ISSN 2667-4211

ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY

A – Applied Sciences and Engineering

Volume 26 Number 2 - June - 2025

ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING
Estuscience – Se

Volume: 26 / Number: 2 / June - 2025

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A- APPLIED SCIENCES AND ENGINEERING
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Estuscience – Se, 2025, 26 (2) pp. 76- 97, DOI:10.18038/estubtda.1468828

RESEARCH ARTICLE

A NEW HYBRID MODEL PROPOSAL FOR FMEA ANALYSIS WITH FUZZY MULTI-CRITERIA DECISION-MAKING TECHNIQUES

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Abstract

Businesses apply various strategies to increase customer satisfaction and to get ahead of their competitors in the market. One of the methods used within the framework of this strategy is the Failure Mode and Effects Analysis (FMEA) method, which enables the discovery of failures in products or services before they occur. In the FMEA method, the severity, likelihood, and detection of potential failures are determined and scored. However, it is possible to state that the FMEA method may be insufficient in cases where more sensitive analysis is required due to the limited nature of the measures used in the scoring process. To prevent this, a hybrid study was conducted in which a new ranking was made using classical FMEA and multiple fuzzy multi-criteria decision-making techniques. Upon reviewing the literature, no FMEA studies using more than two multi-criteria decision-making techniques have been found. Therefore, alongside a standard FMEA study, a separate standard FMEA study was conducted using fuzzy TOPSIS, fuzzy VIKOR, fuzzy GRAY Relational Analysis, and fuzzy MOORA methods, which were randomly selected and weighted using DEMATEL. Subsequently, a new ranking was created by averaging these five results. This aimed to eliminate the disadvantages inherent in each method.

Keywords

FMEA,
Multi-Criteria Decision-Making Techniques,
Fuzzy set

Time Scale of Article

Received :15 April 2024
Accepted : 21 April 2025
Online date : 25 June 2025

1. INTRODUCTION

Today, businesses are in intense competition. This situation has reduced the chances of companies making mistakes to zero. Companies have to work with zero failures to satisfy their customers. In this case, it is not enough to solve existing failures. The likelihood of failure must be identified and eliminated before it occurs. The most commonly used method in this case is FMEA. Determining the current or potential failures with FMEA, the severity, likelihood, and detection of these failures are calculated by scoring. Efforts are made to reduce the scores of high-risk failures identified through the calculation process. As a result of these studies, the related failure is scored again in terms of severity, likelihood, and detection [1]. In this way, the possibility of detected failures occurring again is reduced. Even if a failure occurs, the potential damage that may arise is also reduced.

FMEA is one of the most frequently used methods for detecting existing or potential failures. However, this method has some disadvantages. In particular, scoring tables used for severity, likelihood, and detection limit the decision-makers who analyze in terms of scoring. Therefore, nowadays, by applying

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FMEA studies with the help of a fuzzy set, score restriction can be avoided. If multi-criteria decision-making techniques are used in these methods, the accuracy of the results will be increased [2]. Each multi-criteria decision-making (MCDM) technique has its strengths and weaknesses, which can result in different ranking outcomes. Conventional fuzzy MCDM methods often address satisfaction or risk factors separately, limiting the reliability of long-term assessments [3]. Therefore, considering the results of multiple methods is expected to improve the accuracy of failure prioritization.

A literature review has shown that studies involving more than two multi-criteria decision-making (MCDM) techniques are rare. Additionally, although FMEA has been applied in various industries, comprehensive studies in the connecting elements sector are lacking. Bolts, nuts, and screws, as essential connecting elements, are fundamental products that ensure structural integrity and safety, particularly in the automotive, aerospace, and construction industries. Even minor defects in these components can lead to financial losses and safety issues.

The heat treatment process, a critical stage in the production of these products, enhances their hardness, strength, and durability, making them of vital importance. However, processes involved in heat treatment can result in defects such as cracks, dimensional inaccuracies, and surface irregularities. Addressing and eliminating potential issues during this stage is crucial, as it reduces error rates in subsequent stages and lowers scrap rates. Therefore, this study conducts an FMEA focusing on the heat treatment of connecting elements. By targeting the most critical and error-prone process in the sector, the study aims to improve the reliability of the final product.

2. CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

FMEA is a method that aims to evaluate potential failures and prevent them before they occur by questioning what could go wrong and the consequences of those failures, thus ensuring quality from the very beginning [4].

While FMEA measures severity, likelihood, and detectability based on expert knowledge, measuring risk factors remains challenging. The relative changes in the experts' importance rankings can prevent FMEA from providing clear and accurate results. In this study, five different fuzzy multi-criteria decision-making methods weighted with DEMATEL were employed. Previous research that calculated FMEA using these methods was reviewed, as summarized in Table 1. However, no studies were found that utilized all five methods together.

Table 1. Literature Review

Method	Reference	Year	Subject of Article
VIKOR	Safari et al.[5]	2016	The authors identify and evaluate enterprise architecture risks using FMEA and fuzzy VIKOR. The study aims to provide a robust framework for assessing risks associated with enterprise architecture.
	Hajiagha et al. [6]	2016	This article presents a fuzzy belief structure-based VIKOR method to rank the causes of delays in the Tehran metro system using FMEA criteria, focusing on improving project management and efficiency.
	Yang et al.[7]	2021	The study improves FMEA by employing the IVF and fuzzy VIKOR methods, using a case survey of the workpiece box system in CNC gear milling machines to demonstrate enhanced risk evaluation.
MOORA	Arabsheybani et al. [8]	2018	This study proposes an integrated fuzzy MOORA method and FMEA technique for sustainable supplier selection, considering quantity discounts and supplier risks to optimize procurement processes and risk assessment.
	Mete [9]	2019	This research assesses occupational risks in pipeline construction using an FMEA-based AHP-MOORA integrated approach within a Pythagorean fuzzy environment, aiming to improve safety and risk management practices.
	Emovon and Mgbemena [10]	2019	The article enhances the FMEA technique by combining Expectation interval, TAGUCHI, MOORA, and Geometric mean methods, focusing on improving risk analysis and decision-making processes in industrial engineering.
GRA	Liu et al. [11]	2015	The article evaluates risks in FMEA using an extended VIKOR method under fuzzy conditions, aiming to provide a more nuanced assessment of potential failure modes in various applications.
	Shi et al. [12]	2019	This research applies an FMEA method that combines interval 2-tuple linguistic variables and grey relational analysis in preoperative medical service processes, focusing on improving healthcare service quality and safety.
FMEA	Turan et al. [13]	2019	It is a technique aimed at increasing the reliability of the process and eliminating potential errors, ensuring that mistakes are prevented before reaching customers.
TOPSIS	Kuei et al.[14]	2014	This article integrates the TOPSIS and DEMATEL methods to rank failure risks in FMEA. It aims to enhance decision-making by effectively identifying and prioritizing potential failure modes.
	Hu et al. [15]	2019	The article "Improving Risk Evaluation in FMEA With Cloud Model and Hierarchical TOPSIS Method" presents a method for enhancing risk assessment in FMEA by integrating a Cloud model and hierarchical TOPSIS. This approach addresses uncertainties and complexities, providing more accurate and reliable risk evaluations. The authors illustrate the effectiveness of this combined method through examples and results.
	Mangelia et al. [16]	2019	The study improves risk assessment in FMEA using a nonlinear model, revised fuzzy TOPSIS, and Support Vector Machine. It seeks to enhance the accuracy of risk evaluations through advanced analytical techniques.
	Ersadi and Forouzandeh [17]	2019	This research proposes a hybrid approach for managing information security risks in research information systems. It integrates Fuzzy FMEA, AHP, TOPSIS, and Shannon Entropy to establish a comprehensive risk assessment framework.

3. METHODS

In this study, the most commonly used methods among multi-criteria decision-making techniques have been prioritized. Multi-criteria decision-making (MCDM) methods are widely used in the literature to solve decision problems and rank alternatives. In this study, the TOPSIS, MOORA, GRA, and VIKOR methods were selected. The reasons for choosing these methods are their flexibility, ease of use, and ability to consider different optimization aspects. In particular, these methods enable the evaluation of multiple criteria while being sensitive to the preferences and weights assigned by decision-makers. Additionally, their ability to handle uncertainty and incomplete data enhances their applicability. The GRA method is more suitable for dealing with uncertain data, while the VIKOR method aims to achieve optimal solutions by providing compromise solutions. The fuzzy versions of these methods are used to manage uncertainty more effectively. It has been stated that the selected methods utilize statistical analyses; in this context, weighting, normalization, calculation of criterion weights, and ranking techniques are emphasized. Therefore, these methods are preferred not only for their mathematical foundations but also for the practical benefits they offer in real-world applications. [18,19,20,21]

Multi-criteria decision-making techniques are used to solve problems that managers frequently encounter daily. Managers use this method in real-life issues that they are accustomed to solving and in managerial decision-making processes that they have to solve using mathematics and statistics. Thanks to this method, multiple and conflicting objectives are solved most accurately [22].

The methods used in this study are DEMATEL, VIKOR, TOPSIS, MOORA, and GRA relational analysis methods, and detailed information about them is given in the following headings.

3.1. DEMATEL Method

The DEMATEL method was first developed by the Geneva Battelle Memorial Institute between 1972 and 1976 to address complex problems [23].

The DEMATEL method examines the criteria determined for the related problems under two headings: the cause criteria, which have a greater impact on the other criteria, and the result criteria, which are influenced by other important criteria [24].

In the relevant study, the weighting of severity, likelihood, and detectability scores was conducted using the traditional DEMATEL method instead of the fuzzy DEMATEL approach. This weighting was conducted with a single decision-maker within the company. Therefore, the conventional DEMATEL method was chosen over fuzzy DEMATEL for weighting.

It is possible to apply the DEMATEL method in five steps. These steps and the formulas used are as follows:

Step 1: Creating the Direct Relationship Matrix: In this step, experts on the subject examine how the criteria determined for the relevant subject affect each other, and in the case of N number of experts, N nxn matrices are created [25].

$$a_{ij} = \frac{1}{N}\sum_{k=1}^{N} x_{ij}^{k} \tag{1}$$

The situation where the relevant experts examined the relationship between the determined criteria and scored these relationships is shown in Table 2.

Table 2. Dematel Evaluation Chart [26]

Numerical Method	Definition
0	Ineffective
1	Low Effective
2	Moderate Effective
3	Highly Effective
4	Very Highly Effective

Step 2: Normalizing the Direct Relationship Matrix: The direct relationship matrix created with the help of equation (2) and equation (3) shown below is normalized using the smallest values in its rows and columns. The diagonal values of the normalized X matrix are 0 [27].

$$\boldsymbol{X} = \boldsymbol{k}.\boldsymbol{A} \tag{2}$$

$$\boldsymbol{k} = \frac{\boldsymbol{1}}{\boldsymbol{max}\sum_{j=1}^{n}\boldsymbol{a_{ij}}} \qquad \text{i, j} = 1, 2, \ldots\ldots, \text{n} \tag{3}$$

Step 3: Creating the Total Relationship Matrix: After the direct relationship matrix is normalized, the total relationship matrix (T) is created using equation (4). The 'I' in the equation denotes the unit matrix [28].

$$\boldsymbol{T} = \boldsymbol{X}(\boldsymbol{I} - \boldsymbol{X})^{-1} \tag{4}$$

Step 4: Identifying Influencing and Affected Values: At this stage, the sum of the effect matrices' rows and columns is found using equations (5) and (6). A D vector is used for row sums, and an R vector is used for column sums [29].

$$\boldsymbol{D} = [\sum_{i=1}^{n} \boldsymbol{t_{ij}}]_{ixn} = [\boldsymbol{t_j}]_{nx1} \tag{5}$$

$$\boldsymbol{R} = [\sum_{j=1}^{n} \boldsymbol{t_{ij}}]_{ixn} = [\boldsymbol{t_j}]_{1xn} \tag{6}$$

Step 5: Calculating the Importance Weights of the Criteria: At this stage, as shown in equation (7), the total effects of the D and R vectors and the squared average of the net effects are calculated and the importance weights of the criteria are calculated. [29].

$$\boldsymbol{w_i} = [(\boldsymbol{D_i} + \boldsymbol{R_i})^2 + (\boldsymbol{D_i} - \boldsymbol{R_i})^2]^{1/2} \tag{7}$$

3.2. Fuzzy TOPSIS Method

The TOPSIS method is a multi-criteria decision-making method used to find the best alternative that is the farthest from the best negative alternative solution and closest to the best positive alternative solution [30].

Table 3. Linguistic Expression of the Significance Levels of the Criteria [44]

Numerical Method	Fuzzy Number Equivalent
Very Low	1,1,3
Low	1,3,5
Average	3,5,7
High	5,7,9
Very High	7,9,9

Table 3 presents the linguistic expressions and their corresponding values used for the criteria in the fuzzy TOPSIS method.

Note: The scales used in Table 3 have been applied in all multi-criteria decision-making techniques other than DEMATEL.

Step 1: Creating the Unified Decision Matrix: After the scores given by the decision makers are converted into fuzzy numbers, the decision matrices are combined using Equation (8) and Equation (9).

$$x_{ij} = (a_{ij}, b_{ij}, c_{ij}) \tag{8}$$

$$a_{ij} = min_k(a_{ij}^k), \;\; b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ij}^k, \;\; c_{ij} = max_k(c_{ij}^k) \tag{9}$$

Step 2: Creating the Normalized Decision Matrix: Depending on whether the criteria in the combined decision matrix are benefit or cost-based, Equation (10) is applied for benefit criteria, while Equation (11) is used for cost criteria [31].

$$r_{ij} = (\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}) \text{ and } c_j^* = max_i(c_{ij}) \tag{10}$$

$$r_{ij} = (\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}) \text{ and } a_j^- = min_i(a_{ij}) \tag{11}$$

Step 3: Calculation of the Weighted Normalized Decision Matrix: Equation (12) helps find the weights of the criteria to be evaluated and the weighting of the normalized decision matrix [31].

$$v_{ij} = r_{ij} x w_{ij} \tag{12}$$

Step 4: Calculating Fuzzy Positive and Negative Ideal Solutions: To find the closest results to the ideal solution, the ideal positive solution is found using equation (13), and the ideal negative solution is found using equation (14) [32].

$$\text{When } v_j^* = max_i(v_{ij3}), A^* = (v_1^*, v_2^*, \ldots v_n^*) \tag{13}$$

$$\text{When } v_j^- = min_i(v_{ij1}), A^- = (v_1^-, v_2^-, \ldots v_n^-) \tag{14}$$

Step 5: Calculating Distance to Ideal Solutions: After identifying the ideal solutions, the distances of the alternatives' criteria from the ideal positive solution to the ideal negative solution are calculated using the equation (15) [31].

$$d(x, y) = \sqrt{(\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2])} \tag{15}$$

Step 6: The Distance of Each Alternative to the Ideal Positive and Ideal Negative Solution: Equation (16) and equation (17) are applied to the criteria of each alternative determined in this section [31].

$$d_i^* = \sum_{j=1}^{n} d(v_{ij}, v_j^*) \tag{16}$$

$$d_i^- = \sum_{j=1}^{n} d(v_{ij}, v_j^-) \tag{17}$$

Step 7: Calculating the Closeness Coefficient for Each Alternative: The closeness coefficient for each alternative is calculated using equation (18). The results are ordered from the largest to the smallest, and the best solution is found [33].

$$CC_I = \frac{d_i^-}{d_i^- + d_i^*} \tag{18}$$

3.3. Fuzzy MOORA Method

The fuzzy MOORA method, first introduced by Brauers and Zavadskas in public privatization studies, is a multi-objective optimization approach that provides alternative solutions using proportional analysis in various decision-making problems [34].

The steps of the fuzzy MOORA method can be listed as follows. While the steps are being sequenced, the formation of fuzzy numbers and the creation of the composite decision matrix are the same as fuzzy TOPSIS, so those steps are not explained again. In explaining the subsequent multi-criteria decision-making techniques, this calculation was performed in advance. Therefore, other stages proceeded without reiterating this calculation in the formulas.

Step 1: Creating Decision Matrix with Vector Normalization: In this step, the decision matrix is normalized by applying the operations in Equations (8) and (9). In this step, all three fuzzy numbers are normalized with the help of equations (19), equations (20), and equations (21) so that the normalization process is more accurate and pairwise comparisons can be made better [35].

$$r_{ij}^l = \frac{x_{ij}^l}{\sqrt{(\sum_{i=1}^m [(x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^n)^2])}} \tag{19}$$

$$r_{ij}^m = \frac{x_{ij}^m}{\sqrt{(\sum_{i=1}^m [(x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^n)^2])}} \tag{20}$$

$$r_{ij}^n = \frac{x_{ij}^n}{\sqrt{(\sum_{i=1}^m [(x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^n)^2])}} \tag{21}$$

Step 2: Creating the Weighted Normalized Decision Matrix: In this step, weighted normalized decision matrices are created by using Equation (22), Equation (23), and Equation (24) [36].

$$v_{ij}^l = w_j r_{ij}^l \tag{22}$$

$$v_{ij}^m = w_j r_{ij}^m \tag{23}$$

$$v_{ij}^n = w_j r_{ij}^n \tag{24}$$

Step 3: Calculating Alternatives in Terms of Benefit Criteria: Equations (25), (26), and (27) for the utility criterion; Equations (28), (29), and (30) are used for the cost criterion [35].

$$S_i^{+l} = \sum_{j=1}^{n} v_{ij}^l | j \in J^{max} \tag{25}$$

$$S_i^{+m} = \sum_{j=1}^{n} v_{ij}^m | j \in J^{max} \tag{26}$$

$$S_i^{+n} = \sum_{j=1}^{n} v_{ij}^{n} | j \in J^{max} \tag{27}$$

$$S_i^{-l} = \sum_{j=1}^{n} v_{ij}^{l} | j \in J^{min} \tag{28}$$

$$S_i^{-m} = \sum_{j=1}^{n} v_{ij}^{m} | j \in J^{min} \tag{29}$$

$$S_i^{-n} = \sum_{j=1}^{n} v_{ij}^{n} | j \in J^{min} \tag{30}$$

Step 4: Establishing the Performance Value of Each Alternative: Equation (31) helps create the performance value of each alternative as follows [35].

$$S_i(s_i^+, s_i^-) = \sqrt{(\frac{1}{3}[(s_i^{+l} - s_i^{-l})^2 + (s_i^{+m} - s_i^{-m})^2 + (s_i^{+n} - s_i^{-n})^2])} \tag{31}$$

Step 5: Ranking of Alternatives: The performance index values are analyzed, and the alternatives are ranked accordingly, with the highest-scoring alternative being preferred [36].

3.4. Fuzzy Gray Relational Analysis Method

While the term 'Gray' implies weakness, incompleteness, or uncertainty, Gray Relational Analysis is a method of ranking alternatives by comparing all available criteria in problems that lack sufficient data in multivariate situations or cannot be solved due to uncertainty. [37]. Since the Gray relational analysis method is a solution applied to decision problems in complex relationships, it can be used together with other multi-criteria decision-making techniques or can be used alone [37].

The stages of Gray relational analysis are as follows. Since the conversion of verbal values to fuzzy values is calculated as in fuzzy TOPSIS and fuzzy MOORA, that step is skipped and explanations of other stages are given.

Step 1: Creating the Normalized Decision Matrix: In this step, Equations (32) and (33) below are used, taking into account benefit or cost considerations [38]. The key aspect is whether our decision criteria result in costs or benefits.

$$r_{ij} = (\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}), \quad \text{i=1,….m, j=1,….n if } r_j^+ = mak_i r_{ij} \tag{32}$$

$$r_{ij} = (\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}), \quad \text{i=1,….m, j=1,….n if } l_j^- = min_i l_{ij} \tag{33}$$

Step 2: Determination of the Reference Series: With the help of equation (34) if the objective function is maximizing, and equation (35) if the objective function is minimization, the alternatives that should be chosen to achieve the desired situation in the decision matrix are determined one by one, and a reference series is created [38].

$$\boldsymbol{R_0} = [\boldsymbol{r_{01}}, \boldsymbol{r_{02}}, \ldots\ldots \boldsymbol{r_{0n}} = \boldsymbol{max}(\boldsymbol{r_{ij}})] \quad \text{j=1,2,….n} \tag{34}$$

$$\boldsymbol{R_0} = [\boldsymbol{r_{01}}, \boldsymbol{r_{02}}, \ldots\ldots \boldsymbol{r_{0n}} = \boldsymbol{min}(\boldsymbol{r_{ij}})] \quad \text{j=1,2,….n} \tag{35}$$

Step 3: Creating the Distance Matrix: The distance matrix is calculated using Equation (36), and the distances of the values in the normalized decision matrix to the reference series are determined using the matrix created by this formula. [38].

$$\boldsymbol{d}(\boldsymbol{A}, \boldsymbol{B}) = \sqrt{(\frac{\boldsymbol{1}}{\boldsymbol{3}}[(\boldsymbol{l_1} - \boldsymbol{l_2})^2 + (\boldsymbol{m_1} - \boldsymbol{m_2})^2 + (\boldsymbol{u_1} - \boldsymbol{u_2})^2])} \tag{36}$$

Step 4: Creating the Gray Relational Coefficient Matrix: The formula used to construct the Gray relational coefficient matrix is shown in Equation (37).

$$\boldsymbol{y_{0i}}(\boldsymbol{j}) = \frac{\boldsymbol{\delta_{min}} + \zeta \boldsymbol{\delta_{max}}}{\boldsymbol{\delta_{0i}}(\boldsymbol{j}) + \zeta \boldsymbol{\delta_{max}}}, \qquad \boldsymbol{\delta_{max}} = \boldsymbol{max_i max_j \delta_{0i}}(\boldsymbol{j}), \qquad \boldsymbol{\delta_{min}} = \boldsymbol{min_i min_j \delta_{0i}}(\boldsymbol{j}) \tag{37}$$

The $\boldsymbol{\zeta}$ specified in Equation (37) is a determinant value. It takes a value between 0 and 1. In the literature, this value is usually taken as 0.5. [39]. Even if this coefficient takes a value other than 0.5, the final ranking of the alternatives will remain unchanged. If the value is greater than 0.5, the alternatives move closer to the desired value, whereas if it is less than 0.5, they move away from the desired values [38].

3.5. Fuzzy VIKOR Method

The VIKOR method, a multi-criteria decision-making technique, was developed by Opricovic to assist decision-makers when they are unable to determine or specify their preferences [40]. The fuzzy VIKOR method can be defined as follows: It is a method used to solve discrete fuzzy multi-criteria decision-making techniques that are too conflicting to be compared with each other.

