. (46) show the distribution parameters. It has been stated in the previous sections that in determining the  $x_k$  and  $P_{k|k}$  expressions in the filtering stage of the Kalman filter equations, the likelihood function should be maximized or, equivalently, the sum of squares of the errors  $w_k = y_k - \hat{y}_{k|k-1}$  should be minimized. In this regard, copula log-likelihood functions must be determined to write the  $L_c(prediction)$  and  $L_c(whole)$  expressions shown in Table A1, the joint probability function of the random variables  $x_k$  and  $w_k = y_k - \hat{y}_{k|k-1}$  with normal distribution and the copula function were used.

Let  $y_k = (y_{k1}, y_{k2})'$  be the values observed about the quality characteristics of the production process at the

*k*th stage of the multi-stage manufacturing process. In the case of the existence of an observation set of size *n*, considering the equations  $x_{k|k-1}$ ,  $P_{k|k-1}$ ,  $E(w_k w'_k) = P_k(w)$  in Table A1, the probability density functions and the copula density function are given in Eqs.(51)-(54) where  $w_{ki} = y_{ki} - y_{k|k-1}^{(i)}$ , i = 1,2.

$$f_{k1}(w_{k1}; x_{k1}, \gamma_1)$$

$$=\frac{1}{\sqrt{2\pi\sigma_{k1}^2}}\exp\left\{-\frac{\left(y_{k1}-y_{k|k-1}^{(1)}\right)^2}{2\sigma_{w_{k1}}^2}\right\},$$
(51)

 $f_{k2}(w_{k2};x_{k2},\gamma_2)$ 

$$=\frac{1}{\sqrt{2\pi\sigma_{k2}^2}}\exp\left\{-\frac{\left(y_{k2}-y_{k|k-1}^{(2)}\right)^2}{2\sigma_{w_{k2}}^2}\right\},$$
(52)

 $f_{k12}(w_{k1}, w_{k2}; x_{k1}, x_{k2}, \gamma_1, \gamma_2, \theta)$ 

$$= \frac{1}{2\pi\sqrt{|P_{k}(w)|}} \exp\left\{-\frac{1}{2}(y_{k} - y_{k|k-1})'P_{k}(w)(y_{k} - y_{k|k-1})\right\}$$

$$= y_{k|k-1}$$
(53)

$$= y_{k|k-1} \},$$

$$c(F_{k1}(w_{k1}; x_{k1}, \gamma_1), F_{k2}(w_{k2}; x_{k2}, \gamma_2); \theta)$$

$$(53)$$

$$= \frac{1}{\sigma_{w_{k1}}^2 \sigma_{w_{k2}}^2 - \rho_k^2} \exp\left\{-\frac{(w_{k1}^2 - 2\rho_k w_{k1} w_{k2} + w_{k2}^2)}{2(1 - \rho_k^2)}\right\} \times \exp\left(\frac{w_{k1}^2 + w_{k2}^2}{2}\right)$$
(54)

 $y_{k|k-1}^{(\iota)}$ , i = 1,2 in Eq. (51) and Eq. (52) shows the prediction made for the ith element of vector  $y_k$  based on the values observed until the kth stage.  $P_k(w)$  in Eq. (53) shows the error covariance matrix in the Kalman filter prediction stage and is in the form in Eq. (55).  $\rho_k$ , which shows the correlation between  $w_{k1}$  and  $w_{k2}$  in the sense of Pearson correlation, is a copula correlation parameter for  $y_{k1}$  and  $y_{k2}$  since  $w_k = y_k - \hat{y}_{k|k-1}$  and  $y_{k|k-1}$  are calculated values.

$$P_{k}(w) = \begin{bmatrix} \sigma_{w_{k1}}^{2} & \sigma_{w_{k1}}\sigma_{w_{k2}}\rho_{k} \\ \sigma_{w_{k1}}\sigma_{w_{k2}}\rho_{k} & \sigma_{w_{k2}}^{2} \end{bmatrix}$$
(55)

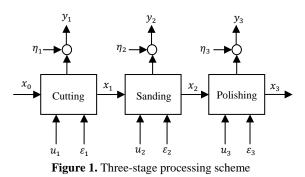
Then, the copula log-likelihood function derived by the log-likelihood expression in Eq. (43) is given Eq. (56).