The following steps should be followed while applying this method. Since the conversion of verbal values to fuzzy values is calculated as in fuzzy TOPSIS, fuzzy Gray relational analysis, and fuzzy MOORA, that step is skipped, and explanations of other stages are given.

Step 1: Determining the Best and the Worst Fuzzy Value: In this step, each column is analyzed individually, and the maximum and minimum values are calculated using Equations (38) and (39) [41].

$$\boldsymbol{f_j^*} = \boldsymbol{max_i x_{ij}} \tag{38}$$

$$\boldsymbol{f_j^-} = \boldsymbol{min_i x_{ij}} \tag{39}$$

Step 2: Determination of $\boldsymbol{S_j}$ and $\boldsymbol{R_j}$ Values: $\boldsymbol{S_j}$ and $\boldsymbol{R_j}$ values are calculated using Equations (40) and (41) below. In these equations, $\boldsymbol{w_i}$ represents the criteria weights. $\boldsymbol{S_j}$ denotes the sum of the distances between the "ith" alternative and the best fuzzy value across all criteria, while $\boldsymbol{R_j}$; represents the distance of the "ith" alternative from the fuzzy worst value according to the "jth" criterion [41].

$$\boldsymbol{S_j} = \sum_{\boldsymbol{j=1}} [\boldsymbol{w_i}(\boldsymbol{f_i^*} - \boldsymbol{x_{ij}})/(\boldsymbol{f_i^*} - \boldsymbol{f_i^-})] \tag{40}$$

$$R_j = max[w_i(f_i^* - x_{ij})/(f_i^* - f_i^-)] \quad (41)$$

Step 3: Determination of Q_i Values with the Help of $S_j^-, S_j^*, R_j^-, R_j^*$: With the help of equation (42) and equation (43) shown below S_j^*, which is the rule of maximum majority, and R_j^*, which expresses the minimum individual regret of those with different opinions. After these calculations, Q_i is found with the help of equation (44) [42].

$$S_j^* = min_j S_j, S_j^- = max S_j \quad (42)$$

$$R_j^* = min_j R_j, R_j^- = max R_j \quad (43)$$

$$Q_j = v(S_j - S^*)/(S^- - S^*) + (1 - v)(R_j - R^*)/(R^- - R^*) \quad (44)$$

Step 4: Clarifying Q_i Values: At this stage, using the BNP (Best Nonfuzzy Performance Value) method, u_i blurring is provided, with m_i showing the upper value of the fuzzy number, l_i the middle value, and Q_i the lower value, and Q_i is used in the ranking of the alternatives [43].

$$BNP_i = [(u_i - l_i) + (m_i - l_i)]/3 + l_i \quad (45)$$

Step 5: Checking If the Best Alternatives Are the Reconciliatory Solution: The alternative conciliatory solution is identified if both conditions are met, with the stages outlined below.

Condition 1: Acceptable Advantage

$$Q(A^{--}) - Q(A^-) \geq DQ \quad (46)$$

$$DQ = \frac{1}{(m-1)} \quad (47)$$

With the help of this equality, the number of alternatives represents the first alternative and the second best alternative [44].

Condition 2: Acceptable Stability

The best alternative should rank as the best in at least one of the S or R-value orderings. On the other hand, if the 1st condition cannot be met at the same time, we can say that $Q(A^m) - Q(A^-) < DQ$ are solutions similar to (A^m) and (A^-) alternatives [45].

Step 6: Choosing the Best Alternative: In this step, the alternative with the smallest Q value is selected as the best alternative [45].

4. CASE STUDY

This study presents a hybrid model proposal for the evaluation process of FMEA. The proposed model was applied in the heat treatment process of a fastener factory.

A review of the literature in the relevant sector reveals no prior studies of this nature. Additionally, given that the fasteners sector directly influences many other industries, addressing failures in this sector is expected to have a direct impact on those industries as well.

The failures that may occur in the department were determined by brainstorming with 1 Chemist who is the process owner, 1 Metallurgical and Materials Engineer, 1 Industrial Engineer who manages the processes before the heat treatment process, and 1 Chemist who is the department manager responsible for coating the material after the heat treatment process. All relevant failure identifiers were determined by personnel directly involved in the heat treatment process. The identified failures were then categorized into two groups: those affecting the process and those affecting the product.

The brainstorming method has identified all the failures. A total of 16 failures affecting the process have been identified. Additionally, 18 failures affecting the product have been identified.

Subsequently, analyses were conducted using DEMATEL-weighted fuzzy TOPSIS, fuzzy MOORA, fuzzy Gray Relational Analysis, fuzzy VIKOR, and classical FMEA methods. As part of the application, process-related failures were identified, as presented in Tables 4 and 5.

Table 4. Failures Affecting the Product in the Heat Treatment Section

Identified Product Failures
The operator throws the wrong product into the oven due to a problem logging into the ERP program.
Poor circulation in the oven
Deterioration of the remaining material in the furnace caused by a power outage.
Product deterioration due to natural gas supply interruption
Washing bath temperatures are not high enough
Inappropriate products produced
The uneven hardness of the bottom product due to excessive product loading in the oven
Oven indicators not working correctly
The curvature of the tape roll caused by a power outage
Heat loss caused by improper insulation
Malfunction of the methanol sprinkler system
Oven belt malfunction
Burning of oil in the furnace mouth caused by a power outage
Incorrect hardness measurement
Failure to form the right atmosphere due to lack of proper insulation
Clogged bath units due to sawdust

Table 5. Failures Affecting the Process in the Heat Treatment Section

Identified Process Failures
Disruption of production due to problems in entering the ERP program
COVID-19 and other work interruptions due to circumstances or conditions.
Failure to process new products originating from reprocessing
Lack of necessary tools or parts during troubleshooting
Failure of components due to power outage
No products from production
Working with missing personnel
No serial products from production
Clogging of heat treatment lines
Inappropriate products from production
Absence of methanol or heat treatment oil required for the operation of the furnace
Unplanned maintenance
Product jamming in the furnace due to excessive product loading in the heat treatment furnace
Oven belt malfunction
Clogging of nozzles at the end of the line
Late product loading due to forklift malfunction or lack of availability
Boilers not being fully loaded before coming from production
Clogged bath units due to sawdust

Since the evaluation of FMEA is subjective, it was decided to use multi-criteria decision-making techniques. The fuzzy set method and multi-criteria decision-making techniques were employed to improve the clarity of verbal expressions. The goal was to minimize the potential shortcomings inherent in multi-criteria decision-making techniques. Therefore, a new hybrid model was developed by integrating four different multi-criteria decision-making techniques with the classical FMEA method.
After the grouping process was made, the severity, likelihood, and detection of each failure were evaluated verbally by the responsible persons determined on a 5-point scale as very high, high, medium, low, and very low. The fuzzy multi-criteria decision-making techniques, determined based on the responses received, were applied sequentially, and a ranking was generated for each.

4.1. Criteria Weighting with DEMATEL Method

Before moving on to fuzzy multi-criteria decision-making methods, severity, likelihood, and detection, which are the criteria determined for FMEA, were weighted with the DEMATEL method.

The weighting process was carried out by the company's quality management officer, and its steps are outlined below.

In this study, Equation (1) was not applied since there is only one decision-maker. Table 6 was created using Table 3 as a reference for severity, likelihood, and detectability.

Table 6. Creation of the Direct Relationship Matrix

Criteria	Severity	Likelihood	Detection
Severity	0	0	3
Likelihood	0	0	2
Detection	0	4	0

In the subsequent steps, the following tables were created sequentially using Equations (2), (3), (4), (5), (6), and (7).

Table 7. Normalized Direct Relationship Matrix

Criteria	Severity	Likelihood	Detection
Severity	0,000	0,000	0,600
Likelihood	0,000	0,000	0,400
Detection	0,000	0,800	0,000

In this step, the rows and columns are added together and the k value is calculated using equation (3). As a result of the operation, the k value is calculated as 0.2. As a result of the calculation, the direct relationship matrix created using the formula specified in equation (2) is normalized. The normalized direct relationship matrix resulting from the calculation is shown in Table 7.

Table 8. Total Relationship Matrix

Criteria	Severity	Likelihood	Detection
Severity	0,000	0,000	0,529
Likelihood	0,000	0,000	0,235
Detection	0,000	0,941	0,000

In this step, the total relationship matrix was created using the identity matrix and equation (4) as shown in Table 8.

Table 9. Influencing and Affected Values

Criteria	D Vector	R Vector
Severity	0,529	0,000
Likelihood	0,235	0,941
Detection	0,941	0,765

In this step, the row and column sums are taken according to equation (5) and equation (6), and the D vector and R vector are created as in Table 9.

Table 10. Calculation of Criterion Importance Weights

Criteria	Criterion Significance Weight
Severity	0,195
Likelihood	0,358
Detection	0,447

In this step, the importance weights of the criteria were calculated based on the net effects of the D and R vectors with the help of equation (7). As a result of the calculation, the importance weights of the criteria were calculated as in Table 10.

The dematel-weighted failures determined with the help of the above-mentioned formulas were solved by each method one by one, and the combined decision matrices were created as shown in Table 11 and Table 12.

Table 11. Unified Decision Matrix for Processes

Failures Affecting the Process	**Severity**			**Likelihood**			**Detection**		
Disruption of production due to problems in entering the ERP program	1	2,5	7	1	4,5	9	1	5	9
COVID-19 and other work interruptions due to circumstances or conditions.	3	7	9	1	5	9	3	5	7
Working with missing personnel	1	6,5	9	1	6	9	1	2,5	5
No serial products from production	1	5,5	9	3	5,5	9	3	6	9
Product jamming in the furnace due to excessive product loading in the heat treatment furnace	3	6,5	9	1	4	7	1	6,5	9
Oven belt malfunction	5	8	9	1	4	7	1	4,5	9
Failure of components due to power outage	5	8	9	1	3,5	9	1	3	9
Absence of methanol or heat treatment oil required for the operation of the furnace	7	9	9	1	1,5	5	1	6	9
No products from production	1	6	9	1	2,5	5	1	5,5	9
Unplanned maintenance	5	7,5	9	1	3,5	9	1	2,5	7
Failure to process new products originating from reprocessing	3	5,5	9	1	2	5	1	4,5	9
Clogging of heat treatment lines	1	6	9	1	4,5	9	1	4	7
Clogging of nozzles at the end of the line	1	5,5	9	1	4,5	9	3	6,5	9
Boilers not being fully loaded before coming from production	1	4	7	3	7,5	9	1	3,5	9
Clogged bath units due to sawdust	3	6	9	1	5,5	9	1	5	9
Lack of necessary tools or parts during troubleshooting	5	7,5	9	1	4	9	1	3	7
Inappropriate products from production	1	2,5	7	1	3,5	9	1	4,5	9
Late product loading due to forklift malfunction or lack of availability	5	8	9	1	6	9	1	3,5	7

Table 12. Unified Decision Matrix for Products

Failures Affecting the Product	Severity			Likelihood			Detection		
The operator throws the wrong product into the oven due to a problem logging into the ERP program	1	2,5	7	1	4,5	9	1	5	9
The uneven hardness of the bottom product due to excessive product loading in the oven	3	7	9	1	5	9	3	5	7
Oven belt malfunction	1	6,5	9	1	6	9	1	2,5	5
Poor circulation in the oven	1	5,5	9	3	5,5	9	3	6	9
Oven indicators not working correctly	3	6,5	9	1	4	7	1	6,5	9
Burning of oil in the furnace mouth caused by a power outage	5	8	9	1	4	7	1	4,5	9
Deterioration of the remaining material in the furnace caused by a power outage	5	8	9	1	3,5	9	1	3	9
The curvature of the tape roll caused by a power outage	7	9	9	1	1,5	5	1	6	9
Incorrect hardness measurement	1	6	9	1	2,5	5	1	5,5	9
Product deterioration due to natural gas supply interruption	5	7,5	9	1	3,5	9	1	2,5	7
Heat loss caused by improper insulation	3	5,5	9	1	2	5	1	4,5	9
Failure to form the right atmosphere due to lack of proper insulation	1	6	9	1	4,5	9	1	4	7
Washing bath temperatures are not high enough	1	5,5	9	1	4,5	9	3	6,5	9
Malfunction of the methanol sprinkler system	1	4	7	3	7,5	9	1	3,5	9
Clogged bath units due to sawdust	3	6	9	1	5,5	9	1	5	9
Inappropriate products produced	5	7,5	9	1	4	9	1	3	7

4.2. FMEA Application with Fuzzy TOPSIS, MOORA, GRA and VIKOR Methods

FMEA calculations were made with fuzzy TOPSIS, MOORA, Gray relational analysis, and VIKOR methods with the help of the above-mentioned formulas. In addition, the classical FMEA method was also applied. The risk rankings of the 5 methods are as in the tables below.

A new ranking was created from the ranking of 5 methods with a new method by scoring over the relevant rankings.

Rankings have been created for five different results, and each method's rankings have been weighted internally. For instance, in the list prepared for failures affecting the process, the failure ranked highest in each method is assigned the highest weight, starting from 18 and decreasing for subsequent rankings. (The intention here is to assign greater importance to the failure ranked first. The weighting is based on the total number of failures identified in the relevant area, which is 18; thus, the highest-ranked failure is given a weight of 18.) This weighting process has been applied to all methods, and the total weight for each failure has been calculated. Based on these totals, a final ranking of failures has been established, ordered from the highest weight to the lowest. As a result of this analysis, the final lists are presented in Table 13 and Table 14.

Table 13. Final FMEA Ranking of Failures Affecting the Process

Failures Affecting the Process	TOPSIS	MOORA	GRA	VIKOR	FMEA	Total
No serial products from production	2	15	18	18	12	65
Working with missing personnel	17	16	11	3	16	63
COVID-19 and other work interruptions due to circumstances or conditions.	3	17	16	16	7	59
Clogged bath units due to sawdust	12	4	13	8	18	55
Unplanned maintenance	14	9	7	9	14	53
Lack of necessary tools or parts during troubleshooting	15	3	9	10	15	52
Absence of methanol or heat treatment oil required for the operation of the furnace	8	11	12	15	6	52
Boilers not being fully loaded before coming from production	16	5	15	14	1	51
Failure of components due to power outage	13	12	8	12	5	50
Clogging of nozzles at the end of the line	1	6	17	17	8	49
Late product loading due to forklift malfunction or lack of availability	18	1	14	13	2	48
Oven belt malfunction	11	13	10	11	3	48
Disruption of production due to problems in entering the ERP program	7	18	4	2	10	41
Clogging of heat treatment lines	10	7	6	5	11	39
Product jamming in the furnace due to excessive product loading in the heat treatment furnace	9	14	5	7	4	39
No products from production	4	10	2	4	13	33
Inappropriate products from production	6	2	3	1	17	29
Failure to process new products originating from reprocessing	5	8	1	6	9	29

When Table 13 is examined, while the errors affecting the process are listed, coefficients starting from 18 to 1 are assigned to the values at the top of the ranking. The coefficients for the relevant error in the five calculation methods are collected and ranked from largest to smallest. In this case, the error that affects the process the most is the failure to receive mass-production products.

Table 14. Final FMEA Ranking of Failures Affecting the Product

Failures Affecting the Product	TOPSIS	MOORA	GRA	VIKOR	FMEA	Total
Oven belt malfunction	16	14	14	15	7	66
Deterioration of the remaining material in the furnace caused by a power outage	12	10	12	16	10	60
Clogged bath units due to sawdust	11	2	15	12	16	56
Oven indicators not working correctly	8	12	9	13	12	54
Product deterioration due to natural gas supply interruption	13	7	10	10	9	49
Malfunction of the methanol sprinkler system	15	3	11	11	8	48
Incorrect hardness measurement	4	8	13	14	6	45
Failure to form the right atmosphere due to lack of proper insulation	9	5	7	8	11	40
The curvature of the tape roll caused by a power outage	7	9	16	6	1	39
The operator throws the wrong product into the oven due to a problem logging into the ERP program	6	16	6	3	5	36
Inappropriate products produced	14	1	2	2	14	33
Heat loss caused by improper insulation	5	6	3	4	15	33
The uneven hardness of the bottom product due to excessive product loading in the oven	3	15	4	7	4	33
Poor circulation in the oven	2	13	5	9	3	32
Washing bath temperatures are not high enough	1	4	8	5	13	31
Burning of oil in the furnace mouth caused by a power outage	10	11	1	1	2	25

In Table 14, the same weighting method was used to rank the products by giving coefficients between 1 and 16. In this ranking, it is seen that the most important fault affecting the product is the malfunction of the oven band.

5. CONCLUSIONS

The most basic rule that businesses must comply with to satisfy their customers is to offer a faultless product or service to the customer. To address this issue, businesses employ various methods to detect failures. Thanks to these measures, failures occurring during production are identified and halted before advancing to the next stages, preventing them from reaching the customer. However, this means both extra work and loss of money for businesses. In addition, potential failures can be overlooked because classical quality control methods see failures after they occur and try to take precautions. For such cases, potentials are measured with FMEA before failures occur, and if necessary, precautions are taken and the likelihood of failure occurring is prevented.

Although the FMEA method ranks failures based on their importance, this ranking may not accurately reflect reality due to the rigidity of the assigned scores. To prevent this, it has been predicted that FMEA ranking and comparison with more than one fuzzy multi-criteria decision-making technique weighted with DEMATEL will yield more accurate results. Thus, the disadvantages of all the methods used will be mitigated to some extent.

In this context, for the heat treatment department of a factory operating in the fastener industry, the failures affecting the products and processes are listed separately by using fuzzy TOPSIS, fuzzy MOORA, fuzzy GRA, fuzzy VIKOR methods, which are fuzzy multi-criteria decision-making techniques. In addition, the classical FMEA method was also applied. The results found were grouped within themselves and a single ranking was created from five separate rankings.

As a result of the literature review on the subject, it has been seen that there are studies in which multiple criteria decision-making techniques are used. However, two methods were generally used in these studies. No study was found in which five different methods were used simultaneously. Additionally, unlike previous studies in the literature, our study conducted an FMEA specifically for product defects. When other studies in the literature are evaluated as the applied sector, no similar study has been found in the fastener sector. For this reason, the study has originality.

The reason for using five different methods is; that the results of each method are different. Therefore, it is important to achieve the most accurate result by minimizing failures in multi-criteria decision-making techniques and classical FMEA.

As a result of the analysis, it was determined that the most important failure affecting the process was “No serial product from production”. For each product type in the heat treatment section, the process needs to be different. For this reason, when different product groups are to be fed into the oven one after the other, the heat treatment band is filled at a distance for two different product groups. This prevents the belt from working efficiently. While planning to eliminate the failure, it was suggested to create a system that would ensure that similar products come one after the other to avoid making constant changes in the heat treatment process and to be able to use the heat treatment band without any gaps.
When the failures affecting the product are examined, it is seen that "Oven belt malfunction" comes first. Failure of the heat treatment furnace band for any reason causes the product to become unusable, especially if there is a product in the furnace. In future studies, the number of currently used multi-criteria decision-making techniques can be increased beyond four, or different multi-criteria decision-making techniques can be employed to analyze how the results might change. In this study, failure mode and effects analysis (FMEA) was applied in the fastener industry using fuzzy multi-criteria decision-making techniques, resulting in an outcome believed to be more accurate. The reason for using multiple techniques in the study is to minimize the margin of error inherent in each method. In future studies, the number of these techniques could be increased to achieve even more accurate results.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

CRediT AUTHOR STATEMENT

Ezgi Günaydın: Formal analysis, Writing – original draft, Investigation, Visualization, Conceptualization**, Mustafa Deste:** Supervision, Visualization, Conceptualization.

REFERENCES

[1] Doshi J, Desai, DA. Application of failure mode & effect analysis (fmea) for continuous quality improvement – multiple case studies in automobile smes. International Journal for Quality Research, 2017;11(2), 345–360.

[2] Efe, B. An integrated fuzzy approach based failure mode and effects analysis for a risk assessment. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 2022; 11(2), 678-693.

[3] Shao J, Zhong S, Tian M, Liu Y. Combining fuzzy MCDM with Kano model and FMEA: a novel 3-phase MCDM method for reliable assessment. Springer, 2024.

[4] Özveri O, Kabak M. The usage of mcdm techniques in failure mode and effect analysis. Journal of Economics and Management Research, 2015; 4 (2): 94-108.

[5] Safari H, Faraji, Z, et al. Identifying and evaluating enterprise architecture risks using FMEA and fuzzy VIKOR. Journal of Intelligent Manufacturing, 2016; 27: 475-486.

[6] Hajiagha S, Hashemi S, etc. Fuzzy belief structure based VIKOR method: an application for ranking delay causes of Tehran metro system by FMEA criteria. Transport, 2016; 31 (1).

[7] Yang H, Li G, et al. Improved FMEA based on IVF and fuzzy VIKOR method: A case study of workpiece box system of CNC gear milling machine. Quality and Reliability Engineering International, 2021; 37 (6): 2478-2498.

[8] Arabsheybani A, Mahdi M, et al. An integrated fuzzy MOORA method and FMEA technique for sustainable supplier selection considering quantity discounts and supplier's risk. Journal of Cleaner Production, 2018; 190 (20): 577-591.

[9] Mete S. Assessing occupational risks in pipeline construction using FMEA-based AHP-MOORA inteGRAted approach under Pythagorean fuzzy environment. Human and Ecological Risk Assessment: An International Journal, 2019; 25 (7).

[10] Emovon I, Mgbemena C. Enhancing the FMEA technique using a combination of Expectation interval, TAGUCHI, MOORA, and Geometric mean methods. Industrial Engineering Journal of Engineering Research, 2019; 7 (4).

[11] Liu H, Nan L, et al. Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment. Expert Systems with Applications, 2015; 39 (17): 12926-12934.

[12] Shi S, Fei H, et al. Application of an FMEA method combining interval 2-tuple linguistic variables and grey relational analysis in preoperative medical service process. IFAC, 2019; 52 (13): 1242-1247.

[13] Turan M, Ocaktan D. Use of Fuzzy HTEA in Risk Analysis in a Transformer Manufacturing Company and Development of Application Software. BAUN Fen Bilimleri Enstitüsü Dergisi, 2019; 21 (1): 474-487.

[14] Kuei H, Yung C, et al. InteGRAting TOPSIS and DEMATEL Methods to Rank the Risk of Failure of FMEA. International Journal of Information Technology & Decision Making, 2014; 13: 1229-1257.

[15] Hu C, Li E, et al. Improving Risk Evaluation in FMEA With Cloud Model and Hierarchical TOPSIS Method. IEEE Transactions on Fuzzy Systems, 2019; 27 (1).

[16] Mangelia M, Shahrakia A, et al. Improvement of risk assessment in the FMEA using a nonlinear model, revised fuzzy TOPSIS, and Support Vector Machine. International Journal of Industrial Ergonomics, 2019; 69: 209-216.

[17] Ersadi M, Forouzandeh M. Information Security Risk Management of Research Information Systems: A hybrid approach of Fuzzy FMEA, AHP, TOPSIS, and Shannon Entropy. Journal of Digital Information Management, 2019; 17 (6).

[18] Hwang CL, Yoon K. Multiple Attribute Decision Making: Methods and Applications. Springer-Verlag; 1981.

[19] Brauers WK, Zavadskas EK. Modeling in management and decision-making: The MOORA method. Technological and Economic Development of Economy. 2006;12(4):445-469.

[20] Deng H. Multicriteria analysis with grey systems. Proceedings of the 1999 IEEE International Conference on Systems, Man, and Cybernetics. 1999;3:3072-3076.

[21] Opricovic S, Tzeng GH. Defuzzification within a multicriteria decision model. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems. 2004;12(3):293-301.

[22] Kabak M, Çınar Y. Multi-Criteria Decision-Making Methods: Applications Solved with MS Excel. 1st Edition. Ankara: Nobel Yayıncılık; 2020.

[23] Gürbüz F, Çavdarcı S. Evaluation of Problem Areas Related to the Recycling Sector Using the DEMATEL and Grey DEMATEL Method. Sakarya Üniversitesi Fen Bilimleri Enstitüsü Dergisi. 2018;22(2):285-301.

[24] Battal Ü. Financing Problems of Air Transportation in Turkey: Application of the DEMATEL Method. Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi. 2018;11(2):96-111.

[25] Ünal Z, Çetin E. Selection of CRM Software in Accommodation Enterprises Using the Integrated DEMATEL and TODIM Method. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 2020; 26 (4): 779-788.

[26] Ünal Z, & Çetin E. Selection of CRM software in accommodation enterprises through the integrated DEMATEL and TODIM method. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 2020;26(4), 779–788.

[27] Badem E, Özel A. Evaluation of Factors Affecting Consumer Choice in Restaurant Selection Using the DEMATEL Method: An Application. Journal of Management Economics Literature Islamic and Political Sciences. 2018;3(1):70-89.

[28] Gök C, Perçin S. DEMATEL-ASS-VIKOR Approach in the Evaluation of Electronic Shopping (E-Shopping) Sites in Terms of E-Service Quality. Anadolu Üniversitesi Sosyal Bilimler Dergisi. 2016;16(2):131-144.

[29] Sarı İ, Ervural B, et al. Investigation of Supplier Evaluation Criteria in Sustainable Supply Chain Management Using the DEMATEL Method and an Application in the Healthcare Sector. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi. 2017;23(4):477-485.

[30] Kabak M. A Fuzzy Approach to Determining Unit Air Defense Priorities. Savunma Bilimleri Dergisi. 2011;10(2):1-17.

[31] Kurt Z, Aytaç Y. Fuzzy TOPSIS Based Decision Model for Evaluating and Prioritizing R&D / Innovation Projects. Electronic Letters on Science & Engineering, 2020; 16 (2): 93-107.

[32] Ögel S, Kerim N. Financial Performance Analysis of Defense Industry Companies Traded on Borsa Istanbul Using the Fuzzy TOPSIS Method. BIMJ. 2021;9(1):307-326.

[33] Unvan Y. Financial Performance Analysis of Banks with TOPSIS and Fuzzy TOPSIS Approaches. Gazi University Journal of Science, 2020; 33 (4): 904-923.

[34] Şişman B, Doğan M. Evaluation of the Financial Performance of Turkish Banks Using Fuzzy AHP and Fuzzy MOORA Methods. Yönetim ve Ekonomi Dergisi. 2016;23(2):353-371.

[35] Şişman B. Selection and Evaluation of Green Supplier Development Programs Using the Fuzzy MOORA Method. Journal of Yasar University. 2016;11(44):302-315.

[36] Organ A, Kenger M. Application of the Integrated Fuzzy AHP–Fuzzy MOORA Approach to the Problem of Market Staff Selection. Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi. 2018;6(18):271-280.

[37] Dinler S. Performance Evaluation of Non-Life Insurance Companies Operating in Turkey Using Grey Relational Analysis. Oltu Beşeri ve Sosyal Bilimler Fakültesi Dergisi. 2021;2(2):200-212.

[38] Şenocak A. A Multi-Criteria Decision-Making and Linear Programming-Based Application for the Sustainable Supplier Selection Problem in a Fuzzy Environment [master's thesis]. Denizli (Türkiye): Pamukkale Üniversitesi, Endüstri Mühendisliği Anabilim Dalı; 2016.

[39] Akyurt İ, Kabadayı N. Cargo Aircraft Type Selection Using Fuzzy AHP and Fuzzy Grey Relational Analysis Methods: An Application in a Turkish Airline Company. Journal of Yasar University. 2020;15(57):38-55.

[40] Yıldız A, Deveci M. Based on Fuzzy VIKOR Approach to Personnel Selection Process. Ege Academic Review, 2013; 13 (4): 427-436.

[41] Yavuz S, Deveci M. Selection of Shopping Center Location with The Methods of Fuzzy VIKOR and Fuzzy TOPSIS and An Application. Ege Academic Review, 2014; 14 (3): 463-480.

[42] Yıldız A, Deveci M. Based on Fuzzy VIKOR Approach to Personnel Selection Process. Ege Academic Review, 2013; 13 (4): 427-436.

[43] Akyüz G. Supplier Selection Using the Fuzzy VIKOR Method. Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi. 2012;26(1):197-215.

[44] Akyol G. Evaluation of Banks' Corporate Sustainability Performance Using the Fuzzy VIKOR Method [master's thesis]. Kocaeli (Türkiye): Kocaeli Üniversitesi, Fen Bilimleri Enstitüsü; 2019.

[45] Faydalı R, Erkan E. Investigation of the Machine Selection Problem Using the Fuzzy VIKOR Method. Journal of Intelligent Systems: Theory and Applications. 2020;3(1):7-12.

ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2025, 26 (2) pp. 98-111, DOI:10.18038/estubtda.1579749

RESEARCH ARTICLE

SOIL STABILIZATION WITH LIME AND SAWDUST AND ITS NUMERICAL ANALYSIS

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Abstract

Due to population growth and rapid industrialization, requirement for new construction sites and transportation routes is increasing worldwide every day. The use of waste materials in different engineering applications not only contributes to the economy of the country but also becomes a determinant in reducing the effects of environmental pollution. In this study, the suitability of the use of easily obtainable lime and sawdust is discussed for soil stabilization. In the laboratory research phase, the effects of the use of sawdust and lime were investigated on soil bearing capacity problems. Artificial neural network and regression analysis were carried out on the test results. As the conclusion of the study, it is suggested that the use of lime and sawdust is a low-cost and easy-to find alternative additives in soil stabilization. The study also highlights the environmental advantages of utilizing biodegradable and non-toxic materials in soil improvement techniques. Furthermore, the combination of mechanical testing and predictive modeling strengthens the reliability of the findings, offering a scientific basis for practical implementation.

Keywords

Soil Stabilization,
Lime,
Sawdust,
ANN,
Regression

Time Scale of Article

Received : 05 November 2024
Accepted : 10 April 2025
Online date :25 June 2025

1. INTRODUCTION

Due to population growth and rapid industrialization, construction on new sites is increasing day by day. Lands that were previously considered unsuitable for transportation or building projects are now being utilized for new investments as part of urbanization efforts. In such cases, soil problems such as low bearing capacity have been frequently encountered. The lack of favorable soil conditions has encouraged the search for soil improvement methods. Innovations in materials, equipment, and design methods have made soil improvement techniques more effective and economical [1]. Attempts to

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enhance soil properties through stabilization methods have become common in many countries today [2].

In cases where traditional soil stabilization methods are costly, the use of waste materials or economical additives presents an alternative approach. Soil stabilization using waste materials has been increasingly employed to enhance soil engineering properties in a cost-effective and sustainable manner. Various waste materials, including waste calcium carbide (WCC), wood ash (WA), cow bone ash (BA), sawdust ash (SDA), sawdust (SD), and lime, have been investigated for their effectiveness in improving soil strength, plasticity, and load-bearing capacity. In one study, WCC and WA were mixed with natural soil at specific ratios, and their stabilization effects were evaluated through Atterberg limits, compaction properties, and California Bearing Ratio (CBR) tests. The results indicated that these materials reduced the liquid limit and shrinkage, increased the optimum moisture content, slightly decreased the maximum dry density, and significantly improved CBR values, demonstrating that WCC and WA provide an economical and sustainable stabilization method [3].

Similarly, lateritic soil stabilization was examined using cow bone ash (BA) and sawdust ash (SDA) in varying proportions (2%, 4%, 6%, and 8%). Geotechnical testing, including Atterberg limits, compaction, and CBR assessments, revealed that the optimal mix of 4% BA and 2% SDA significantly improved soil strength by increasing the maximum dry density and CBR while reducing moisture content, proving their suitability as cost-effective stabilizers for lateritic subgrade soils in road construction [4]. Another study focused on problematic laterite soil, where SDA was first incorporated, followed by an optimum amount of lime (4%), determined using the Eades and Grim method. Geotechnical tests, including compaction, unconfined compressive strength (UCS), and CBR, showed that SDA increased the optimum moisture content while reducing the maximum dry density, and when combined with lime, it formed cementitious compounds that significantly enhanced the soil's strength and load-bearing capacity [5]. Additionally, an investigation comparing raw sawdust (SD) and SDA as soil stabilizers aimed to determine whether SD could serve as an alternative to SDA, reducing incineration and air pollution. Clayey soil was stabilized with SD and SDA at varying proportions (2%, 5%, 8%, 12%, 15%, and 20%), followed by Atterberg limits, modified Proctor, and Direct Shear tests. The findings showed that both SD and SDA reduced the plasticity index and maximum dry unit weight while increasing optimum moisture content, with 5% SD providing the highest bearing capacity improvement (31.89%), making SD a more effective and environmentally friendly stabilizer than its incinerated counterpart [6].

The use of waste materials in different engineering applications contributes both to the national economy and plays a crucial role in reducing environmental pollution. Waste disposal through proper methods is essential for nature conservation in both rural and urban areas. Waste materials from various industries are frequently utilized, particularly in road construction and embankment fillings. The insufficient bearing capacity of such fills can lead to serious consequences, including economic losses, structural failures, and even potential loss of life and property if not properly stabilized. Therefore, the disposal of waste materials by incorporating them into the construction sector is seen as a sustainable and practical solution [7-10]. With the increasing number of scientific studies today, different waste materials are continuously being evaluated for new engineering applications, contributing to both sustainability and economic development.

The leading methods for soil stabilization involve cement or chemical stabilization, using cementitious materials such as lime, fly ash, and sludge [11-15]. Additionally, cement and polymeric materials are widely used as grout mixes with some additives—particularly waste materials—to reduce costs while achieving improved engineering properties with early strength gain [16]. Furthermore, research findings suggest that cement kiln powder, when added to peat soil, enhances its geotechnical properties [17-18].

Various alternative materials such as gas concrete [19], marble powder [20], biopolymer xanthan sand, synthetic fiber, rubber waste, silica fume, and lime [21-26] have also been explored for their positive effects on the mechanical and physical properties of problematic soils. Particularly in lime stabilization, it has been observed that the elasticity modulus of stabilized clay increases [27], and that a combination of lime and pozzolana significantly enhances the compaction and strength of soft clay soils [28-29].

Swelling clay soils, which absorb water and expand in volume, exert pressure on structures, leading to deformations if not adequately stabilized. When light structures fail to compensate for swelling pressures, significant damages can occur. To mitigate this issue, lime treatment is commonly used, triggering chemical reactions that alter the soil's microstructure. The addition of lime to clay soils leads to a cation exchange process, where Ca^{2+} and Mg^{2+} ions replace Na^{+} or K^{+} ions in the clay matrix. This reaction, known as flocculation-agglomeration, causes clay particles to aggregate and form larger structures, effectively reducing plasticity and increasing strength. As a result, the soil loses its clay-like behavior and transitions from a plastic to a solid state, significantly enhancing its bearing capacity, strength, and elasticity modulus. Lime stabilization is widely applied in clay-rich fills, particularly in road construction [21-26].

Recently, the use of sawdust as a waste material in various applications has gained attention [30-31]. Studies indicate that sawdust enhances the strength of binding agents such as cement, fly ash, and lime. Soil stabilization using lime and sawdust is conducted by mixing the soil with lime-sawdust or lime-sawdust slurry, followed by compaction. Lime and sawdust mixtures are particularly effective for high-plasticity and cohesive soils, offering both short-term and long-term improvements. In the short term, sawdust addition enhances flocculation-agglomeration, leading to an immediate strength increase, reduced plasticity, improved workability, and decreased swelling potential. In the long term, reactions between lime and sawdust further contribute to strength enhancement. Additionally, lime alters the compaction characteristics of the soil, improving its overall stability.

Sawdust is a by-product or waste product of woodworking operations. It can be found easily worldwide. It has been reported that approximately 500 million tons/year of waste sawdust are produced in Japan and only 20% of this waste is recycled. Lime is a inorganic-based binding material when mixed with water. Approximately 500 thousand tons are produced annually in the world.

In this study, the suitability of easily available lime and sawdust for soil stabilization is investigated. The selection of these materials is based on their cost-effectiveness and accessibility. Lime is an inexpensive, widely available stabilizer, while sawdust is an abundant by-product of the wood processing industry. Laboratory studies were conducted to examine the effects of sawdust and lime on soil bearing capacity, and a numerical model was developed using artificial neural networks and regression analysis to predict the behavior of stabilized soils. The results of this research aim to provide a sustainable and efficient stabilization method, utilizing waste materials to improve soil properties while reducing environmental impacts.

2. METHOD AND MATERIAL

The study was conducted in Eskisehir Technical University Soil Mechanics Laboratory, Turkey. Five different natural soil samples are taken from two different locations in Eskisehir, Turkey. All soil index tests are conducted to determine the soil properties. The results of the experiments performed according to the ASTM standards on the soil samples are given in Table 1.

Table.1 Experiment results of the soil samples

Notations	w (%)	Gs (g/cm^3)	Grain size distribution (%)			Consistency limits (%)	
			Gravel	Sand	Silt & Clay	LL	PL
Sample-1	16.40	2.55	3	13	84	37	24
Sample-2	23.81	2.50	1	7	92	39	25

Waste sawdust was obtained from a wood factory operating in the provincial centre of Eskisehir. And lime was obtained from a lime factory from Eskisehir. In the study. the addition of sawdust was kept constant at 0.5% and 1.0% by weight. while the lime ratio was applied at % 0.5. % 1.0. % 2.0. % 5.0. % 10.0. % 15.0 and 20.0%. Technical specifications of lime are min: 80% $Ca(OH)_2$, Fineness: 0% above 150 microns.

The reconstituted soil samples having 7cm diameter and 14 cm long were prepared. Compaction parameters for soil samples were determined and reference samples were prepared with optimum water content. Although the optimum water content value was determined as 20% for Sample-1 and 22% for Sample-2. water content was applied as 25% and 30% respectively. Thus. it is aimed to determine whether the improvement can be achieved in the soft consistency of the soil. Unconfined compression tests were conducted on reconstituted samples. The experiments were repeated 3 times and the results are averaged. The tests were performed according to the ASTM standards.

3.EXPERIMENTAL RESULTS

A maximum stress value of 321 kPa was observed in the unconfined compression test on Sample-1 and it was observed as 312 kPa for Sample-2. The results of the unconfined compression test of the soil samples together with the lime and sawdust mixtures concerning Sample-1 were presented in Figure 1 and Figure 2. The results of the unconfined compression test of soil samples together with lime and sawdust mixtures concerning Sample-2 were presented in Figure 3 and Figure 4.

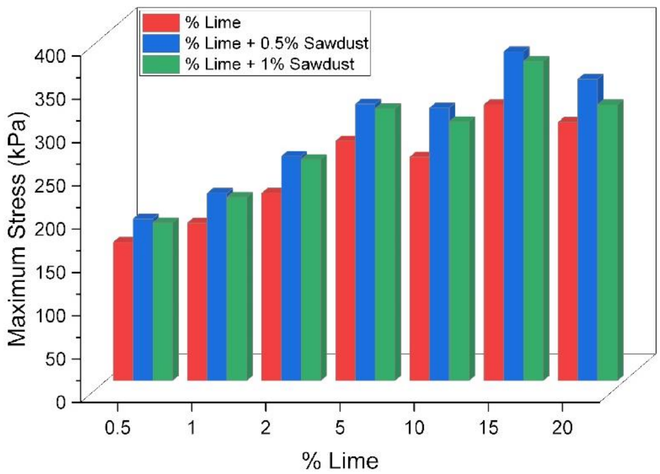


Figure 1. Unconfined compression test results with 25% water content concerning Sample-1

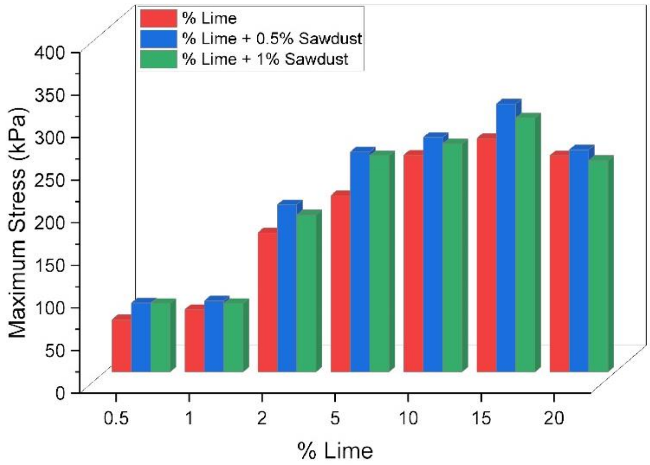


Figure 2. Unconfined compression test results with 30 % water content concerning Sample-1

Test results showed that sample from Sample-1 prepared with 30% Water + 15% Lime + 0.5% and 1% sawdust. maximum stress was determined as 275.3 kPa for lime. 299.2 kPa and 315.8 kPa for the sawdust. In the same soil. for the samples with 25% water + 5% Lime + 0.5% and 1% sawdust. it was determined to be 260.6 kPa for lime. 590.5 kPa and 580.6 kPa for sawdust.

It is seen from the test. samples from Sample-2 that prepared with 30% water. the values increased up to 398.1 kPa with the addition of lime. and up to 435.4 kPa and 453.5 kPa with the addition of sawdust + lime. In the samples with 25% water + 5% Lime + 0.5% and 1% sawdust. the stress values were obtained as 423.9 kPa for lime. 511.4 kPa and 519.2 kPa for sawdust.

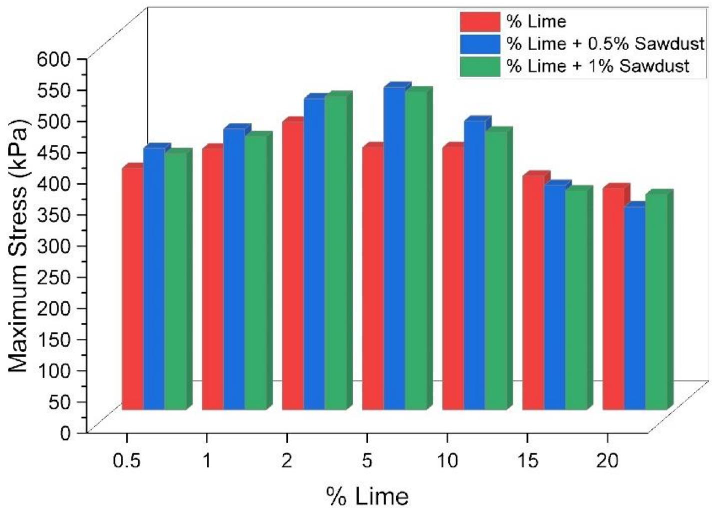


Figure 3. Unconfined compression test results with 25 % water content concerning Sample-2

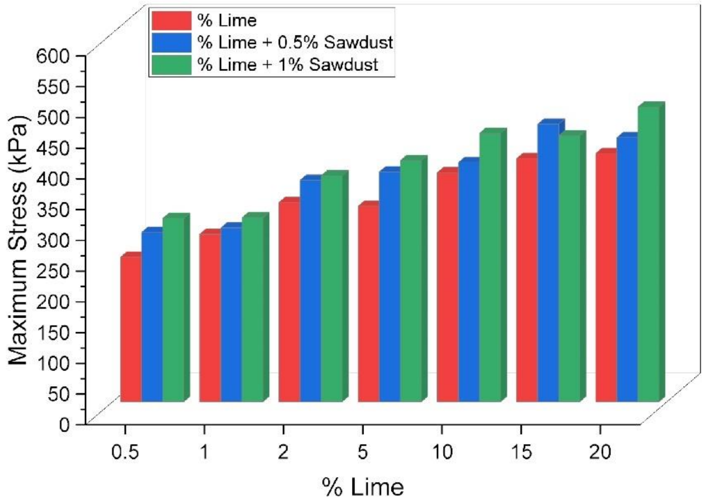


Figure 4. Unconfined compression test results with 30 % water content concerning Sample-2

4.NUMERICAL ANALYSIS

Artificial neural network (ANN) and multiple regression analysis (MRA) models were used on the test results of the samples to estimate the maximum unconfined compression test values of soils stabilized with lime and sawdust. In all models. water. lime and sawdust amounts were applied as percentages and the strength value was found as kPa.

4.1 Ann Model Development

In the development of the ANN model. a feed-forward neural network with a back-propagation training algorithm was employed due to its effectiveness as a general-purpose model [32-33]. The dataset for Sample-1. consisting of 45 data points. was divided into 30 for training. 6 for validation. and 9 for simulation. The performance of the model was validated by cross-checking the results against actual data.

The architecture of the neural network was carefully designed with three input neurons. a single hidden layer containing five neurons. and an output layer. The hyperbolic tangent sigmoid activation function was utilized for all layers. ensuring non-linearity and smooth transitions between nodes. The selection of five neurons in the hidden layer was based on iterative experimentation to balance the trade-off between model complexity and overfitting.

MATLAB's Neural Network Toolbox was used to perform the necessary computations and optimize the model. The statistical parameters for both training and simulation data are provided in Table 2 and Table 3. respectively. which further demonstrate the model's accuracy and reliability.

The chosen hyperparameters. including the learning rate and number of epochs. were fine-tuned through multiple trials to achieve the best performance. This approach ensured that the model effectively captured the underlying patterns in the data while avoiding overfitting. By providing detailed insights into the architecture and the rationale behind the parameter selection. this study aims to enhance the transparency and reproducibility of the ANN model.