$$L_{c}(w_{k}|y_{1},...,y_{k-1}) = \sum_{\substack{j=1 \\ n}} \ln c(F_{k1}(w_{k1j};x_{k1},\gamma_{1}),F_{k2}(w_{k2j};x_{k2},\gamma_{2});\theta) + \sum_{\substack{j=1 \\ n}} \ln f_{k1}(w_{k1j};x_{k1},\gamma_{1}) + \sum_{\substack{j=1 \\ j=1}}^{n} \ln f_{k2}(w_{k2j};x_{k2},\gamma_{2})$$
(56)

As seen in Eq. (56), when the copula density function dependence parameter is different from zero, the copula log-likelihood function creates an increasing or decreasing effect on its value. The equations  $x_{k|k}$  and  $P_{k|k}$ , which are the expressions of the Kalman filter filtering stage estimates, emerge as a result of the optimization of the copula log-likelihood functions according to  $w_{k1}$  and  $w_{k2}$  are obtained by using maximum likelihood (MLE) or minimization of the mean squared error (MMSE) approaches, effective estimates for  $x_k$  are obtained. When the marginal probability distributions of observation vectors  $y_k$  and error vectors  $w_k$  are distributions other than the normal distribution, the effectiveness of Kalman filter estimations may decrease.

#### 5. Application of the proposed approach

In this section, a multi-stage manufacturing process is simulated with the modeling method presented and the results are discussed. The production process in the simulation study is based on assumption. Assume that parts are processed in the wood workshop of a factory. The wooden pieces, which are processed through a three-stage manufacturing process, are expected to weigh 150 grams (g) and be 30 centimeters (cm) long at the end of the production process. When unprocessed wood pieces arrive at the factory, they are weighed and their lengths are measured in the input quality control department. Based on past measurements, it will be assumed that the lengths of untreated wood pieces have a normal distribution with a mean of 32 cm and a standard deviation of 0.5 cm. Similarly, the weights of the raw parts will be assumed to have a normal distribution with a mean of 152g and a standard deviation of 1.1g. It will be assumed that the parts entering the processing process are cut in the first stage, sanded in the second stage and polished in the last stage. Fig.(1) shows a representative version of this process.



The wooden parts, first checked in the input quality control department, are cut to the desired size during the cutting stage. After the parts are sanded, they move on to the polishing stage. Then, the products are left to dry to take their final form. It is assumed that the parts are weighed at the end of each stage and their length measured. Under these assumptions, the state equation will be as in Eq. (57), and the output (measurement) equation will be as in Eq. (58) where  $D_k = I_k$  and  $H_k = I_k$ .

$$x_k = A_{k-1} x_{k-1} + B_k u_k + \varepsilon_k, \qquad k = 1,2,3 \quad (57)$$

 $y_k = C_k x_k + \eta_k$ , k = 1,2,3 (58) In a multi-stage processing process revealed by the linear state-space model,  $x_k$  is the directly unobservable quality characteristic of the product being inspected.  $x_k$  is a vector that contains all the information about the current state of the process at the kth stage. In this simulation study, the state vector  $x_k$ consists of two quality characteristics:  $x_{k1}$  represents the actual value of the part size at the kth stage;  $x_{k2}$ shows the actual value of the part weight at the kth stage. The vectors  $x_k = \begin{bmatrix} x_{k1} & x_{k2} \end{bmatrix}', k = 1,2,3$  in size  $(2 \times 1)$  are known positive definite matrices that show the deviation during the transition from the kth stage to the (k + 1)th stage of the process given as  $A_0 = [-0.645 \ 0.343; -3.165 \ 1.660],$  $A_1 = [-0.639 \ 0.329; -3.170 \ 1.670]$  and  $A_2 = [-0.761 \ 0.352; -3.660 \ 1.730]$ with MATLAB notation.