Table 2. Statistical parameters of data set considered for training

	Sample-1				Sample-2			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Water	27.64	2.53	25.00	30.00	27.64	2.53	25.00	30.00
Lime	9.56	0.32	0.50	30.00	8.15	7.67	0.50	20.00
Sawdust	0.54	0.40	0.00	1.00	0.53	0.41	0.00	1.00
Strength	238.44	76.64	75.20	370.40	390.28	63.24	274.80	519.20

Table 3. Statistical parameters of data set considered for simulation

	Sample-1				Sample-1			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Water	27.78	2.64	25.00	30.00	27.50	2.67	25.00	30.00
Lime	7.44	6.87	0.50	20.00	8.44	6.65	0.50	20.00
Sawdust	0.33	0.43	0.00	1.00	0.44	0.42	0.00	1.00
Strength	209.08	103.93	63.00	380.50	413.80	88.41	236.60	511.40

The architecture of the artificial neural network used in the estimation of the strength of the soil samples reinforced with lime and sawdust is shown in Figure 5.

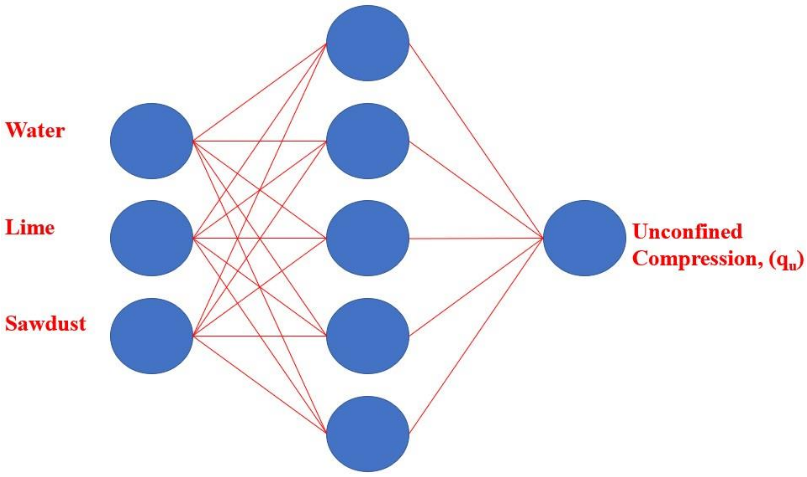


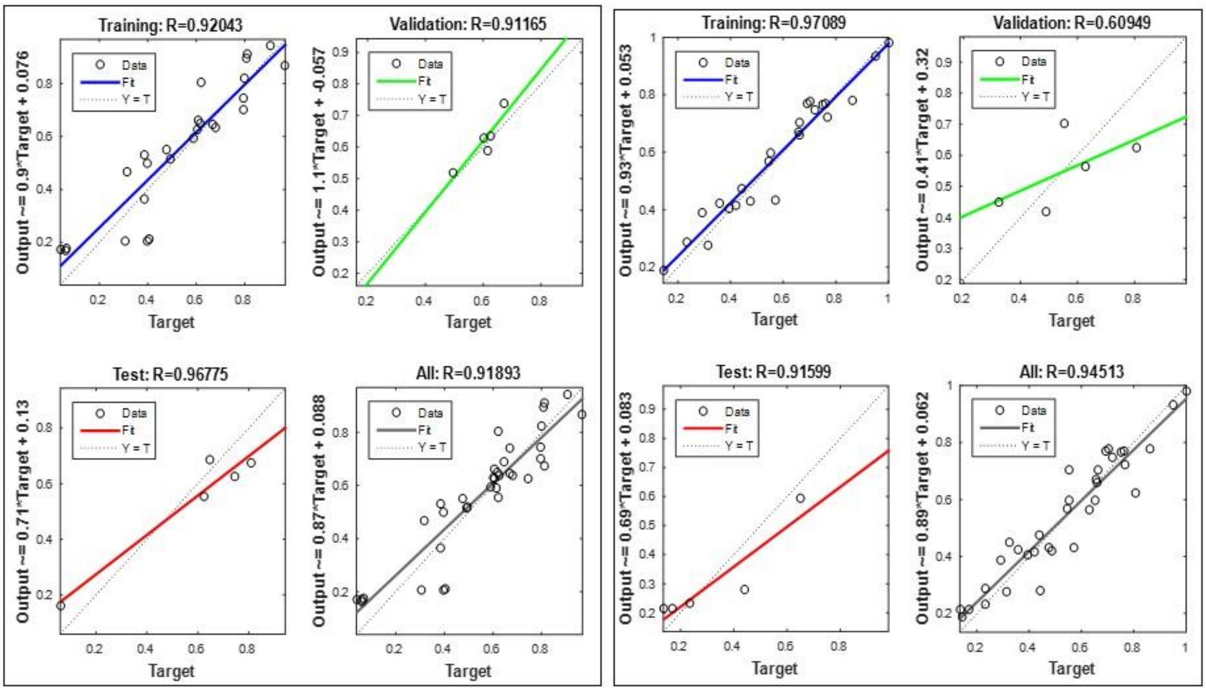
Figure 5. Architecture of the Neural Network model for prediction

The connection weights and biases of ANN model for prediction of unconfined compression of lime and sawdust stabilized soil are shown in Table 4.

Table 4. Connection weights and biases of ANN model for prediction

	Sample-1						Sample-2					
Neuron	Water	Lime	Sawdust	Strength	bhk	bo	Water	Lime	Sawdust	Strength	bhk	bo
Hidden neuron (k=1)	-1.512	-1.043	0.955	2.697	0.367	0.160	-1.258	-2.873	-0.644	-1.994	-3.330	-1.881
Hidden neuron (k=2)	-1.259	-2.006	0.036	-0.278	-1.161		-0.077	2.944	-0.280	1.699	3.503	
Hidden neuron (k=3)	2.639	0.022	-0.528	-0.278	-1.161		-1.169	-1.451	-2.227	-0.463	1.187	
Hidden neuron (k=4)	-1.972	1.782	0.115	-0.702	0.754		-1.070	-0.157	1.579	-0.912	-2.455	
Hidden neuron (k=5)	0.01	1.961	1.621	-2.091	-0.389		2.198	1.878	-0.209	-2.625	2.872	

The ANN model learning graphs of soil stabilized with lime and sawdust are shown in Figure 6. and the graph plotted between estimated and observed values are visualized in Figure 7. The estimated and actual observed values using the ANN model are nine simulation datasets for Sample-1 and eight for Sample-2.



a b

Figure 6. Learning outcome of ANN model: a) Sample-1 b) Sample-2

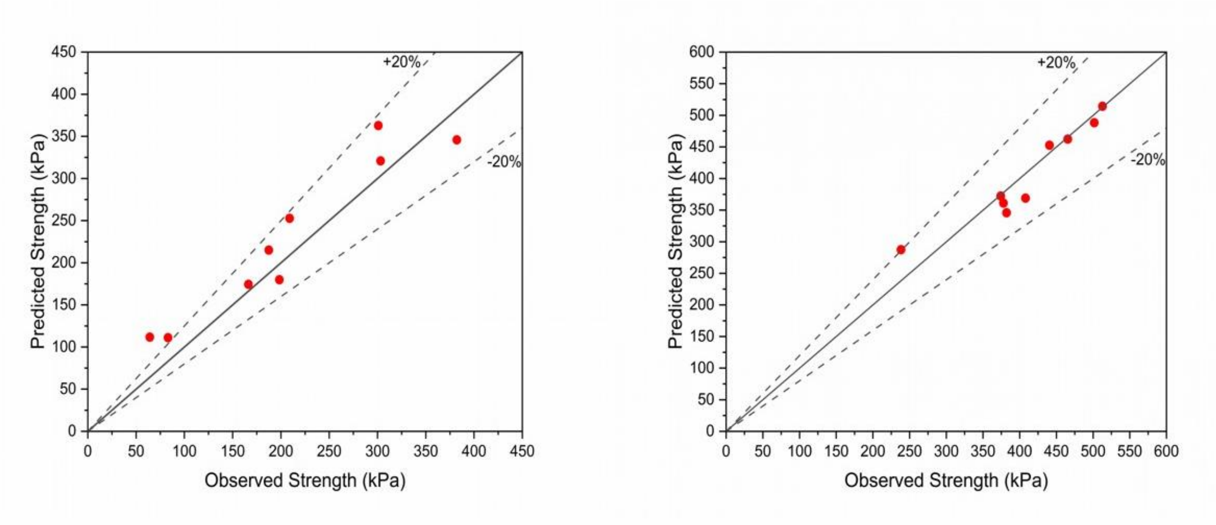


Figure 7. Simulation result of ANN model with predicted and observed values

It is observed that there is a high correlation between the observed and the estimated values. Coefficient of determination (R^2) value is 0.913 and coefficient of correlation (R) value is 0.956 for Sample-1. However. for Sample-2; R^2 value is 0.924 and R value is 0.961.

4.2 MRA Model Development

Multiple regression analysis (MRA) is one of the most widely used techniques to analyse multifactor data [34]. The MRA Model was developed using the SPSS software package as;

For Sample-1;

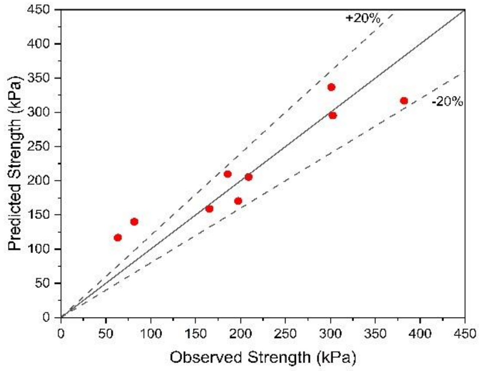
$$q_u = 654.859 - 18.021*W - 6.086*L + 42.983*S + 0.512*W*L - 0.673*W*S$$

For Sample-2;

$$q_u = 1257.116 - 32.402*W - 72.354*L - 80.771*S + 2.678*W*L + 3.932*W*S$$

- W: Water content (%)
- L: Amount of lime (%)
- S: Amount of sawdust (%)

Figure 8 shows the graph plotted between observed and predicted values. The predicted values were obtained through the MRA model. R2 value for Sample-1 is 0.879 with an R-value is 0.938 and R2 value is 0.791 with an R-value of 0.890 for Sample-2. If R ≥ is 0.8 value. there are two variables with strong correlation [35]. It can be argued that there is a significant correlation between the calculated and estimated values.



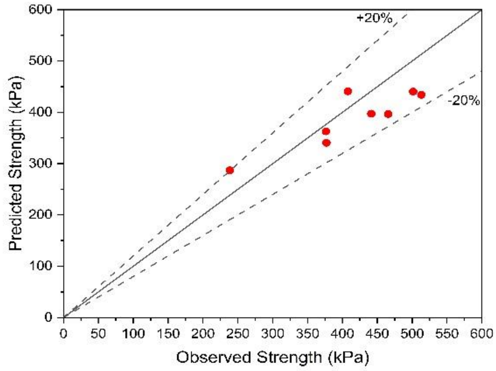


Figure 8. Simulation result of MRA model

4.3 MRA and ANN Comparison

A comparison of the predictive capabilities of the ANN and MRA model is shown in Table 5. Mean square error (MSE). mean absolute error (MAE). root mean square error (RMSE) and R^2 are considered as the parameters for comparison. The table indicated that the ANN model has less RMSE. MSE and MAE values and more R^2 than the MRA model.

Table 5. Comparison of the prediction capabilities of ANN and MRA Models

Soil Sample	Model	Data Set Used	RMSE (%)	MSE (%)	MAE (%)	R^2
Sample-1	ANN	9	2.413	5.823	9.885	0.914
	MRA	9	2.895	8.381	9.136	0.880
Sample-2	ANN	8	0.866	0.749	5.329	0.923
	MRA	8	1.250	1.561	11.289	0.791

The results show that the ANN model provides better results than the MRA model. The following summarizes the formulations used in the error calculations.

$$MSE = \frac{1}{n}\sum_{i}^{n} = 1e_t^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n} = 1e_t^2}$$

$$MAE = \frac{1}{n}\sum_{i}^{n} = 1|e^t|$$

5.CONCLUSION

One of the popular subjects in geotechnical engineering today is soil stabilization. The basis of soil stabilization works is to provide sufficient bearing capacity through additional additives to existing soil. Research studies are particularly focused on easy-to-find and low-cost additives.

In this study. soil stabilization was investigated through the addition of sawdust and lime. The main objective of this research is to find a suitable solution to the bearing capacity problems of soft soils. Lime. along with sawdust. can be used as waste materials to improve the soil. Unconfined compression tests were conducted on the prepared samples. Then. a numerical method was applied using an artificial neural network (ANN) and multiple regression analysis (MRA). The ANN model provided better results compared to the MRA model following the prediction modeling. The same simulation data were utilized in both the ANN and MRA models. When the MRA model was applied without simulation discretization. the R^2 value increased. However. common simulation data were selected and discretized to compare the models.

The findings indicate that this approach can serve as a low-cost and easy-to-find alternative for soil stabilization. Additionally. the environmental and economic impacts of sourcing lime and sawdust were considered. Lime. a widely available material. can enhance soil strength. while sawdust. as a by-product of the wood industry. provides a sustainable option for recycling waste. However. the potential limitations. such as the long-term durability of the stabilized soil and the variability in the quality of waste materials. need further investigation. Comparing these results with previous studies highlights the effectiveness of the ANN model in capturing complex relationships within the data. while the MRA model's performance improved with proper discretization.

Future research could explore the long-term performance of lime and sawdust-stabilized soils under varying environmental conditions. assess the scalability of this method for large-scale infrastructure projects. and investigate the environmental footprint of the materials used. Additionally. practical recommendations for field applications. such as optimal mixing ratios and curing times. should be developed to facilitate implementation in real-world scenarios.

ACKNOWLEDGEMENTS

This study was supported by Eskisehir Technical University Scientific Research Projects Commission under the grant no: 23LÖP028 and 24LÖP019.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Mehmet İnanç Onur: Conceptualization, Supervision, **Janvier Hobonimana:** Investigation, Methodology, **Pınar Öztürk Kardoğan**: Formal analysis, Writing – Review & Editing, **Ahmet Erdağ:** Writing – Original Draft, Visualization, **Fatih Karaçor:** Software, Validation.

REFERENCES

[1] Boulanger R, Hayden R. Aspects of compaction grouting of liquefiable soil. Journal of Geotechnical Engineering, 1995; 121(12): 844–855. https://doi.org/10.1061/(ASCE)0733-9410(1995)121:12(844)

[2] Baker W. Embankment Foundation Densification by Compaction Grouting. Issues in Dam Grouting, 1985; p 104-122.

[3] Saleh S, Surajo I, Surajo M, Idris A, T&Umar A. Calcium carbide and wood ash as environmentally friendly soil stabilizers for enhanced subgrade performance. Archives of Advanced Engineering Science, 2025; 3(1): 22–28. https://doi.org/10.47852/bonviewAAES42022403

[4] Akinwunmi A, Agbude P. Stabilization of Lateritic Soil for Road Application Using Lime and Cow Bone Ash. Journal of Engineering Research and Reports, 2023;25 (6), 109-121. https://doi.org/10.9734/jerr/2023/v25i6927

[5] Parayil A, Salini U. Stabilization of weak lateritic soil with sawdust ash and lime. Indian Geotechnical Journal, 2024; 1–12. https://doi.org/10.1007/s40098-024-00980-z

[6] Fawaz A, Alhakim G, Jaber L. The stabilisation of clayey soil by using sawdust and sawdust ash. Environmental Technology, 2024; 45(26), 5712–5722. https://doi.org/10.1080/09593330.2024.2304674

[7] Munirwan R, Taib A, M Taha, MR AbdRahman, N Munirwansyah. Utilization of coffee husk ash for soil stabilization: A systematic review. Physics and Chemistry of the Earth, Parts A/B/C, 2022; 128, 103252. https://doi.org/10.1016/j.pce.2022.103252

[8] Orense R, P Morita, Y Ide M. Assessment and mitigation of liquefaction risk for existing building foundation. In ISRM International Symposium. ISRM, 2000

[9] Salley B, A Bradshaw J, G Neilson BJ. Results of comparative studies of preservation techniques for nutrient analysis of water samples, 1987

[10] Lunardi P. Ground improvement by means of jet-grouting. Proceedings of the Institution of Civil Engineers - Ground Improvement, 1997; 1(2), 65–85. https://doi.org/10.1680/gi.1997.010201

[11] Firoozi A, A Naji, M Dithinde, M Firoozi AA. A Review: Influence of Potential Nanomaterials for Civil Engineering Projects. Iranian Journal of Science and Technology- Transactions of Civil Engineering, 2020. https://doi.org/10.1007/s40996-020-00474-x

[12] Kirsch F, Sondermann W. Ground improvement and its numerical analysis. In International Conference on soil mechanics and geotechnical engineering, 2001; 1775-1778.

[13] Lebo Ž, Bačić M, Jurić-Kaćunić D, Kovačević MS. Zagreb clay improved with various binders. GRAĐEVINAR, 2021; 73(9), p 871-880. https://doi.org/10.14256/JCE.3300.2021

[14] Omine K, Ohno S. Deformation analysis of composite ground by homogenization method. Proc. Of 14th International Conference on Soil Mechanics and Foundation Engineering, 1997; 719-722.

[15] Pinto A, Tomásio R, Pita X, Pereira A. Ground Treatment Solutions using Jet Grouting, 2016; p 2112–2121. https://doi.org/10.1061/9780784412350.0186

[16] Çelik S, Majedi P, Akbulut S. Granular Soil Improvement by Using Polyester Grouts. Iranian Journal of Science and Technology - Transactions of Civil Engineering, 2019; 43(3), 599–606. https://doi.org/10.1007/s40996-018-0203-3

[17] Badv K, Hoseinpour LJ. Treatment of Urmia Peat by Cement Kiln Dust. Iranian Journal of Science and Technology - Transactions of Civil Engineering, 2018: 42(4), 451–459. https://doi.org/10.1007/s40996-018-0112-5

[18] Vukićević M, Pujević V, Marjanović M, Jocković S, Maraš-Dragojević S. Stabilization of fine-grained soils with fly ash, 2015; 67(8), p 761-770. https://doi.org/10.14256/JCE.1281.2014

[19] Han J. Principles and Practice of Ground. New Jersey Wiley 2015.

[20] Bell A. Principles of Foundation Engineering: Treatment of Soils. Taylor & Francis London, 2000.

[21] Bell F. An assessment of cement-PFA and lime-PFA used to stabilize clay-size materials. Bulletin of the International Association of Engineering Geology, 1994; 49(1), 25–32. https://doi.org/10.1007/bf02594997

[22] Chang I, Im J, Prasidhi A, Cho G. Effects of Xanthan gum biopolymer on soil strengthening. Construction and Building Materials, 2015; 74, 65–72. https://doi.org/10.1016/j.conbuildmat.2014.10.026

[23] Ghazavi M, Sakhi M. Influence of Optimized Tire Shreds on Shear Strength Parameters of Sand. International Journal of Geomechanics, 2005; 5(1), 58–65. https://doi.org/10.1061/(asce)1532-3641(2005)5:1(58)

[24] Harichane K, Ghrici M, Kenai S, Grine K. Use of Natural Pozzolana and Lime for Stabilization of Cohesive Soils. Geotechnical and Geological Engineering, 2011; 29(5), 759–769. https://doi.org/10.1007/s10706-011-9415-z

[25] Little D. Handbook for stabilization of pavement subgrades and base courses with lime. National Lime Association, 1995; p 219.

[26] Zaimoglu A. Freezing-thawing behavior of fine-grained soils reinforced with polypropylene fibers. Cold Regions Science and Technology, 2010; 60(1), 63–65. https://doi.org/10.1016/j.coldregions.2009.07.001

[27] Yarbaşi N, Kalkan E, Akbulut S. Modification of the geotechnical properties. as influenced by freeze-thaw. of granular soils with waste additives. Cold Regions Science and Technology, 2007; 48(1), 44–54. https://doi.org/10.1016/j.coldregions.2006.09.009

[28] Kalkan E. Utilization of red mud as a stabilization material for the preparation of clay liners. Engineering Geology, 2006; 87, 220–229. https://doi.org/10.1016/j.enggeo.2006.07.002

[29] Tanzadeh R, Vafaeian M, Fard MY. The influence of lime powder on the behaviour of clay soil, 2021; 73(9), p 907-915. https://doi.org/10.14256/JCE.1871.2016

[30] Butt W, Gupta K, Jha J. Strength behavior of clayey soil stabilized with saw dust ash. International Journal of Geo-Engineering, 2016; 7(1). https://doi.org/10.1186/s40703-016-0032-9

[31] Khan S, Khan H. Improvement of mechanical properties by waste sawdust ash addition into soil. Jordan Journal of Civil Engineering, 2016; 10(1), 18–28. https://doi.org/10.14525/JJCE.10.1.3402

[32] Chowdhury S, Saha Das P. Artificial neural network (ANN) modeling of adsorption of methylene blue by NaOH-modified rice husk in a fixed-bed column system. Environmental Science and Pollution Research, 2013; 20(2), 1050–1058. https://doi.org/10.1007/s11356-012-0912-2

[33] Shandilya P, Jain P, Jain N. RSM and ANN modeling approaches for predicting average cutting speed during WEDM of SiCp/6061 Al MMC, Procedia Engineering, 2013; 767–774. https://doi.org/10.1016/j.proeng.2013.09.152

[34] Paulo DJ, Oliveira C, Cardoso A. Predicting the geometric form of clad in laser cladding by powder using multiple regression analysis Materials and Design, 2008; 29(2), 554–557. https://doi.org/10.1016/j.matdes.2007.01.023

[35] Chakraborty A, Goswami D. Prediction of slope stability using multiple linear regression (MLR) and artificial neural network Arabian Journal of Geosciences, 2017; 10(17), 1–11. https://doi.org/10.1007/s12517-017-3167-x

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A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2025, 26 (2) pp. 112-131, DOI: 10.18038/estubtda.1590581

RESEARCH ARTICLE

ENHANCED PRODUCTION QUALITY PREDICTION IN COLD ROLLING PROCESSES USING TABTRANSFORMER AND MACHINE LEARNING ALGORITHMS

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Abstract

In this study, the impact of production parameters on product quality in cold rolling processes was examined, and the qualitative status of products was predicted using machine learning algorithms. While existing literature focuses on production efficiency, this study stands out by systematically comparing eight different machine learning algorithms: Decision Tree, KNN, Naive Bayes, Logistic Regression, Random Forest, XGBoost, Support Vector Machines, and TabTransformer. The results reveal that TabTransformer, a transformer-based model designed for tabular data, outperforms the other algorithms in terms of accuracy and generalization capability, making significant contributions to the automation of quality control in production processes. Additionally, feature importance analysis provides critical insights into parameter optimization, making this study a valuable addition to the literature on industrial quality prediction.