 $B_k$  is defined as the input matrix at the kth stage and  $u_k = \begin{bmatrix} u_1^{(k)} & u_2^{(k)} \end{bmatrix}', k = 1,2,3$  is defined as a  $(2 \times 1)$  dimensional vector showing the contribution of the *k*th stage in the state equation. Here  $u_i^{(k)}$ , i = 1,2; k =1,2,3 is the contribution of the kth stage to the ith quality characteristic. This contribution is provided by the multiplication of the known matrix  $B_k$  and the vector  $u_k$ . In this application,  $B_1u_1 = [-0.01 - 0.025]'$ ,  $B_2u_2 = [-0.01 - 0.01]'$  and  $B_3u_3 = 0.011 - 0.011'$ [0.01 0.01]'. Let the unobservable process noise be defined as  $\varepsilon_k = [e_1^{(k)} e_2^{(k)}]', k = 1,2,3$ . In the simulation study, it is assumed that  $e_i^{(k)} \sim N(\mu =$  $(0, \sigma^2), i = 1, 2; k = 1, 2, 3$ . It is also assumed that the measurements can be taken from every stage. In this case, the measurement vector  $Y_k = [y_{k1} \quad y_{k2}]'$ , k =1,2,3 can be observed for every value of the phase index k. Let the  $C_k$  matrices, which provide the transition between the actual values of the quality characteristics and the measurement values, be determined as  $C_1 = [1.30 - 0.01; 0.01 \ 0.99], C_2 = [1.01 - 0.01; 0.01 \ 0.99],$  and  $C_3 = [1.01 - 0.01; 0.01 \ 0.99],$ 0.001; 0.01 0.99].

The elements of the vector  $\eta_k = [\xi_1^{(k)}\xi_2^{(k)}]'$ , k = 1,2,3, which show the measurement error are distributed normally given as  $\xi_i^{(k)} \sim N(\mu = 0, \sigma^2)$ , i = 1,2; k = 1,2,3. In this study, different correlation coefficient values (0.99, 0.90, 0.70, 0.50, 0.30 and 0.1) were tested for 0.1, 0.5 and 1 values of the  $\sigma^2$  parameter, which indicates the noise level. Additionally, it is assumed that the dependency structure between the length and the weight measurement values can be determined with the Gaussian copula.

In this case, the Kalman filter equations in Table 2 will be taken into consideration for the observed values of quality characteristics  $y_k = (y_{k1}, y_{k2})'$  in the *k*th stage of the multi-stage manufacturing process. Pearson correlation ( $\rho$ ) between  $w_{k1}$  and  $w_{k2}$  is a copula correlation parameter for  $y_{k1}$  and  $y_{k2}$  since  $w_k = y_k - \hat{y}_{k|k-1}$  and  $y_{k|k-1}$  are calculated values. The values of the Gaussian copula dependence parameter which models the dependency structure between  $y_{k1}$  and  $y_{k2}$ are calculated for each stage by a MATLAB code. As previously shown in Eq. (22) and Eq. (23), by expressing the  $\sigma_{k12}$  covariance in terms of copula, the adequacy of combining copula functions in the estimation of state-space models through the Kalman filter was demonstrated. The obtained Gaussian copula dependence parameter values were used instead of  $\rho_k$ in the matrix given in Eq. (55). The prediction stage covariance matrix  $P_k(w)$  is included in the Kalman gain matrix as in  $K_k = P_{k|k-1}C'_kP_k^{-1}(w)$ . As a result, the Kalman filter equations and copula functions have been integrated.

Assume that 100 wooden parts go through this machining process under the defined conditions. Due to the structure of the multi-stage manufacturing process, the output of the previous stage will be the input for any stage. For example, the outputs from the cutting stage will be the input for the sanding stage. The outputs obtained in the sanding stage will be the input for the polishing stage (see in Figure 1).

Table 3. MAPE values (%) for the simulation study

		Cutting Sandin		ding	Poli	shing	
ρ	$\sigma^2$	L	W	L	W	L	W
0.99	0.1	4.95	9.28	0.85	0.84	8.85	1.07
0.99	0.5	4.80	9.27	2.26	1.14	8.91	1.62
0.99	1.0	5.03	9.25	2.57	1.28	8.49	1.96
0.90	0.1	4.97	9.27	1.21	0.93	8.51	1.11
0.90	0.5	4.92	9.24	2.06	1.17	8.93	1.66
0.90	1.0	4.64	9.27	3.55	1.68	7.90	2.05
0.70	0.1	4.95	9.26	1.12	0.89	8.64	1.08
0.70	0.5	4.87	9.26	2.09	1.15	8.51	1.77
0.70	1.0	4.74	9.26	3.09	1.37	8.52	2.02
0.50	0.1	4.96	9.25	1.02	0.88	8.76	1.28
0.50	0.5	4.84	9.26	2.23	1.14	8.64	1.44
0.50	1.0	4.75	9.30	2.48	1.18	9.05	2.06
0.30	0.1	4.90	9.27	1.01	0.90	8.71	1.15
0.30	0.5	4.99	9.25	2.18	1.19	8.78	1.55
0.30	1.0	4.91	9.29	4.02	2.11	8.94	3.04
0.10	0.1	4.88	9.24	1.29	0.95	8.76	1.09
0.10	0.5	4.97	9.26	2.32	1.21	8.50	1.96
0.10	1.0	4.95	9.23	2.90	1.19	8.81	1.71

A MATLAB code was written to obtain simulation values for the quality characteristics, weight (W) and length (L), for each production stage under the assumptions. The mean absolute percentage error (MAPE) criterion was used to measure the performance of the Kalman filter model under the copula dependency. Table 3 displays the MAPE values that are obtained for various noise levels ( $\sigma^2$ ) and correlation

coefficients ( $\rho$ ). Since every MAPE value is less than 10%, it is evident that the proposed model, which provides remarkably accurate predictions, allows for the examination of the dependencies between quality characteristics at every stage [46].

#### 6. Conclusions

In this study, the state-space model established for the dependency between the stages in the multi-stage manufacturing process is integrated with the copula modeling used to reveal the internal dependency structure between the quality characteristics in a stage. The importance of the conditional variance of the prediction error in the Kalman filter equations in the estimation of  $x_k$  has been revealed and it has been emphasized that it constitutes the main element that needs to be addressed. In the application part of the study, first, the dependency structure between the quality variables of interest in a hypothetical production process was expressed with copulas, system state predictions were made with the Kalman filter, and evaluated under the mean absolute percentage error (MAPE) criterion. The resulting model has shown that it is a model that allows examining the dependency between quality characteristics at every stage and gives extremely accurate predictions.

The original contribution of this study to the theory, method and practice on the subject is as follows: The Kalman filter estimation method, based on state-space models of multi-stage manufacturing processes, has been presented in a broad perspective, with a solution algorithm proposed and subject-specific comments. In order to take into account the statistical dependence between the quality characteristics of interest at any stage of the process, the dependence was expressed with copula functions and integrated with the Kalman filter method.

The innovations and improvements that the specified original contributions brought to the modeling and analysis of multi-stage manufacturing processes are as follows: The fact that quality characteristics are essentially interdependent is reflected in the models and internalized in the analyses. Model components, structure and calculation steps that are dependent on modeling and analysis are clearly stated. The internal dependency structure that can exist between the quality characteristics of interest at any production stage is integrated with the dependency structure between the stages.

In order to further the results put forward in the study, future studies that are deemed useful are as follows: Prediction methods for various copulas that can be used in modeling the internal dependency between the quality characteristics of interest at any stage of multistage manufacturing process structures can be investigated and implemented. State-space modeling generalizations involving dependency can be made with multivariate copula models for more than two quality characteristics. In the presence of models containing noise terms and observation errors with distributions other than normal distribution, the robustness of Kalman filter estimates can be addressed.