Keywords

Quality prediction,
Cold rolling,
Tabtransformer,
Machine learning

Time Scale of Article

Received : 24 November 2024
Accepted : 10 April 2025
Online date :25 June 2025

1. INTRODUCTION

Production systems operate in interaction with a set of parameters, influencing the speed, quality, cost, and capacity of production [1]. As one of the most critical components of modern industry, the efficiency and effectiveness of production systems directly affect the competitive strength of businesses [2]. Production parameters are fundamental elements of the production process and are typically aimed at achieving production goals in the right quantity, with the right quality, and on time [3]. Unexpected variability can occur during the production process, and unforeseen conditions can negatively impact quality [4]. The qualitative conditions within the processes are of great importance in ensuring the success of production and the satisfaction of the final product for the customer [5].

To prevent negative situations, it is necessary to determine under which conditions a machine produces substandard output [6]. When making this determination, statistical tools, data from the machine, and the experience of the relevant production unit can be particularly useful [7]. Given the ease of access to open information sources today, processing data obtained from machines and making forward-looking decisions has become quite important. Within the scope of technology [8], machine learning emerges as

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a powerful tool in the detection and management of qualitative conditions on production lines [9]. Especially classification models play a critical role in determining whether quality standards are met by using information obtained from production data [10].

Several stages are required for the application of machine learning models in the detection of qualitative conditions [11]. These stages are grouped into four main sections in this article. A model can only be established and achieve success after applying the mentioned sections [12]. First, the step of data collection and preparation must be implemented. Data is collected from various sources, such as sensor data from production processes [13], machine settings, and process parameters. The collected data is used to train classification models. The second step can be defined as feature engineering [14]. This is the process of selecting and extracting the features that impact quality [15]. Feature selection and extraction are critical to improving the model's accuracy [16]. The third step is model training and evaluation [17]. The selected classification model is trained on the prepared data. The model's accuracy, precision, and reliability are evaluated using various metrics [18]. The fourth step is quality prediction. The trained model makes real-time quality predictions during production processes and detects potential quality deviations [19]. By using the mentioned techniques, quality control in production processes can be automated [20]. This allows businesses to make faster and more effective decisions [21]. Accurate detection of qualitative conditions contributes to proactively addressing issues on the production line and enhancing customer satisfaction [22].

The present study offers several distinctive contributions that advance the field of quality prediction in manufacturing processes beyond existing approaches in the literature. While recent works have explored predictive maintenance and quality control in various production environments, our research stands out in several key aspects. For instance, [23] introduced a hybrid prognostic approach based on deep learning for machinery degradation prediction, focusing primarily on equipment health monitoring rather than product quality outcomes. Similarly, [24] conducted a comparative analysis of machine and deep learning for predictive maintenance applications, emphasizing equipment failure prevention. In contrast, our study specifically addresses product quality prediction in cold rolling processes, targeting the qualitative outcomes rather than just equipment performance. Furthermore, unlike previous research that typically evaluates only two or three algorithms, our comprehensive comparison of eight different algorithms, including traditional approaches and the novel TabTransformer model, provides unprecedented breadth in algorithm assessment for this specific industrial application.

The integration of TabTransformer represents a significant advancement over existing methodologies in the literature. While transformer architectures have revolutionized natural language processing and computer vision, their application to tabular manufacturing data remains relatively unexplored. Our study demonstrates that TabTransformer's attention mechanisms can effectively capture complex interactions between production parameters that traditional algorithms might miss, achieving superior performance metrics (accuracy of 0.96 and ROC-AUC of 0.80) compared to conventional approaches. Additionally, our feature importance analysis provides actionable insights into the specific production parameters that influence quality outcomes in cold rolling processes, information that is notably absent in more general predictive maintenance studies. The practical implications of our research extend beyond theoretical model comparison, offering concrete guidance for parameter optimization in real-world cold rolling operations, thereby bridging the gap between advanced analytical methods and practical industrial applications.

While extensive research exists on production efficiency and process optimization, there remains a significant gap in the systematic evaluation of modern machine learning algorithms for quality prediction in cold rolling processes specifically. This study is motivated by the need to identify the most effective predictive models that can be deployed in real-time production environments to reduce defects, minimize waste, and enhance product consistency. Our primary contributions include: (1) a comprehensive comparative analysis of eight different machine learning algorithms, including both traditional approaches and the novel TabTransformer model; (2) the application of transformer-based architecture to tabular production data, which represents a significant advancement over existing quality prediction methods; (3) detailed feature importance analysis that provides actionable insights for parameter optimization in cold rolling processes; and (4) a framework for automated quality control that can be adapted to similar production environments in the metallurgy industry. These contributions collectively address the growing need for advanced analytical methods that can enhance decision-making in increasingly complex manufacturing processes.

2. MATERIAL METHOD

The rolling process is frequently used in the metallurgy industry to improve the mechanical properties and surface quality of metals. This process is applied to reduce the thickness of metals, achieve desired shapes and sizes, and ensure surface smoothness. Rolling operations play a critical role, particularly in the production of metal sheets and plates. Rolling generally occurs as either hot or cold rolling. The operation applied in this article is cold rolling. Cold rolling is carried out at room temperature or slightly above it, with the expectation of improving surface quality. Rolling enhances the mechanical properties of the metal, particularly its strength and hardness. Cold rolling offers more precise dimensional control and superior surface quality. The success of the rolling process depends on various parameters. The speed used during rolling affects both production efficiency and product quality. Extremely high speeds can cause surface defects, while very low speeds can reduce production efficiency. The load applied by the machines determines the deformation of the metal and the properties of the final product. Correctly adjusting the load is critical to achieving the desired thickness and surface quality. The tension forces applied during rolling affect the dimensional stability and surface smoothness of the metal. Proper tension settings ensure that the product meets the correct dimensions. The quality of the rolling process directly impacts the performance of the final product. Surface defects can reduce the product's performance. Therefore, continuous monitoring and control of surface quality are important. Quality control tests ensure that these properties comply with standards. The conformity of the product to the desired dimensions indicates the success of the rolling process. Precise measurement devices and methods ensure the control of dimensional accuracy.

The initial dataset collected from production signals and SAP records contained 33 features across 30,000 production instances. These features can be categorized into several distinct groups:

1. **Numerical Production Parameters:**

- **Process Variables**: Including rolling speed (0.5-5.0 m/s), applied load (10-500 kN), oil temperature (20-80°C), mill motor temperature (25-90°C), and tension forces (5-70 kN).
- **Material Dimensions**: Thickness (0.1-5.0 mm), width (100-1500 mm), and weight (500-10000 kg).
- **Operating Conditions**: Bending average (0.2-4.5), average total load (25-450 kN), uncoiler force (10-200 kN), and recoiler force (10-180 kN).
- **Temporal Features**: Month (1-12), day (1-31), and associated time stamps that capture temporal patterns.

2. **Categorical Features:**

- **Product Specifications**: Product group (15 distinct categories), intended application (8 categories), and surface finish requirements (5 categories).
- **Material Properties**: Alloy compositions (27 distinct alloy types), grade designations (12 categories), and quality control mode (3 categories).
- **Production Equipment**: Casting machine identifiers (5 distinct machines) and various processing routes (4 categories).

Text Data Transformation Process: The textual categorical data were transformed into numerical representations using one-hot encoding to make them suitable for machine learning algorithms. This process involved the following steps:

1. For each textual feature, all unique values were identified across the dataset. For example, the "product group" feature contained 15 distinct categories.
2. Each categorical feature was transformed into multiple binary columns, with each column representing the presence (1) or absence (0) of a specific category. For instance, the "product group" feature was expanded into 15 binary columns.
3. This transformation process expanded the original 33 features (which included both numerical and categorical variables) into 77 features, all in numerical format.
4. Following the encoding process, the original text-based columns were removed from the dataset, resulting in the final structure of 30,000 instances with 72 features (excluding the 5 original categorical columns but including their 44 one-hot encoded replacements).

All numerical features were subsequently scaled to the range of 0-1 using MinMaxScaler to standardize their influence on the machine learning models. The dataset was verified to contain no missing values, as the production data collection system ensures continuous monitoring and complete recording of all parameters.

The quality class column, derived from internal failure reports, was designated as the target variable for prediction, resulting in a final matrix structure of 30,000×71 for the feature set, with 80% (24,000 instances) allocated to the training set and 20% (6,000 instances) to the test set using stratified sampling to maintain the class distribution.

The data for this study was collected from signals on production lines over a two-year period. Each data point was linked to production records through time and date constraints via the signals, with production data recorded in SAP based on feedback. The initial dataset had a matrix structure of 30000×33, created by temporally matching the 2-year signaling data of the production line with the SAP data of production reported on the machine in the same time period.

The dataset includes several categories of quality-related features that characterize the production conditions:

Features including alloy compositions (specifically Alloy-1 and Alloy-2 as identified in our correlation analysis), material thickness, width, and weight measurements. These properties directly influence the mechanical characteristics of the final product. Critical operational variables such as rolling speed, applied load, oil temperature, mill motor temperature, and tension forces during the rolling process. These parameters control the deformation behavior of the metal. Features related to equipment status, including casting machine identifiers (Casting Machine-1 and Casting Machine-2), uncoiler force, recoiler force, and bending average values. These conditions influence the stability and consistency of the rolling process. Temporal features such as month, day, and associated production shifts, which can account for seasonal variations and operator-dependent factors.Features that categorize the intended purpose and characteristics of the product, including product group (identified as highly correlated with quality) and specific product requirements.

The target variable in this study is the "quality class" column, which is a binary classification variable characterizing each production as either meeting quality standards (labeled as 0) or exhibiting quality defects (labeled as 1). This classification was derived from internal failure reports that document instances where products failed to meet the established quality criteria. In our dataset, the distribution of the target variable shows an imbalanced nature, with approximately 6.2% of the productions classified as defective (class 1) and 93.8% meeting quality standards (class 0). This imbalance reflects the real-world production environment where defective outputs constitute a minority of total production, presenting a class imbalance challenge that our modeling approach needed to address.

After data preprocessing, which included converting textual expressions into numerical form and removing the original textual columns, the final dataset structure was established as 30000×72. The quality class column was designated as the prediction target, with the remaining 71 columns serving as predictive features. This comprehensive set of features allowed our models to capture the complex interactions between production parameters and their collective impact on product quality.

The application was evaluated using a total of seven algorithms: Decision Tree, KNN, Naive Bayes, Logistic Regression, Random Forest, XGBoost, Support Vector Machine, and TabTransformer.

- Decision Tree: This algorithm models decisions in the form of a tree structure. Each internal node represents a condition or test on a feature, each branch corresponds to an outcome of the test, and each leaf node holds the final decision or output. It's a simple and interpretable model, well-suited for both classification and regression tasks.

- K-Nearest Neighbors (KNN): KNN is a non-parametric algorithm that classifies a data point by considering the labels of its closest "k" neighbors in the feature space. The prediction is made by majority voting for classification or by averaging the neighbor values for regression. It's intuitive and works well for smaller datasets.

- Naive Bayes: This algorithm is based on Bayes' Theorem and assumes that the features are independent of each other (hence "naive"). Despite this strong assumption, it often performs surprisingly well for classification tasks, particularly in problems like text classification and spam detection.

- Logistic Regression: A statistical method for binary classification, logistic regression models the probability that a given input belongs to a particular class using a logistic function. It's widely used when the output is categorical and interprets the data in terms of odds and probabilities.

- Random Forest: This is an ensemble learning method that creates a "forest" of decision trees during training. It makes predictions by aggregating (averaging for regression or majority voting for classification) the results of these trees. Random Forest reduces the risk of overfitting by introducing randomness in tree building.

- XGBoost: This is an advanced implementation of gradient-boosting techniques. It builds multiple decision trees sequentially, with each tree correcting errors from the previous one. XGBoost is known for its efficiency and accuracy, particularly in handling large datasets and complex problems.

- Support Vector Machine (SVM): SVM classifies data by finding the hyperplane that best separates the classes in the feature space. It aims to maximize the margin between different classes, which helps improve the generalization ability of the model. It works well for both linear and non-linear classification tasks using kernel functions.

- TabTransformer: TabTransformer is a transformer-based deep learning model specifically designed for tabular data. It leverages attention mechanisms from the transformer architecture to capture complex interactions between features, both numerical and categorical. By embedding categorical features and applying self-attention, TabTransformer can model intricate relationships that traditional algorithms might miss. This allows the model to learn rich feature representations, improving predictive performance on classification and regression tasks. It's particularly effective in situations where the dataset contains mixed data types and requires modeling non-linear feature interactions.

For the evaluation of the models, accuracy, sensitivity (recall), F1 score, ROC curve, cross-validation, and confusion matrix were used.

- Accuracy: Accuracy measures the percentage of correct predictions out of the total number of predictions made. It's a straightforward metric calculated by dividing the number of correct predictions by the total number of instances. While accuracy is useful, it can be misleading in imbalanced datasets where one class dominates.

- Recall: Also known as sensitivity or true positive rate, recall measures the ability of a model to identify all relevant instances of a class. Specifically, it looks at the proportion of actual positives correctly identified by the model. High recall means the model captures most of the positive cases.

- F1 Score: The F1 score combines both precision and recall into a single metric by taking their harmonic mean. It is especially useful when the dataset is imbalanced because it balances the trade-off between false positives and false negatives.

- ROC Curve (Receiver Operating Characteristic Curve): The ROC curve is a graphical representation of a model's performance across different thresholds. It plots the true positive rate (recall) against the false positive rate (1 - specificity) at various thresholds. The area under the curve (AUC) quantifies the model's ability to distinguish between classes, with higher values indicating better performance.

- Cross-Validation: This is a technique for evaluating the performance of a model by dividing the dataset into multiple folds. The model is trained on some of these folds and tested on the remaining fold(s). The process is repeated several times (usually "k" times in "k-fold cross-validation"), and the results are averaged to give a more robust estimate of model performance, reducing the risk of overfitting.

- Confusion Matrix: A confusion matrix is a table that provides insight into the performance of a classification model by showing the number of true positives (correct positive predictions), true negatives (correct negative predictions), false positives (incorrectly predicted positives), and false negatives (missed positive predictions). This matrix allows the calculation of various metrics like precision, recall, and accuracy.

The study was conducted using the Python programming language. The categorical data within the dataset were transformed into numerical form by being organized into columns. The categorical data were then removed from the table. As a result of these processes, the dataset was structured as a 30,000*72 matrix.

In the machine learning models built on the dataset, a correlation analysis was conducted by focusing on the target column labeled "quality class." From the correlation matrix, five parameters that most significantly impact the quality class were identified. The parameters with high correlation to the quality class were determined to be two types of material alloys, two casting machines, and the product group. The data containing the correlation values are provided in Table 1.

Table 1. Parameters with high correlation to quality classification

#	Parameter	Correlation Values
1	Product Group	0.12
2	Alloy -1	0.10
3	Alloy -2	0.07
4	Casting Machine-1	0.07
5	Casting Machine-2	0.07

The product group has the highest positive correlation with the target variable. However, a value of 0.119 indicates a weak positive relationship, suggesting that the product group may cause only a minor change in the target variable. There is a slight positive relationship between Alloy-1 and the target variable. The correlation value of 0.095 indicates that this variable has a very small effect on the target. Alloy-2 has a weak positive correlation with the target variable. A value of 0.065 indicates that this variable's impact on the target variable is quite limited. Casting Machine-1 has a very weak positive relationship with the target variable, with its effect also being quite limited. Similarly, Casting Machine-2 shows a very weak positive correlation, having an almost negligible effect on the target variable. The dataset was split into training and testing sets with an 80% to 20% ratio. The training data size was 24,000×71 and the test data size was 6,000×71. The data were normalized using MinMaxScaler and were scaled between 0 and 1. The machine learning algorithms applied included Decision Tree, KNN, Naive Bayes, Logistic Regression, Random Forest, XGBoost, Support Vector Machine, and TabTransformer. TabTransformer, a transformer-based model designed specifically for tabular data, was incorporated to capture complex feature interactions that traditional models might miss. By leveraging attention mechanisms, TabTransformer aims to improve predictive performance by effectively handling both numerical and categorical features. Including TabTransformer allowed us to explore whether advanced neural network architectures could outperform traditional algorithms in predicting product quality.

The target variable in this study ("quality class") was assigned binary labels based on internal failure reports from the production process. Products meeting all quality standards were labeled as Class 0 (acceptable quality), while products with any documented quality defects were labeled as Class 1 (defective quality).

The dataset exhibits a significant class imbalance that reflects real-world manufacturing conditions. From the total 30,000 production records:

- 28,116 records (93.72%) belong to Class 0 (acceptable quality)
- 1,884 records (6.28%) belong to Class 1 (defective quality)

This imbalance ratio of approximately 15:1 is characteristic of industrial quality control scenarios where defective products constitute a small minority of total production. This class distribution was maintained in both training and testing sets using stratified sampling to ensure representative proportions in both datasets.

The accuracy, precision, recall, and F1 score of the algorithms are provided in Table 2.

Table 2. Model performance evaluation based on key performance metrics for both training and test sets

#	Algorithm	Dataset	Accuracy	Precision	Recall*	Recall (Class 1)**	F1 Score
1	Decision Tree	Training	0.97	0.96	0.97	0.68	0.97
		Test	0.94	0.94	0.94	0.52	0.94
2	KNN	Training	0.95	0.94	0.95	0.27	0.94
		Test	0.94	0.92	0.94	0.16	0.92
3	Naive Bayes	Training	0.93	0.90	0.93	0.04	0.91
		Test	0.93	0.89	0.93	0.03	0.91
4	Logistic Regression	Training	0.94	0.89	0.94	0.00	0.91
		Test	0.94	0.88	0.94	0.00	0.91
5	Random Forest	Training	0.99	0.98	0.99	0.83	0.98
		Test	0.94	0.93	0.94	0.16	0.93
6	XGBoost	Training	0.98	0.97	0.98	0.72	0.97
		Test	0.94	0.93	0.94	0.05	0.91
7	Support Vector Machine	Training	0.94	0.89	0.94	0.00	0.91
		Test	0.94	0.88	0.94	0.00	0.91
8	TabTransformer	Training	0.97	0.96	0.97	0.69	0.97
		Test	0.96	0.95	0.96	0.60	0.96

*Note: The Recall column represents macro-averaged recall across both classes, which gives equal weight to the performance on each class regardless of class imbalance.
**Note: Recall (Class 1) specifically measures the model's ability to identify instances of the positive class (defective products), which constitutes approximately 6.2% of the dataset. This metric is particularly important for quality control applications where detecting defects is the primary concern.

The performance evaluation reveals distinct patterns among the algorithms tested. TabTransformer demonstrates superior performance across all metrics (accuracy: 0.96, precision: 0.95, recall: 0.96, F1 score: 0.96), outperforming all traditional algorithms. Among conventional approaches, Decision Tree and Random Forest show the strongest overall performance (both with 0.94 accuracy), with Decision Tree achieving better balance between precision and recall (F1 score: 0.94). While Logistic Regression and Support Vector Machine maintain high accuracy (0.94), they struggle with class imbalance, as evidenced by their lower precision scores (0.88). The consistently high performance of TabTransformer validates the advantage of attention-based mechanisms in capturing complex feature interactions for quality prediction in cold rolling processes.

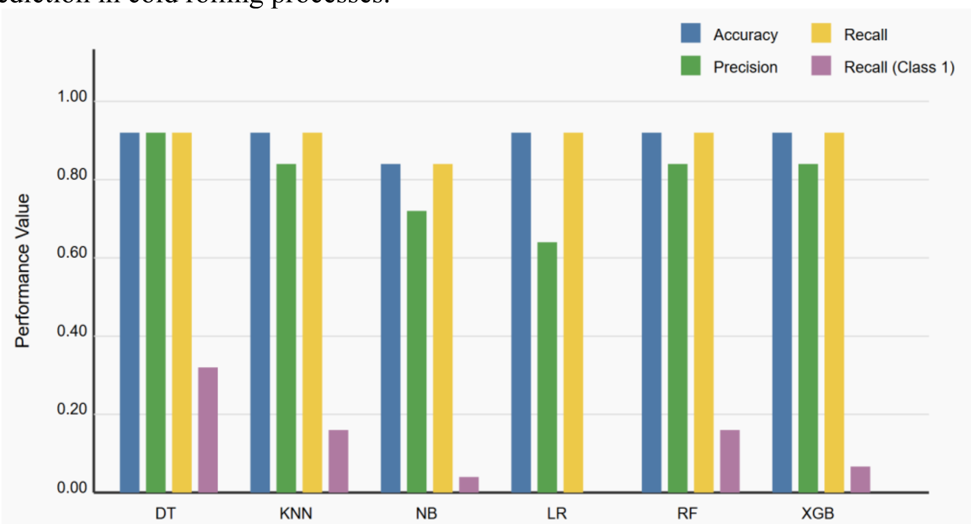

Figure 1. Model Performance Comparison Chart

The figure 1 chart compares all eight algorithms across four key metrics: accuracy, precision, recall, and recall for Class 1 (defective products). TabTransformer is highlighted separately at the bottom to emphasize its superior performance. The chart clearly shows how TabTransformer outperforms other algorithms, particularly in identifying the minority class (defective products).

Comments on the Evaluation of Metrics Based on Algorithms:

Decision Tree (0.964) and Random Forest (0.955) models show the best performance in terms of overall accuracy. This indicates that these models correctly predicted the majority of classes in the test dataset. Naive Bayes (0.937) has the lowest accuracy, indicating that it made more errors compared to the other models. XGBoost (0.739) and Random Forest (0.709) have high precision rates, meaning that a large portion of the positively predicted instances are truly positive. Naive Bayes (0.123) has the lowest precision, indicating that most of its positive predictions are incorrect. For Logistic Regression and Support Vector Machine, precision is undefined (0/0 situation) because these models did not detect the positive class at all.