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Appendix

N .	
Stages	Related Equations
<u>nitial:</u>	
κ <sub>0</sub> , Ρ <sub>0</sub>	
Prediction stage:	
$\hat{k}_{k k-1}$	(Table 2) $\hat{x}_{k k-1} = A_{k-1}\hat{x}_{k-1 k-1} + B_k u_k$
$P_k(y)$	(Table 2) $P_k(y) = C_k [A_{k-1}P_{k-1 k-1}A'_{k-1} + D_k Q_k D'_k]C'_k + H_k R_k H'_k$
$w_k = y_k - \hat{y}_{k k-1}$	(Table 2) $w_k = C_k (x_k - \hat{x}_{k k-1}) + H_k \eta_k$
$P_k(w) = E(w_k w'_k)$	(Table 2) $P_k(w) = C_k P_{k k-1}C'_k + H_k R_k H'_k$
Estimation prediction stage –	General: Eq. (43)
copula likelihood function	$n \sum_{n}$
$L_c(prediction)$	$\mathcal{L}_{c}^{(k)} = \sum_{i=1}^{k} \ln f_{k12}(y_{1k}, y_{2k}; \gamma, \theta)$
	n
	$= \sum \ln c(F_{k1}(y_{k1}; \gamma_1), F_{k2}(y_{k2}; \gamma_2); \theta)$
	$\sum_{\substack{i=1\\n}} n$ n
	$= \sum_{\substack{i=1\\n}} \ln c(F_{k1}(y_{k1};\gamma_1),F_{k2}(y_{k2};\gamma_2);\theta) + \sum_{\substack{i=1\\i=1}}^n \ln f_{k1}(y_{k1};\gamma_1) + \sum_{\substack{i=1\\i=1}}^n \ln f_{k2}(y_2;\gamma_2)$
	$\sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i$
	Specific:
	Copula likelihood function for $\hat{x}_{k k-1}$ and $w_k$
	······································
Estimation-filtering stage	
Estimation-filtering stage $\hat{s}_{k k}$	
$\hat{k}_{k k}$	(Table 2) $\hat{x}_{k k} = \hat{x}_{k k-1} + K_k \{ y_k - C_k \hat{x}_{k k-1} \}$
$\hat{t}_{k k}$ $P_{k k}$ Copula likelihood function for	(Table 2) $\hat{x}_{k k} = \hat{x}_{k k-1} + K_k \{ y_k - C_k \hat{x}_{k k-1} \}$
$\hat{k}_{k k}^{p}$	(Table 2) $\hat{x}_{k k} = \hat{x}_{k k-1} + K_k \{ y_k - C_k \hat{x}_{k k-1} \}$

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Use a standard font of the **11-point type: Times New Roman** is preferred. It is necessary to single line space your manuscript. Normally manuscripts are expected not to exceed 25 single-spaced pages including text, tables, figures and bibliography. All illustrations, figures, and tables are placed within the text at the appropriate points, rather than at the end.

During the submission process you must enter: (1) the full title, (2) names and affiliations of all authors and (3) the full address, including email, telephone and fax of the author who is to check the proofs. Supply a brief **biography** of each author at the end of the manuscript after references.

- Include the name(s) of any **sponsor(s)** of the research contained in the paper, along with **grant number(s)**.
- Enter an **abstract** of no more than 250 words for all articles.

#### <u>Keywords</u>

Authors should prepare no more than 5 keywords for their manuscript.

Maximum five **AMS Classification number** (http://www.ams.org/mathscinet/msc/msc2010.html) of the study should be specified after keywords.

# Writing Abstract

An abstract is a concise summary of the whole paper, not just the conclusions. The abstract should be no more than 250 words and convey the following:

- 1. An introduction to the work. This should be accessible by scientists in any field and express the necessity of the experiments executed.
- 2. Some scientific detail regarding the background to the problem.
- 3. A summary of the main result.
- 4. The implications of the result.
- 5. A broader perspective of the results, once again understandable across scientific disciplines.

It is crucial that the abstract conveys the importance of the work and be understandable without reference to the rest of the manuscript to a multidisciplinary audience. Abstracts should not contain any citation to other published works.

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Reference citations in the text should be identified by numbers in square brackets "[]". All references must be complete and accurate. Please ensure that every reference cited in the text is also present in the reference list (and vice versa). Online citations should include date of access. References should be listed in the following style:

## Journal article

Author, A.A., & Author, B. (Year). Title of article. Title of Journal, Vol(Issue), pages.

Castles, F.G., Curtin, J.C., & Vowles, J. (2006). Public policy in Australia and New Zealand: The new global context. Australian Journal of Political Science, 41(2), 131–143.

## Book

Author, A. (Year). Title of book. Publisher, Place of Publication.

Mercer, P.A., & Smith, G. (1993). Private Viewdata in the UK. 2nd ed. Longman, London.