Decision Tree (0.521) performs better than other models in correctly identifying the positive class. Naive Bayes (0.027) and XGBoost (0.045) have very low recall, meaning they missed most of the positive examples. Logistic Regression and Support Vector Machine models did not detect the positive class at all (recall = 0). Decision Tree (0.524) achieved the best F1 score, balancing precision and recall effectively. Random Forest (0.264) has the second-best F1 score, showing balanced performance. Naive Bayes (0.044) and XGBoost (0.084) have low F1 scores, indicating poor performance in identifying the positive class. Logistic Regression and Support Vector Machine models are ineffective in terms of positive class performance, resulting in F1 scores of zero. Decision Tree and Random Forest models stand out with a balanced combination of accuracy, precision, and recall. The XGBoost model performs well in terms of precision but fails to detect the positive class adequately due to its low recall. Naive Bayes is overall a weak model due to its poor performance in both precision and recall. Logistic Regression and Support Vector Machine failed to identify the positive class, resulting in F1 scores of zero. TabTransformer (0.96) achieves the highest overall accuracy among all models, indicating superior performance in correctly predicting classes in the test dataset. TabTransformer has a high precision of 0.95, meaning that a large portion of its positive predictions are correct. With a recall of 0.96, TabTransformer effectively identifies the positive class, outperforming other models in correctly capturing positive instances. TabTransformer achieves the highest F1 score of 0.96, demonstrating an excellent balance between precision and recall. The model's superior metrics suggest that TabTransformer effectively captures complex feature interactions, leading to better predictive performance compared to traditional algorithms.

The ROC curve (AUC) values for the established models are provided in Table 3.

Table 3. Roc curve values of algorithms

#	Algorithm	ROC Curve (AUC)
1	Decision Tree	0.73
2	KNN	0.73
3	Naive Bayes	0.51
4	Logistic Regression	0.50
5	Random Forest	0.57
6	XGBoost	0.52
7	Support Vector Machine	0.50
8	TabTransformer	0.80

Interpretation of ROC Curve Values Based on Algorithms:

Both algorithms have the highest AUC values. This indicates that these models have better discriminative power between classes compared to other algorithms. An AUC of 0.73 suggests that the overall performance of the model is good but could be further improved.

- Naive Bayes:

- With an AUC of 0.51, Naive Bayes is almost making random predictions, indicating that this model struggles to differentiate between classes on this dataset.

o Logistic Regression and Support Vector Machine (SVM):

- Both algorithms have an AUC of 0.50, meaning their performance is equivalent to random guessing.
- This indicates that these algorithms are not effectively working on this dataset and need improvement.

o Random Forest:

- An AUC of 0.57 indicates that the model has some discriminative capabilities, but they are limited.
- Random Forest usually performs better, suggesting that this model may require optimization or parameter tuning.

o XGBoost:

- An AUC of 0.52 shows that XGBoost has very little discriminative power between classes.
- This algorithm is generally strong on complex datasets, so these results are surprising and may require parameter adjustments.

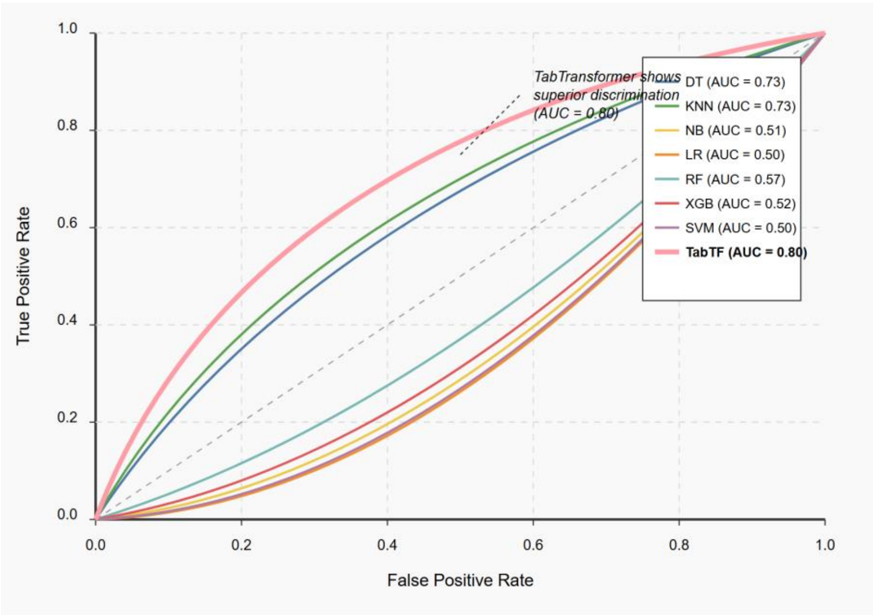

Figure 2. ROC Curve Comparison Plot

The figure 2 displays ROC curves for all eight algorithms, visualizing why TabTransformer achieved the highest AUC value (0.80). The curves show the trade-off between true positive rate and false positive rate across different classification thresholds. TabTransformer's curve (shown with a thicker line) demonstrates better performance by extending further toward the top-left corner of the plot.

Decision Tree and KNN stand out as the algorithms providing the best class separation. Logistic Regression and SVM show performance equivalent to random guessing, suggesting these models should be reviewed and optimized. Random Forest and XGBoost demonstrate moderate performance, indicating the need for further tuning.

o TabTransformer:

The TabTransformer model achieved the highest AUC value of 0.80, surpassing all other evaluated models. This indicates that TabTransformer has superior discriminative power between classes compared to the traditional algorithms. An AUC of 0.80 suggests that the model performs very well in distinguishing between the positive and negative classes. The high AUC value demonstrates TabTransformer's effectiveness in capturing complex feature interactions within the dataset, leading to better class separation and predictive performance. This superior performance highlights the advantage of using transformer-based architectures for tabular data, especially in cases where traditional models may not fully capture underlying patterns.

A method called feature importance, which shows how much certain features influence the prediction outcomes of a machine learning model, has been applied. The resulting parameter matrix and the table containing the values of the parameters are presented in Table 4 and Table 5, respectively.

The feature importance analysis in our study was conducted using algorithm-specific importance methods appropriate for each model type. For tree-based models (Decision Tree, Random Forest, and XGBoost), we used the built-in feature importance calculation based on the Gini impurity decrease or information gain. This approach measures how much each feature contributes to decreasing impurity across all trees in the model.

For TabTransformer, we extracted attention weights from the self-attention mechanism, which indicate how strongly different features influence the model's predictions. These weights were normalized to create comparable importance scores across features.

For other algorithms like KNN, Naive Bayes, Logistic Regression, and SVM, we employed a permutation importance technique. This method measures the decrease in model performance when values of a single feature are randomly shuffled, thereby breaking the relationship between the feature and the target variable. The resulting performance decrease indicates the feature's importance to the model.

All importance values were normalized to a scale where higher values indicate greater importance to the model's predictions. This normalization allows for comparability across different algorithms despite their distinct internal mechanisms for determining feature relevance.

Table 4. Names of influencing parameters.

#	Algorithm	P. 1 Name	P. 2 Name	P. 3 Name	P. 4 Name	P. 5 Name
1	Decision Tree	No	Day	Oil Temperature	Month	Weight
2	KNN	Weight	Mill Motor Temperature	Average Total Load	Oil Temperature	No
3	Naive Bayes	Average Total Load	Quality Control Mode	Uncoiler Force	Recoiler Force	Mill Motor Temperature
4	Logistic Regression	Mill Motor Temperature	Width [mm]	Bending Average	Month	Speed
5	Random Forest	No	Mill Motor Temperature	Oil Temperature	Average Total Load	Mill Motor Temperature _2
6	XGBoost	No	Width [mm]	Product Group	Month	Thickness
7	Support Vector Machine	Weight	Mill Motor Temperature	Average Total Load	Oil Temperature	No
8	TabTransformer	Product Group	Alloy-1	Alloy-2	Casting Machine-1	Casting Machine-2

Table 5. Values of influencing parameters.

#	Algorithm	P. 1 Name	P. 2 Name	P. 3 Name	P. 4 Name	P. 5 Name
1	Decision Tree	0.4422	0.0448	0.0436	0.0392	0.0392
2	KNN	0.1804	0.0152	0.0134	0.0131	0.0131
3	Naive Bayes	0.0011	0.0005	0.0005	0.0002	0.0002
4	Logistic Regression	-0.0026	-0.0016	0.0013	-0.0012	0.0012
5	Random Forest	0.0879	0.0522	0.0521	0.0519	0.0514
6	XGBoost	0.5550	0.0860	0.0591	0.0280	0.0277
7	Support Vector Machine	0.1032	0.0547	0.0529	0.0524	0.0522
8	TabTransformer	0.6507	0.1523	0.1056	0.0512	0.0507

Comments on Feature Importance Based on Algorithms:

Decision Tree:

- P.1: 0.4422 — This feature plays the most significant role in the model's decisions.
- P.2: 0.0448, P.3: 0.0436, P.4: 0.0392, P.5: 0.0392 — The importance of the other features is lower but relatively similar to each other.

KNN:

- P.1: 0.1804 — Weight is the most influential feature in this model.
- P.2: 0.0152, P.3: 0.0134, P.4: 0.0131, P.5: 0.0131 — The remaining features contribute much less to the model, indicating a clear distinction in importance, with Weight being dominant.

Naive Bayes:

- The features have very low importance values. This is common with Naive Bayes, which often gives low importance to features, especially with continuous variables.

Logistic Regression:

- The features have negative or low importance values. The negative values for P.1 and P.2 suggest that these features might negatively contribute to the model.

Random Forest:

- The importance values are more balanced, but P.1 still has the highest importance. The other features (P.2, P.3, P.4, P.5) show similar values, indicating they all play significant but secondary roles.

XGBoost:

- P.1: 0.5550 — This feature is of utmost importance, as XGBoost places a significant emphasis on it.
- P.2: 0.0860, P.3: 0.0591, P.4: 0.0280, P.5: 0.0277 — The other features are less influential, but P.2 and P.3 are still noteworthy.

Support Vector Machine (SVM):

- P.1: 0.1032 — Weight is the most influential feature in the SVM model.
- P.2: 0.0547, P.3: 0.0529, P.4: 0.0524, P.5: 0.0522 — The other features have moderately high importance values, indicating a balanced contribution across these parameters.

TabTransformer

- TabTransformer differs from the other models by significantly emphasizing Product Group as the most critical feature, with an importance value of 0.6500, far exceeding the top features in other models. This indicates that Product

Group has a profound impact on product quality when assessed with TabTransformer.

- The Decision Tree algorithm heavily relies on the "No" feature, which plays a dominant role in its decisions.
- KNN emphasizes Weight as the most significant factor, with the other features contributing far less to the model's predictions.
- Naive Bayes and Logistic Regression do not seem to leverage feature importance effectively, with Naive Bayes showing very low values and Logistic Regression even displaying negative values for certain features.
- Random Forest shows a balanced approach, but with a clear emphasis on the most important feature, "No."
- XGBoost places a significant emphasis on the top feature, with a sharp drop-off in the importance of the others.
- Support Vector Machine shows a relatively balanced distribution of importance across its top features, but with Weight being the most influential.
- The high importance values assigned to Alloy-1 and Alloy-2 by TabTransformer highlight the model's ability to capture the influence of material composition on product quality.
- Unlike models such as Naive Bayes and Logistic Regression, which show negligible feature importance, TabTransformer provides clearer insights into which parameters most significantly affect the target variable.
- Overall, TabTransformer not only improves predictive performance but also enhances interpretability by highlighting key features that influence product quality. Its transformer-based architecture effectively captures complex relationships between categorical and numerical variables, making it a valuable tool for industrial quality prediction and process optimization.

3. THE RESEARCH FINDINGS AND DISCUSSION

The model was evaluated using cross-validation, a technique used to assess the generalization ability of a machine learning model. This method involves splitting the data into multiple subsets to more reliably measure the model's performance. Fundamentally, it allows for more effective management of the training and testing processes. Cross-validation is an effective method to evaluate the robustness of a model’s performance and to reduce the risk of overfitting. The results of cross-validation applied to the algorithms are provided in Table 6.

Table 6. Cross validation results

#	Algorithm	Cross-Validation Scores	Average Score	Standard Deviation
1	Decision Tree	[0.92; 0.93; 0.92; 0.93; 0.92]	0.92	0.01
2	KNN	[0.93; 0.94; 0.93; 0.93; 0.93]	0.93	0.00
3	Naive Bayes	[0.92; 0.93; 0.92; 0.92; 0.92]	0.92	0.00
4	Logistic Regression	[0.93; 0.94; 0.93; 0.94; 0.93]	0.94	0.00
5	Random Forest	[0.94; 0.95; 0.94; 0.94; 0.94]	0.94	0.00
6	XGBoost	[0.93; 0.94; 0.93; 0.94; 0.93]	0.94	0.00
7	Support Vector Machine	[0.93; 0.94; 0.93; 0.94; 0.93]	0.94	0.00
8	TabTransformer	[0.95; 0.96; 0.96; 0.96; 0.95]	0.96	0.005

Decision Tree:

- Average Score: 0.92
- Standard Deviation: 0.01
- The Decision Tree shows generally good performance, but its scores are slightly more variable. The low standard deviation indicates that the scores are close to each other.

KNN (K-Nearest Neighbors):

- Average Score: 0.93
- Standard Deviation: 0.00
- The KNN model's performance is very consistent. The scores are very close, and the zero standard deviation suggests that the model is very stable.

Naive Bayes:

- Average Score: 0.92
- Standard Deviation: 0.00
- Naive Bayes performs similarly to the Decision Tree, but its scores are more stable. There is no variability in the model's performance.

Logistic Regression:

- Average Score: 0.94
- Standard Deviation: 0.00
- Logistic Regression has the highest average score and is very stable, showing excellent performance.

Random Forest:

- Average Score: 0.94
- Standard Deviation: 0.00
- Random Forest shares the same average score as Logistic Regression and is very consistent, demonstrating high performance.

XGBoost:

- Average Score: 0.94
- Standard Deviation: 0.00
- XGBoost shares the same average score as Random Forest and Logistic Regression and shows high performance. The model is very stable.

Support Vector Machine (SVM):

- Average Score: 0.94
- Standard Deviation: 0.00
- SVM also demonstrates high performance with very consistent scores, providing results similar to other high-performing models.

TabTransformer:

- Average Score: 0.96
- Standard Deviation: 0.005
- TabTransformer demonstrates the highest average cross-validation score among all models, indicating superior performance. The low standard deviation suggests that the model's performance is highly consistent across different folds, reflecting its robustness and reliability.

- TabTransformer:
  - The cross-validation scores are [0.95; 0.96; 0.96; 0.96; 0.95], showing consistently high performance.
  - Average Score: 0.96
  - Standard Deviation: 0.005
  - The model not only achieves the highest average score but also maintains a low standard deviation, indicating that it generalizes well across different subsets of the data.

- Interpretation: TabTransformer's ability to capture complex feature interactions and handle both numerical and categorical variables effectively contributes to its superior and stable performance.

- TabTransformer outperforms all other models with the highest average score and low variability, demonstrating its effectiveness for this classification problem.

XGBoost, Random Forest, Logistic Regression, and SVM all show similar high performance with very stable results, indicating that they are reliable models. KNN and Naive Bayes also show consistent performance, though at a slightly lower level, with the Decision Tree showing slightly more variability but still delivering good results.

A confusion matrix is a useful tool in classification problems to identify where a model performs well and where it fails. Interpreting this matrix helps to understand which classes are better or worse predicted, which is crucial for identifying areas where the model needs improvement. The confusion matrices for the algorithms used in this study are shown in Table 7.

Table 7. Confusion matrix results

#	Algorithm	Evulation	0	1
1	Decision Tree	Actual 0	5465	174
		Actual 1	179	195
2	KNN	Actual 0	5569	70
		Actual 1	316	58
3	Naive Bayes	Actual 0	5568	71
		Actual 1	364	10
4	Logistic Regression	Actual 0	5639	0
		Actual 1	374	0
5	Random Forest	Actual 0	5615	25
		Actual 1	313	61
6	XGBoost	Actual 0	5633	6
		Actual 1	357	17
7	Support Vector Machine	Actual 0	5639	0
		Actual 1	374	0
8	TabTransformer	Actual 0	5600	39
		Actual 1	150	224

Summary of Model Performance in Distinguishing Positive and Negative Classes (from Table 7):

- Decision Tree:
  - True Positive (TP): 195
  - False Positive (FP): 174
  - False Negative (FN): 179
  - True Negative (TN): 5465
  - The Decision Tree model detects the positive class with reasonable accuracy, but both false positives and false negatives are somewhat high, indicating a need for improvement to reduce false alarms and missed detections.

KNN (K-Nearest Neighbors):
  - True Positive (TP): 58
  - False Positive (FP): 70
  - False Negative (FN): 316
  - True Negative (TN): 5569
  - The KNN model struggles to detect the positive class (low TP). The high number of false negatives indicates this issue. However, it does a good job of identifying the negative class.

Naive Bayes:
- True Positive (TP): 10
- False Positive (FP): 71
- False Negative (FN): 364
- True Negative (TN): 5568
- The Naive Bayes model almost fails to detect the positive class, missing a large number of positive examples.

Logistic Regression:
- True Positive (TP): 0
- False Positive (FP): 0
- False Negative (FN): 374
- True Negative (TN): 5639
- The Logistic Regression model fails completely to detect the positive class (TP = 0), missing all positive examples (FN = 374), making it impractical for use.

Random Forest:
- True Positive (TP): 61
- False Positive (FP): 25
- False Negative (FN): 313
- True Negative (TN): 5615
- The Random Forest model is somewhat more successful in detecting the positive class. The low false positive rate indicates that it produces fewer false alarms.

XGBoost:
- True Positive (TP): 17
- False Positive (FP): 6
- False Negative (FN): 357
- True Negative (TN): 5633
- The XGBoost model has a very low TP. The high false negative rate indicates that it struggles to detect positive examples.

Support Vector Machine (SVM):
- True Positive (TP): 0
- False Positive (FP): 0
- False Negative (FN): 374
- True Negative (TN): 5639
- Like Logistic Regression, the SVM model fails to detect the positive class (TP = 0), missing all positive examples, which severely limits its practical application.

TabTransformer:
- True Positive (TP): 224
- False Positive (FP): 39
- False Negative (FN): 150
- True Negative (TN): 5600

- Logistic Regression, Random Forest, XGBoost, and SVM models have high accuracy but struggle with the detection of positive classes, particularly Logistic Regression and SVM, which fail to detect any positives at all.
- The Decision Tree model has a balanced but less accurate performance, with room for improvement in reducing both false positives and false negatives.
- Naive Bayes and KNN show significant weaknesses in detecting positive classes, which suggests these models may need further refinement or may not be suitable for this particular classification problem.
- The TabTransformer model has the highest number of true positives (224) among all models, indicating a strong ability to correctly identify the positive class.

- The number of false negatives (150) is significantly lower compared to other models, meaning it misses fewer positive cases.
- The false positive rate is relatively low (39), showing that the model does not frequently misclassify negative instances as positive.
- The high true negative count (5600) confirms the model's effectiveness in correctly identifying negative cases.

4. RESULTS

This study investigated the efficacy of various machine learning algorithms to predict production quality in the metallurgy sector, particularly in cold rolling operations. We executed classification tasks using algorithms such as Decision Tree, K-Nearest Neighbors (KNN), Naive Bayes, Logistic Regression, Random Forest, XGBoost, Support Vector Machines (SVM), and the TabTransformer model, taking into account production parameters that influence quality performance.

The findings of the study indicate that the TabTransformer algorithm provided the highest accuracy rates and the most consistent results compared to other algorithms. TabTransformer, a transformer-based model designed specifically for tabular data, effectively captures complex feature interactions between numerical and categorical variables through its attention mechanisms. This allows the model to weigh the importance of different features dynamically, leading to superior predictive performance. The model not only achieved the highest accuracy but also demonstrated excellent precision, recall, and F1 scores, as well as the highest ROC AUC value, indicating strong discriminative power between classes. Random Forest and XGBoost also demonstrated strong performance among the traditional algorithms. The Random Forest algorithm, which operates on the principle of averaging the outcomes of multiple decision trees, is less affected by minor changes in the dataset and offers high generalization capability. XGBoost enhances the model's learning capacity and minimizes error rates by using powerful gradient boosting techniques. These algorithms contribute to automating quality control in production processes, reducing the need for human intervention and increasing production efficiency.

Additionally, the correlation analyses conducted on the dataset played a critical role in identifying the parameters that most significantly affect the quality class. The careful selection and modeling of these parameters during feature engineering contributed significantly to improving classification success. In particular, TabTransformer's ability to handle categorical features effectively allowed it to assign higher importance to key parameters such as the product group and alloy types, aligning with our initial correlation analysis. This enhanced interpretability helps in understanding the underlying factors affecting product quality, providing valuable insights for process optimization. In this context, properly processing the data obtained from sensors on the production line and modeling it with advanced algorithms like TabTransformer is essential for optimizing production quality. The model's superior performance not only improves predictive accuracy but also enhances the reliability of quality predictions, making it a valuable tool for industrial applications.

The findings of this study provide a solid foundation for the integration of advanced machine learning-based quality control systems, such as those utilizing transformer architectures, in cold rolling processes in the industry. Such systems will enable businesses to produce higher-quality products at lower costs and gain a competitive advantage. Future research could enhance the effectiveness of these systems by focusing on larger datasets, different production conditions, and various parameters. Overall, this study illustrates the practicality and efficiency of advanced machine learning algorithms, particularly transformer-based models like TabTransformer, in enhancing production quality and streamlining procedures in the metallurgical industry. The findings greatly contribute to the digitalization and automation of quality control operations in the sector.

This study has the potential to provide input to reverse engineering applications that can be realized over longer time periods. By estimating the quality of the produced product, the production conditions of poor-quality and high-quality products can be determined, and thus limit values can be set for the productions. With the limit values set, control limits are provided during production, preventing poor-quality production. This leads to cost savings, increased efficiency, and labor gains by reducing reprocessing times, additional operation times, and the use of other production consumables. This study presents an innovative approach to automating quality control in production processes using advanced machine learning algorithms. Unlike existing literature, this work provides a comparative analysis of various algorithms, including transformer-based models, and offers practical applications for quality improvements in industrial production processes. The superior performance of the TabTransformer model highlights the potential of transformer architectures in industrial applications, paving the way for further research and development in this area.

5. CONCLUSIONS

This study assessed the efficacy of different machine learning algorithms in predicting product quality during cold rolling procedures in the metallurgy industry. The study evaluated eight algorithms, including Decision Tree, KNN, Naive Bayes, Logistic Regression, Random Forest, XGBoost, Support Vector Machines, and TabTransformer, and identified TabTransformer as the most proficient model. This transformer-based algorithm not only attained the highest accuracy but also exhibited exceptional generalization abilities, rendering it especially appropriate for real-time quality control in production settings.

The feature importance analysis revealed that parameters such as product group, alloy types, and casting machines significantly influenced the model's predictions. The TabTransformer model effectively captured complex feature interactions and handled categorical variables more efficiently due to its attention mechanisms, leading to superior performance. While Random Forest and XGBoost also demonstrated strong performance, TabTransformer surpassed them by providing better predictive accuracy and interpretability.

Despite the promising results, this study has several limitations that should be acknowledged. First, the dataset used for training and evaluation was collected from a specific production environment with particular operational characteristics, which may limit the generalizability of our findings to other manufacturing contexts or different cold rolling setups. Second, while TabTransformer demonstrated superior performance, its computational complexity and training requirements are higher than traditional machine learning algorithms, potentially posing implementation challenges in resource-constrained environments. Third, our analysis focused primarily on classification performance and did not extensively explore the real-time deployment aspects, including latency considerations and integration with existing production systems. Fourth, the temporal stability of the models was not evaluated over extended periods, leaving questions about how frequently retraining might be required to maintain performance as production conditions evolve. Finally, the interpretability of the TabTransformer model, while better than some black-box approaches, still presents challenges for complete transparency in decision-making compared to simpler models like Decision Trees.

Overall, the findings suggest that the application of advanced machine learning techniques, particularly transformer-based models like TabTransformer, in production quality control can enhance decision-making, reduce human intervention, and optimize production efficiency. Future studies could build on this research by exploring larger datasets, more complex production environments, or additional transformer-based machine learning techniques to further refine quality control systems in industrial settings.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Yavuz Selim Balcıoğlu: Formal analysis, Writing - original draft, Visualization, Conceptualization, **Semih Göksu:** Formal analysis, Investigation, Conceptualization, **Bülent Sezen:** Supervision.

REFERENCES

[1] Marchi B, Zanoni S, Jaber MY. Economic production quantity model with learning in production, quality, reliability and energy efficiency. Computers & Industrial Engineering. 2019; 129: 502-511.

[2] Qorbani D, Grösser S. The impact of Industry 4.0 technologies on production and supply chains. arXiv preprint arXiv:2004.06983. 2020.

[3] Rüttimann BG, Stöckli MT. From batch & queue to industry 4.0-type manufacturing systems: a taxonomy of alternative production models. Journal of Service Science and Management. 2020; 13(2): 299-316.

[4] Carneiro F, Azevedo A. A six sigma approach applied to the analysis of variability of an industrial process in the field of the food industry. In: 2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM). December 2017: 1672-1679.

[5] Pulakanam V. Responsibility for product quality problems in sequential manufacturing: a case study from the meat industry. Quality Management Journal. 2011; 18(1): 7-22.

[6] Niemiec K, Krenczyk D. Selected quality indicators and methods of their measurement. In: IOP Conference Series: Materials Science and Engineering. August 2018; 400(2): 022039.

[7] Tchigirinsky J, Chigirinskaya N, Evtyunin A. Stability assessment methods of technological processes. In: MATEC Web of Conferences. 2021; 346: 03013.

[8] Kovac D, Vince T, Molnar J, Kovacova I. Modern Internet Based Production Technology. In: Er MJ, ed. New Trends in Technologies: Devices. Computer, Communication and Industrial Systems. In Tech; 2010. DOI: 10.10438.

[9] Wuest T, Weimer D, Irgens C, Thoben KD. Machine learning in manufacturing: advantages, challenges, and applications. Production & Manufacturing Research. 2016; 4(1): 23-45.

[10] Kang Z, Catal C, Tekinerdogan B. Machine learning applications in production lines: A systematic literature review. Computers & Industrial Engineering. 2020; 149: 106773..

[11] Sankhye S, Hu G. Machine learning methods for quality prediction in production. Logistics. 2020; 4(4): 35.

[12] Ramezani J, Jassbi J. Quality 4.0 in action: smart hybrid fault diagnosis system in plaster production. Processes. 2020; 8(6): 634.

[13] Maropoulos G. Advanced Data Collection and Analysis in Data Driven Manufacturing Process. Chinese Journal of Mechanical Engineering. 2020; 33(3): 32-52.

[14] Huang PX, Zhao Z, Liu C, Liu J, Hu W, Wang X. Implementation of an Automated Learning System for Non-experts. arXiv preprint arXiv:2203.15784. 2022.

[15] Eppinger SD, Huber CD, Pham VH. A methodology for manufacturing process signature analysis. Journal of Manufacturing Systems. 1995; 14(1): 20-34.

[16] Roh Y, Heo G, Whang SE. A survey on data collection for machine learning: a big data-ai integration perspective. IEEE Transactions on Knowledge and Data Engineering. 2019; 33(4): 1328-1347.

[17] Liang H, Sun X, Sun Y, Gao Y. Text feature extraction based on deep learning: a review. EURASIP Journal on Wireless Communications and Networking. 2017; 2017: 1-12.

[18] Wu H, Meng FJ. Review on evaluation criteria of machine learning based on big data. In: Journal of Physics: Conference Series. April 2020; 1486(5): 052026.

[19] Duan GJ, Yan X. A real-time quality control system based on manufacturing process data. IEEE Access. 2020; 8: 208506-208517.

[20] Bai Y, Li C, Sun Z, Chen H. Deep neural network for manufacturing quality prediction. In: 2017 Prognostics and System Health Management Conference (PHM-Harbin). July 2017: 1-5.

[22] Straat M, Koster K, Goet N, Bunte K. An Industry 4.0 example: Real-time quality control for steel-based mass production using Machine Learning on non-invasive sensor data. In: 2022 International Joint Conference on Neural Networks (IJCNN). July 2022: 01-08.

[23] Kara A. A hybrid prognostic approach based on deep learning for the degradation prediction of machinery. Sakarya University Journal of Computer and Information Sciences. 2021; 4(2): 216-226.

[24] Hatipoğlu A, Güneri Y, Yılmaz E. A comparative predictive maintenance application based on machine and deep learning. 2024.

ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2025, 26 (2) pp. 132-149, DOI: 10.18038/estubtda.1624909

RESEARCH ARTICLE

AUDIO COPY-MOVE FORGERY DETECTION WITH MACHINE LEARNING METHODS

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Abstract

Converting original sounds into fake sounds using various methods and using these sounds for fraud or misinformation purposes poses serious risks and threats. In this study, a classification system using machine learning methods is created and performance analysis is performed in order to detect sounds created with copy-move forgery, which is one of the types of sound forgery. Sound files are treated as raw data. Then, Mel-spectrograms are obtained to visually represent the spectral features of the sound over time. Logistic Regression, Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN) and XGBoost algorithms are used in the classification phase. As a result of the performance analysis of the created models, the highest success is achieved with the XGBoost algorithm. The performance of the XGBoost algorithm is further improved by performing hyperparameter optimization with the Random Search method. The results of the models are analyzed using various metrics. According to the study results, it is seen that it gives competitive results with the XGBoost algorithm.

Keywords

Audio,
Copy-Move Forgery,
Machine Learning,
XGBoost

Time Scale of Article

Received : 22 January 2025
Accepted : 13 June 2025
Online date :25 June 2025

1. INTRODUCTION

With the rapid development of the modern age, digital voices are used extensively in all areas of our lives. Voice recordings of individuals are strong evidence especially in legal and forensic cases. In such a case, it is of great importance to verify the authenticity of the voice recording. As a result of the rapid increase in technological innovations, it has become much easier to create fake voices. Unfortunately, even non-professionals can easily manipulate sounds and produce fake audio.

Given the growing ease with which audio can be manipulated, detecting forged or tampered audio has become a critical challenge. Traditional methods of authentication often fall short when dealing with subtle manipulations, necessitating the adoption of more advanced solutions. Machine learning techniques have emerged as powerful tools in this regard, capable of identifying patterns and anomalies in audio data that are imperceptible to human hearing. By leveraging these technologies, it is possible to build systems that automatically detect tampering with high accuracy, providing a robust solution in the face of increasingly sophisticated audio forgeries.

Machine learning methods have been used effectively in studies on the classification or detection of sound-based events. In a study from 2024, the classification process for hate speech detection from an audio file was performed using Support Vector Machines, Random Forest, eXtreme Gradient Boosting and multilayer perceptron (MLP). First, various features were extracted from the audio files and then

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machine learning methods were used to classify hate speech. The voices in the dataset consist of English and Kiswahili languages. While Random Forest gave the most successful result with 95.8% in the classification process using the voices in English language, XGB gave the most successful result with 91.8% in the classification process using the voices in Kiswahili language [1].

In another study carried out in 2024, sound classification was performed using “UrbanSound8K” and “Sound Event Audio Classification dataset” [2-3]. Mel-frequency cepstral coefficients (MFCC) feature extraction was applied to the “UrbanSound8K” dataset and STFT feature extraction process was applied to the “Sound Event Audio Classification dataset”. Both datasets were classified using Artificial Neural Network model, Logistic Regression, SVM, KNN, Naive Bayes, Decision Tree and RF algorithms. The datasets for which classification is performed have 10 and 8 different classes respectively. As a result of the study, the artificial neural network model gave the most successful result on both datasets with 91.41% and 91.27% respectively [4].

In 2021, a dataset consisting of real voices and computer-generated voices is used in a study to distinguish between fake and original voices [5]. In this study, two methods, feature-based classification and image-based classification, were created. Under the feature-based classification approach, 20 MFCCs were considered in addition to extracting various audio features in the feature extraction step. These features were then provided as input to machine learning algorithms. Within the scope of the study, five machine learning algorithms including SVM [6], Light Gradient-Boosting Machine (LGBM) [7], XGBoost [8], KNN [9], RF [10] were employed. GridSearchCV was used for parameter optimization. When the test results were analyzed, SVM algorithm gave the most successful result with 67% [11].

The techniques that researchers have developed as a solution to the challenges of digital voice authentication are divided into passive and active methods. The passive method is the detection of forgery through the signal itself and its characteristics. Active is the method of detecting this situation as a result of embedding certain information in the audio with various techniques. For example, active methods such as watermarking involve embedding additional information in the signal. In many cases, watermarks may not be able to detect areas that need to be deleted, and in some cases, counterfeiting can be done without serious damage to the watermark. For such a situation, passive forgery detection would be a more appropriate solution [12].

Copy-move forgery, which is one of the passive methods, is basically based on copying certain parts of a sound recording and moving them to another part within the same recording. By creating a fake audio recording in this way, the meaning of the phrase is completely changed [13]. Due to the methodology used, it is difficult to recognize the production of forged audio as a result of the changes made within the same audio recording. Therefore, an efficient and reliable method for detecting the authenticity of audio recordings is an important need in this field.

Copy-move forgery is a security threat on digital media. Unfortunately, audio files are also subject to such manipulations. One of the detection techniques for copy-move forgery is based on pitch similarity. Pitch is associated with the frequency of a sound and is a feature that allows the ranking of sounds based on their frequency [14]. In one of the studies, after the pitch sequences of the sound were extracted, a detection study was carried out as a result of calculations and comparison with threshold values [15]. In a study conducted to detect such forgeries, Discrete cosine transform (DCT) of audio signals and voice activity detection (VAD) algorithm are used together [16].

In a recent copy-move detection study, a fake audio file was created using the TIMIT dataset [17] [18]. Then, MFCC, delta-MFCC, delta-delta-MFCC and LPC data were obtained by feature extraction. Afterwards, the original and fake data detection process was performed with an artificial neural network. Tests were performed using various epoch numbers and batch sizes. From the results obtained, 76.48% test accuracy was achieved using 1500 epochs and batch size of 8 [19].

Considering all these, detecting copy-move forgery is of great importance for ensuring digital data security. In particular, the use of digital content as evidence in legal, commercial and social fields makes the detection of such forgeries more critical. For this reason, the development of reliable methods that can detect copy-move forgery is essential to preserve the authenticity and integrity of the audio recording. In this study, we use a copy and paste forgery dataset created using audio recordings of 100 people in different environments. The dataset was collected in 2024 using up-to-date technologies and designed to reflect real-life scenarios, allowing for effective analysis against modern copy-move forgery techniques. The 200 texts included in the dataset were either purposefully produced or carefully selected to be suitable for copy-move forgery, ensuring that no semantic or logical inconsistencies occur after manipulation. The texts incorporate various communicative functions such as requests, announcements, and informational messages, with linguistic and expressive features that vary depending on the assumed speaker and the topic. Furthermore, a wide range of sentence types affirmative, negative, interrogative, exclamatory, imperative are exemplified using simple, compound, sequential, and complex sentence structures. This diversity enables realistic testing of forgery detection methods and allows the evaluation of machine learning models in the context of linguistic variability. In addition to the contribution of a newly collected and linguistically diverse Turkish audio dataset for copy-move forgery detection, this study presents a systematic evaluation of several classical machine learning algorithms. While many recent approaches focus computationally expensive deep learning methods, our work offers a reproducible and computationally efficient classical ML baseline, which can be especially useful in settings where access to advanced computational resources is limited. With an optimized XGBoost model achieving reliable accuracy, the results demonstrate that well-tuned classical algorithms remain a viable and interpretable alternative for audio forgery detection tasks in resource-constrained environments. Within the scope of the study, six machine learning methods are used for forgery detection. The performance of machine learning methods on forgery detection is interpreted with the outputs obtained. The rest of the paper is as follows: Copy-move forgery is discussed in Section 2. The machine learning algorithms used in the study are given under Section 3. Examination of the dataset, feature selection and Mel-spectrogram for fake audio detection experimental outputs are analyzed in Section 4. Finally, Section 5 discusses the study with a conclusion.

2. COPY-MOVE FORGERY

Emerging artificial intelligence techniques have made it possible to imitate a person's voice, manipulate their speech, change the content of the speech or, in addition to all these, produce completely fake voices. The privacy of individuals is also threatened by voice forgery. In addition, individuals' speech recordings are used as evidence in courts of law.

Voice forgery is basically the alteration of original voice recordings using various techniques. In some cases, voice forgery is also performed by creating completely fake voices without manipulating the voice. Voice forgery can be performed using digital audio processing methods. Figure 1 shows the grouping scheme of digital audio forgery types.

As shown in Figure 1, audio forgery methods are primarily categorized as Active and Passive. In active audio forgery, certain information is embedded into the original audio using Digital Audio Watermarking, Digital Audio Signatures and Hash Values techniques shown in Figure 1. In this approach, in order to preserve the authenticity of the audio data, it is analyzed to determine whether there is any forgery in the audio recording by analyzing whether the pieces of information actively embedded in the audio are preserved. Passive analysis, on the other hand, focuses on the characteristics of the audio signals and does not require any extra information to be embedded. Audio copy-move, Audio Splicing and Audio Compression are passive audio analysis techniques [19]. Such methods are of great importance for analyzing audio manipulation or detecting audio forgery.

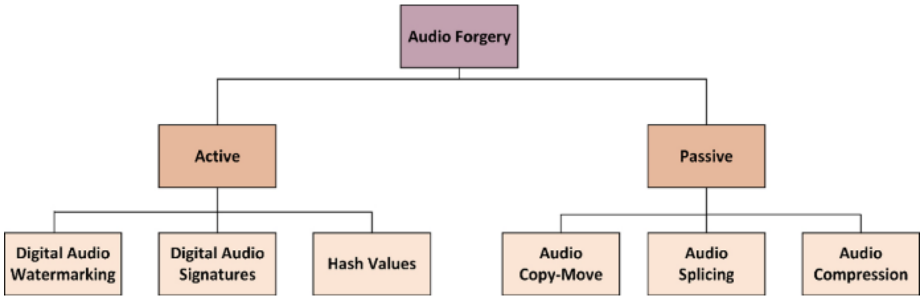


Figure 1. Types of voice forgery [19]

The copy-move method is one of the most common audio forgery techniques. In this method, the attacker copies some parts of a person's voice recording and pastes them into another part of the same voice recording. This type of forged data is usually not recognized as it is derived from the same speech recording. Detecting forged audio recordings only by listening to them without using any technical methods will result in time waste and low accuracy [20]. Figure 2 (a) and (b) show the time domain signals of the original and copy-move generated fake audio files, respectively. In Figure 2(b), the part where a different word is pasted with the copy-move method is marked with a red box. However, it should be noted that the pasted region is only identifiable when prior knowledge about the forgery location is available. Without such information, it is practically impossible to distinguish between the original and fake signals through visual inspection alone. Subtle spectral and temporal inconsistencies, phase discontinuities, and slight changes in background noise patterns introduced by the copy-move operation are not easily perceivable by the human eye in the time domain. Therefore, automatic detection relies on machine learning algorithms capable of analyzing fine-grained signal characteristics that are beyond human perception.

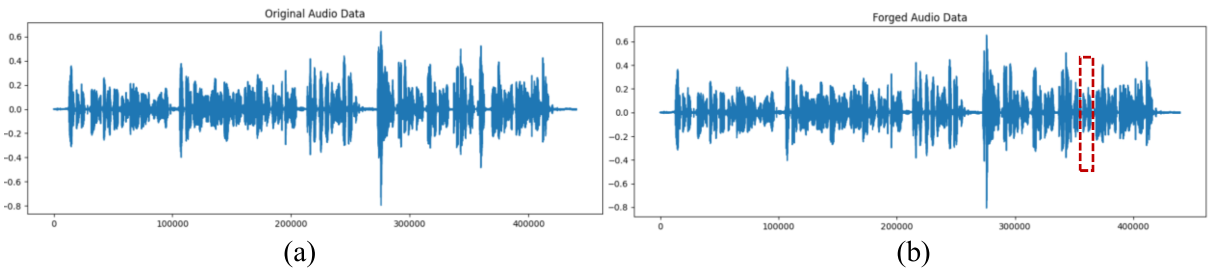


Figure 2. An example to copy-move forgery. Time signal of (a) original sound (b) fake sound.

The text of the data, whose original audio file is given in Figure 2 (a) in Turkish, reads as follows: “Bir isim fiil ile bir çekimli fiilin bir araya geliş ilişkilerinden, ortaya çıkan birimin cümlede ve bağlam içinde kazandığı değere kadar taşıdığı ipuçları bizi çok farklı yaklaşımlara sevk edebilir. Bu bağlamda Trabzon ağızlarının fiil şekilleri ve özellikle zarf fiiller açısından ele alınması önem kazanır.” The data of the fake voice obtained with the copy-move method is given in Figure 2(b) and its text is as follows: Bir isim fiil ile bir çekimli fiilin bir araya geliş ilişkilerinden, ortaya çıkan birimin cümlede ve bağlam içinde kazandığı değere kadar taşıdığı ipuçları bizi çok farklı yaklaşımlara sevk edebilir. Bu bağlamda Trabzon ağızlarının fiil şekilleri ve özellikle ~~zarf~~ isim fiiller açısından ele alınması önem kazanır."

Copy-move audio forgery analysis can detect internal manipulations of an audio recording. Especially in legal investigations, it is very important to determine the reliability of the audio recording. Therefore, such analysis is necessary to ensure the reliability of audio recordings.

3. MACHINE LEARNING ALGORITHMS

3.1. Logistic Regression

Logistic Regression (LR) is characterized as both a regression and a classification algorithm. However, it is generally used for binary classification problems. It is one of the most frequently used supervised machine learning algorithms [21] [22].

This algorithm can be used, for example, to predict whether a person is “sick” or “healthy”. Logistic regression estimates the probability and performs the classification process using this probability. In other words, the predicted value is compared with a threshold value and classification is performed. Due to its simple and straightforward structure, it is one of the first preferred algorithms in classification studies. Figure 3 illustrates the decision boundary of the LR classifier. The model estimates the probability that a given input belongs to one of two classes using a sigmoid function. Data points located near the lower end of the curve are classified into one class (orange circles), while those near the upper end are classified into the other (blue circles). The nonlinear S-shaped curve reflects the gradual probability transition across the feature space, with the decision boundary typically set at a probability threshold of 0.5.

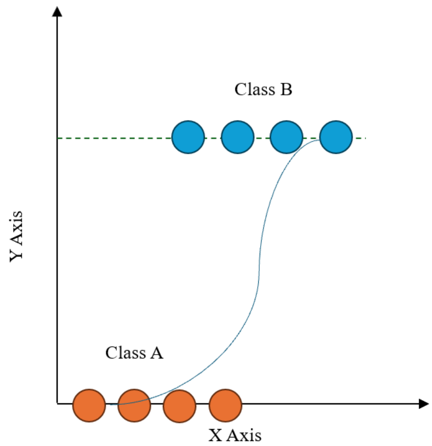


Figure 3. Binary Classification with LR algorithm [23]

3.2. Support Vector Machine (SVM)

SVM is one of the supervised machine learning algorithms developed in the 1990s. It can be used in various tasks such as classification and regression. The main goal of the algorithm is to find the hyperplane that provides the most optimal separation of data points. That is, the distance between the hyperplane and the data points closest to the boundary should be maximum. This system provides a more accurate separation of classes and a better classification of incoming data [6] [24] [25]. The data classification representation of the support vector machines algorithm is given in Figure 4.

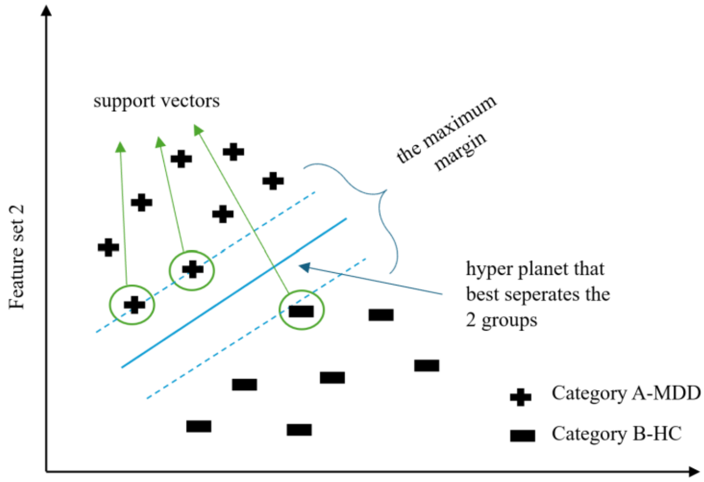


Figure 4. Demonstration of the separation of data into two classes with SVM (where the classes are Major depressive disorder (MDD) and Healthy controls (HC) [26].

When the figure is analyzed, firstly, the two axes of the graph represent certain features belonging to two different classes. Classification is done based on these features. According to the algorithm, a hyperplane is drawn to separate these data in the best way. The maximum margin represents the plane that widens the difference between the groups the most. The data points on this margin are defined as support vectors.

3.3. Random Forest (RF)

RF, proposed in 2001, is one of the most widely used machine learning algorithms for classification and regression problems. RF consists of multiple decision trees. Randomization is used to generate multiple decision trees. In accordance with the type of problem, the output of the trees are combined into a single result using voting for classification and averaging for regression [10] [27] [28]. The basic representation of the RF algorithm is given in Figure 5.