## Chapter

Author, A. (Year). Title of chapter. In: A. Editor and B. Editor, eds. Title of book. Publisher, Place of publication, pages.

Bantz, C.R. (1995). Social dimensions of software development. In: J.A. Anderson, ed. Annual review of software management and development. CA: Sage, Newbury Park, 502–510.

## Internet document

Author, A. (Year). Title of document [online]. Source. Available from: URL [Accessed (date)].

Holland, M. (2004). Guide to citing Internet sources [online]. Poole, Bournemouth University. Available from: http://www.bournemouth.ac.uk/library/using/guide\_to\_citing\_internet\_sourc.html [Accessed 4 November 2004].

## Newspaper article

Author, A. (or Title of Newspaper) (Year). Title of article. Title of Newspaper, day Month, page, column.

Independent (1992). Picking up the bills. Independent, 4 June, p. 28a.

Thesis

Author, A. (Year). Title of thesis. Type of thesis (degree). Name of University.

Agutter, A.J. (1995). The linguistic significance of current British slang. PhD Thesis. Edinburgh University.

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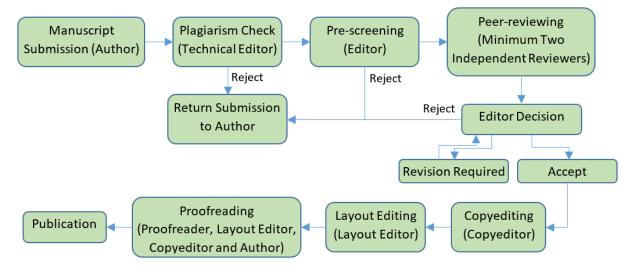
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Kleinert S & Wager E (2011). Responsible research publication: international standards for editors. A position statement developed at the 2nd World Conference on Research Integrity, Singapore, July 22-24, 2010. Chapter 51 in: Mayer T & Steneck N (eds) Promoting Research Integrity in a Global Environment. Imperial College Press / World Scientific Publishing, Singapore (pp 317-28). (ISBN 978-981-4340-97-7) [Link].

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## Reference:

Wager E & Kleinert S (2011) Responsible research publication: international standards for authors. A position statement developed at the 2nd World Conference on Research Integrity, Singapore, July 22-24, 2010. Chapter 50 in: Mayer T & Steneck N (eds) Promoting Research Integrity in a Global Environment.

Imperial College Press / World Scientific Publishing, Singapore (pp 309-16). (ISBN 978-981-4340-97-7) [Link].

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Homes I (2013). COPE Ethical Guidelines for Peer Reviewers, March 2013, v1 [Link].

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# An International Journal of Optimization and Control: Theories & Applications

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	CONTENTS
2	
294	List coloring based algorithm for the Futoshiki puzzle
	Banu Baklan Şen, Oznur Yasar Diner
308	Early prediction of fabric quality using machine learning to reduce rework in manufacturing processes
	Sema Aydın, Koray Altun
322	Witte's conditions for uniqueness of solutions to a class of Fractal-Fractional ordinary differential equations
	Abdon Atangana, Ilknur Koca
336	Influence of rotation on peristaltic flow for pseudoplastic fluid: a wavy channel
	Hayat Adel Ali, Mohammed R. Salman
346	A comparative view to H_infinity-norm of transfer functions of linear DAEs
	Hasan Gündüz, Ercan Çelik, Mesut Karabacak
355	Fuzzy-PID and interpolation: a novel synergetic approach to process control
	Devashish Jha, Arifa Ahmed, Sanatan Kumar, Debanjan Roy
365	Global mathematical analysis of a patchy epidemic model
	Lahcen Boulaasair, Hassane Bouzahir, Mehmet Yavuz
378	An Inverse recursive algorithm to retrieve the shape of the inaccessible dielectric objects
	Ahmet Sefer
394	A local differential quadrature method for the generalized nonlinear Schrödinger (GNLS) equation
	Meirikim Panmei, Roshan Thoudam
404	Modeling the dependency structure between quality characteristics in multi-stage manufacturing processes with copula functions
	Pelin Toktaş, Ömer Lütfi Gebizlioğlu





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