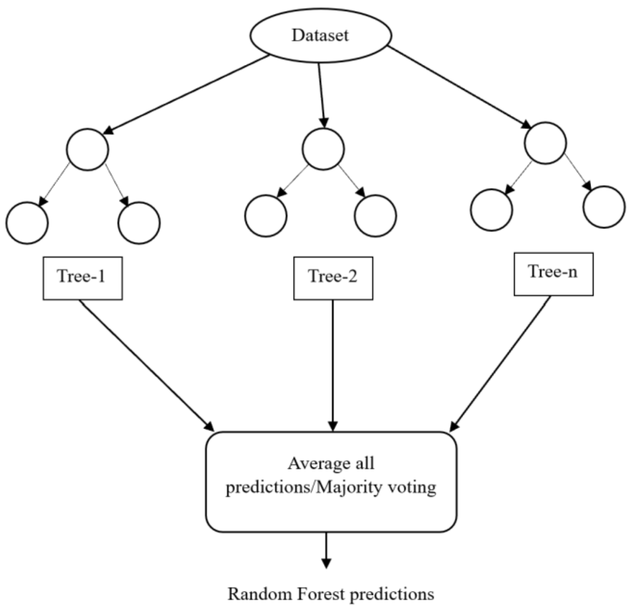


Figure 5. Structure of Random Forest [29] [30].

When Figure 5, which explains the basic structure of Random Forest, is examined, each tree produces a prediction in classification problems. The class that reaches the majority among the trees is considered as the prediction result of the model. If the problem is a regression problem, the model result is obtained by averaging the prediction results. The random forest algorithm provides diversity and improves prediction performance by using multiple trees instead of a single tree.

3.4. K-Nearest Neighbors (KNN)

KNN is one of the supervised learning algorithms used in classification and regression problems. The basic logic of the algorithm is that when making a decision about a data point, other data surrounding it is considered. Therefore, the entire training data set is consulted during classification. The decision to classify each new data point is made by using all the examples in the data set.

When determining which class a new data point belongs to, the class of the *K* closest data points belonging to that data point is considered. The class to which the most data belongs is the class of the new data point. The *K* value is usually chosen as a small integer value such as 3 and 5. In the KNN algorithm, Euclidean distance calculation is usually used to measure the distance between data. Euclidean distance is the distance calculated along a straight line between two points. This means that data with the same class label are close to each other in terms of distance [9] [31]. Figure 6 shows a basic representation of the KNN algorithm.

Figure 6, where the classification process is performed using the KNN algorithm, shows two classes consisting of blue squares and green circles. The data to be classified is indicated by the black plus symbol. The k value of the algorithm is set to 3. Therefore, the three closest neighbors of the data to be classified are examined. Two of the examined neighbors belong to class A and one belongs to class B. For this reason, our data is included in class A.

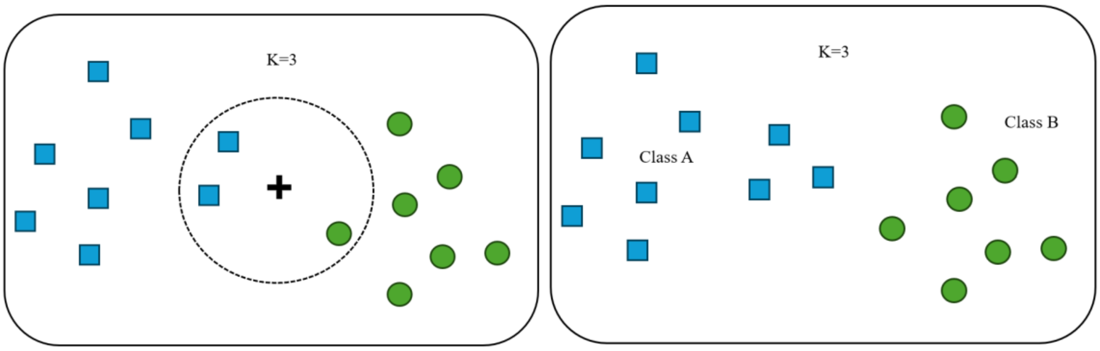


Figure 6. Demonstration of basic classification with KNN algorithm.

3.5. Extreme Gradient Boosting (XGBoost)

XGBoost was developed by Chen et al [8]. This method is a scalable implementation of gradient boosting machines. Boosting is an ensemble method where new models are added to correct the errors of the models. The added models are added recursively until a significant improvement is seen in the result. Gradient boosting is an algorithm in which the errors of previous models are estimated and determined, and new models are developed and combined to form the outcome prediction. A gradient descent algorithm is used to minimize the loss when adding new models.

In order to achieve an optimal result, the parameters of the XGBoost algorithm should be set correctly. This is quite difficult as XGBoost has a large number of parameters. "Grid Search" or 'Random Search' methods are used for the parameter tuning task. In this study, "Random Search" technique is used for hyperparameter tuning of XGBoost algorithm. The random search method usually shows a fast performance [8] [32] since it tries on a certain number of random samples instead of trying all combinations. A basic illustration of the XGBoost algorithm is given in Figure 7.

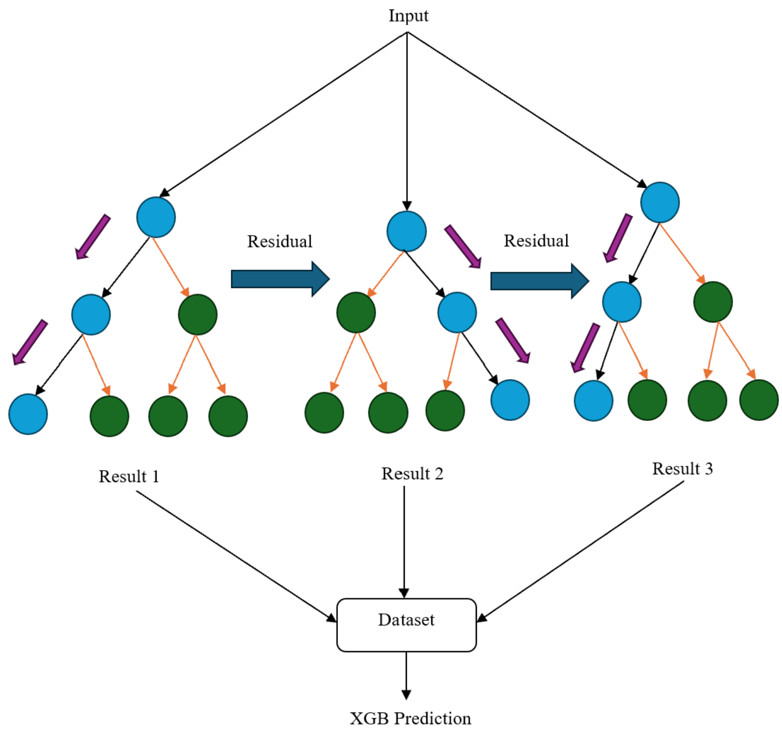


Figure 7. XGBoost [33]

Figure 7, which shows the fundamental operation of XGBoost, shows that a new tree is added to the model to eliminate the error generated by the previous tree. This process improves the performance of the model. This process continues for several cycles until no further improvement is achieved or until the number of trees reaches a specified upper limit.

4.EXPERIMENTAL RESULTS

4.1. Dataset

The data set used in this study consists of 100 different people, 50 women and 50 men, reading 200 different texts. The texts were read in three different environments: office, cafeteria and quiet room. The ages of the speakers are 50 people between 18-25 years old, 30 people between 25-35 years old and 20 people between 35-55 years old. The audio files have a sampling rate of 44.1 kHz and 16-bit coding. The voice files are in wav format.

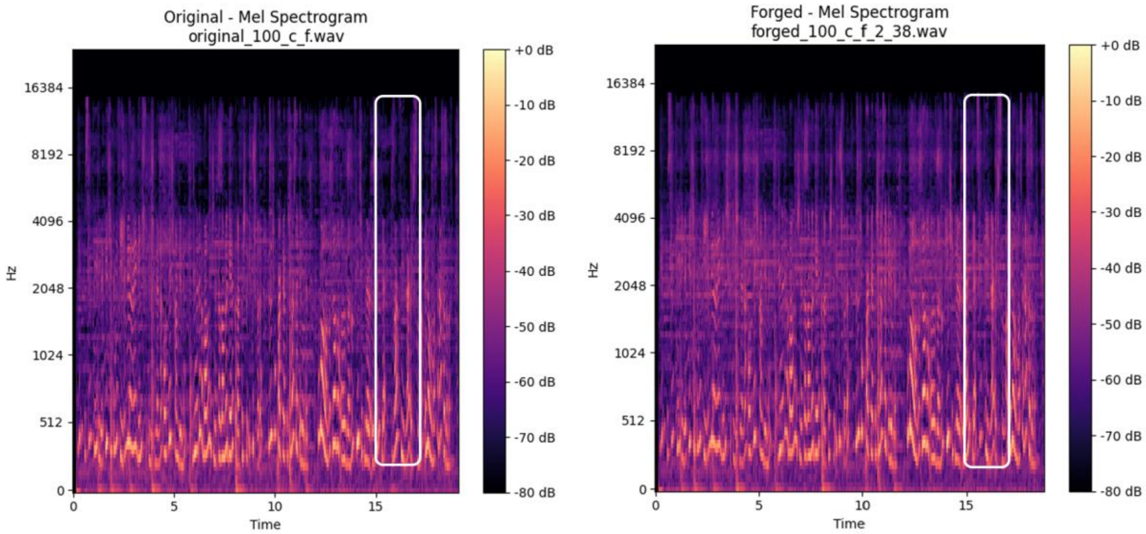
Within the scope of the dataset, fake voices are created by copy-move method using the original voice recordings. First, Matlab's speech2text tool is used to detect the beginning and end of the words in the original voices. Then, word pairs are determined for the copy and paste process. Thus, fake audio recordings are created by copy-paste forgery. Table 1 gives a detailed representation of the dataset [34].

Table 1. Distribution of the dataset used in the study

Environment	Voice recording counts	
	Original	Fake
Office	200	349
Cafe	200	349
Quiet room	200	349

As can be seen in Table 1, each environment has 200 original voice recordings. A total of 600 original audio recordings were used to generate 1047 fake voices. Since the sounds were taken in three different environments, the noise levels may vary.

Extracting features is an important step to study and analyze audio signals. In this study, the mel-spectrogram feature is considered. The mel spectrogram represents the frequency components of audio signals similar to human hearing. It is effective in time-frequency analysis of audio signals. In order to classify audio signals, audio files are visualized with mel spectrogram. Sample mel-spectrogram representations of the sounds in the dataset are given in Figure 8.



(a) (b)

Figure 8. Mel-spectrogram representation a) original sound b) fake sound

In this study, mel-spectrograms were computed using a window size (win_length) of 2048 samples and a hop length of 512 samples, which corresponds to approximately 10.67 milliseconds of temporal resolution at a 48 kHz sampling rate. A 2048-point FFT was applied with a Hann window function to reduce spectral leakage. These settings allow for a detailed time-frequency analysis suitable for capturing subtle manipulations in the audio signals. Mel-spectrograms show the change of the audio signal over time. The horizontal axis shows time and the vertical axis shows frequency components. Figure 8(a) shows the mel-spectrogram representation of the original audio file with the file name 'original_100 c_f', while Figure 8(b) shows the mel-spectrogram representation of the forged audio file named 'forged_100_c_f_2_38' obtained using the same audio file. Mel-spectrograms visually show how the energy of a sound signal is distributed across its frequency components over time, and as a result, such manipulations can sometimes lead to spectral anomalies. In particular, the addition of the copied region can create inconsistencies in frequency components, as well as noticeable repetitions or discontinuities along the time axis. These issues may manifest in the mel-spectrogram as differences in color intensity or spectral patterns. However, factors such as the scale of the manipulation and the similarity of the audio source can affect the visibility of these changes. Small-scale manipulations may create subtle differences, making it difficult to detect them visually. Therefore, detecting such forgery may not always be possible through traditional visual inspection, which is why more precise and automated machine learning algorithms are needed.

4.2. Fake Voice Detection with Mel-spectrogram Feature

After extracting the mel-spectrogram features of both original and fake audio files in the dataset, machine learning methods are used to classify the original and fake audio. Figure 9 shows a flow diagram of the study.

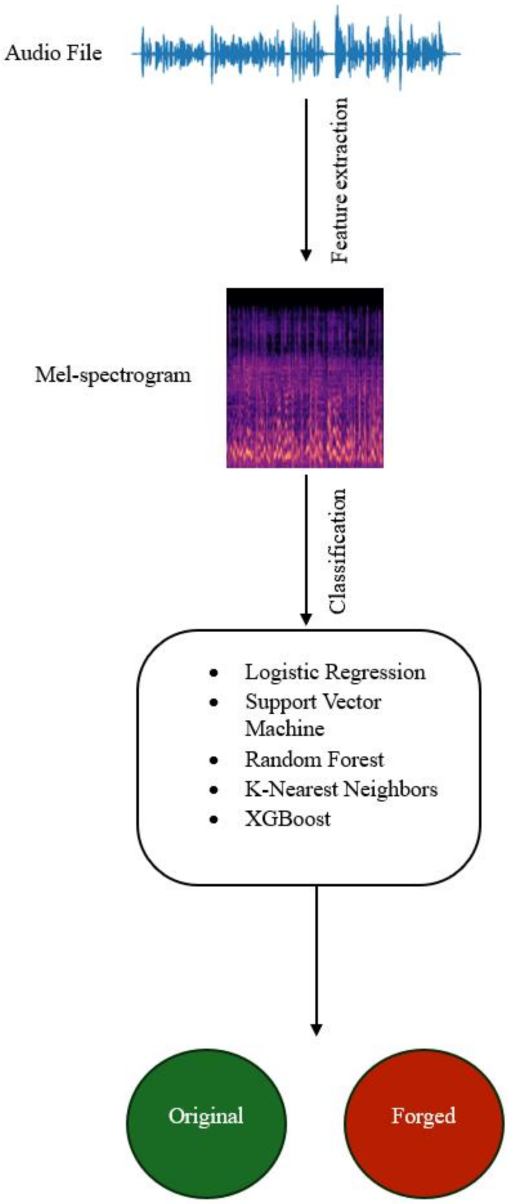


Figure 9. Real and forged audio classification flow diagram

The steps of forgery detection from an audio file are given in Figure 9. First, the audio file is received as input to the system as raw data. Then, the raw audio signal is analyzed with time and frequency components and converted into a Mel-spectrogram. Using the Mel-spectrogram, the changes of the sound over time are presented visually. This feature is then presented as input to machine learning algorithms. The classification step indicated in the diagram involves different machine algorithms. These are LR, SVM, RF, KNN and XGBoost algorithms. The most successful result among the algorithms was obtained with XGBoost. Parameter tuning is performed with 'Random Search' to improve the performance of the XGBoost algorithm. While LR makes a probabilistic classification, SVM aims to find the hyperplane that best classifies the data. On the other hand, decision tree-based algorithms such as RF and XGBoost provide high accuracy on complex data structures. Finally, KNN performs the classification process based on the nearest neighbors of the data. According to the results of these algorithms, it is finally determined whether the sound is original or fake. Parameters of the algorithms used in the study are shown in Table 2.

Table 2. Hyperparameters of the algorithms used in the study

Methods	Hyperparameters	Definition
Logistic Regression	• max_iter=100 • solver='lbfgs' • tol=1e-4 • class_weight= None	• Maximum number of iterations. • Optimization algorithm used: 'lbfgs' • Stopping criterion of optimization • It is used to determine the weights of the classes. The default value is None and each class has equal weight.
Support Vector Machine	• kernel='rbf' • C=1.0	• The kernel function • The penalty parameter
Random Forest	• ntree=100	• The number of trees
K-Nearest Neighbors	• K=5 • weights: uniform	• Number of neighbors • Weight function used in prediction
XGBoost	• max_depth=6 • colsample_bytree=1 • subsample=1 • learning_rate=0.3 • n_estimators=100	• Maximum depth of a tree • Subsample ratio of columns when constructing each tree • Subsample ratio of the training instance • Control the learning rate • Number of trees
XGBoost (XGBoost with hyperparameters tuned using Random Search)	• n_estimators= [100, 200, 300] • learning_rate= uniform (0.01,0.2) • max_depth= [3,5,7] • subsample=uniform (0.7, 1.0) • colsample_bytree=uniform (0.7, 1.0)	• Number of trees • Control the learning rate • Maximum depth of a tree • Subsample ratio of the training instance • Subsample ratio of columns when constructing each tree

In this study, the XGBoost algorithm used for audio forgery detection was optimized using the Random Search method. This approach involved performing random searches over various hyperparameters to maximize the model's performance. The parameters used include 'n_estimators' (100, 200, 300) to determine the number of trees, 'learning_rate' (random between 0.01 and 0.2) to control the learning rate, 'max_depth' (3, 5, 7) to limit the tree depth, 'subsample' (random between 0.7 and 1.0) to define the sample ratio for each tree, and 'colsample_bytree' (random between 0.7 and 1.0) to define the feature selection ratio for each tree. Each of these hyperparameters was carefully selected and optimized to improve the overall performance of the model.

Figure 10 shows the Confusion Matrix outputs obtained to evaluate the classification performance of the algorithms. Confusion matrix is an evaluation tool used to analyze the performance of a machine learning model and shows the true and false classifications of the model in a quantitative table.

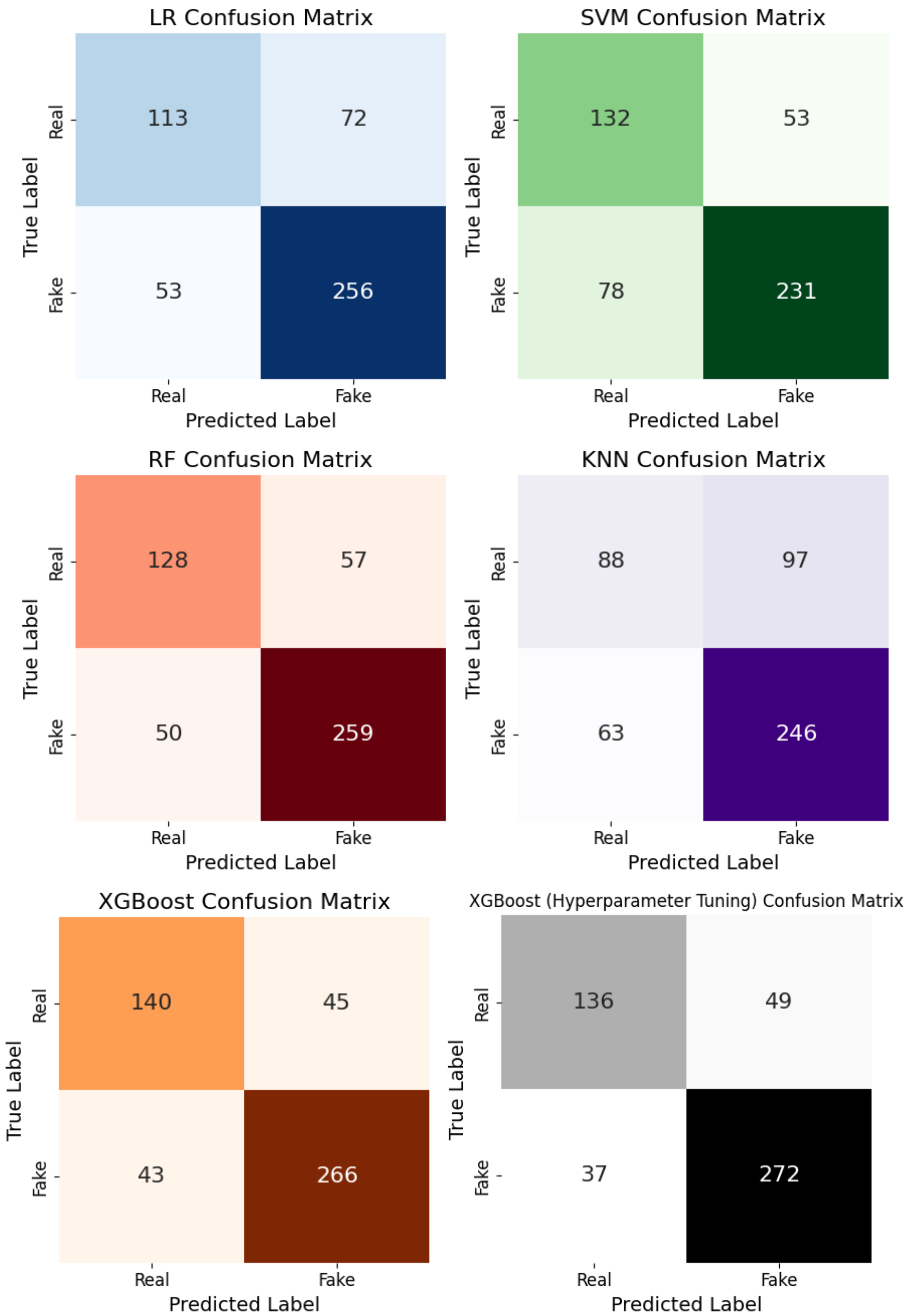
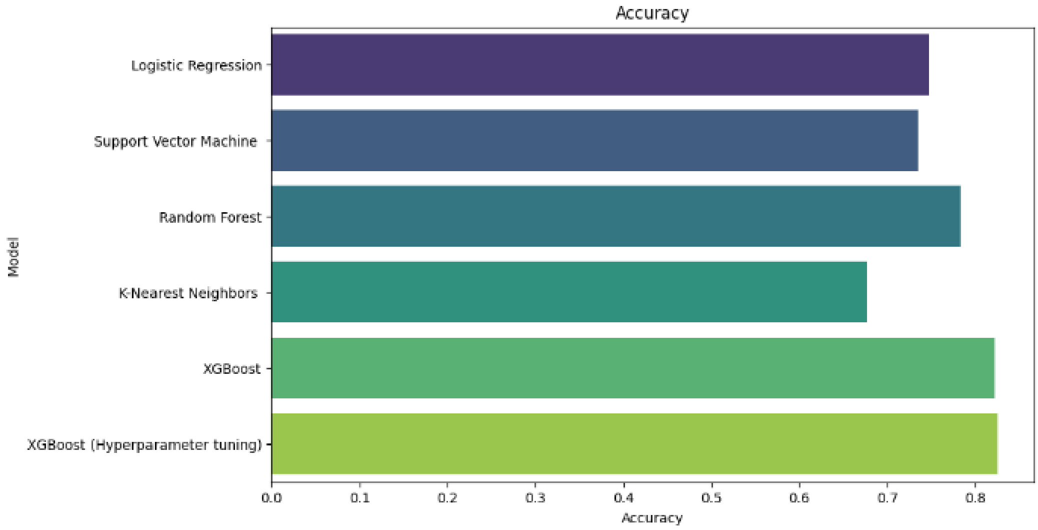
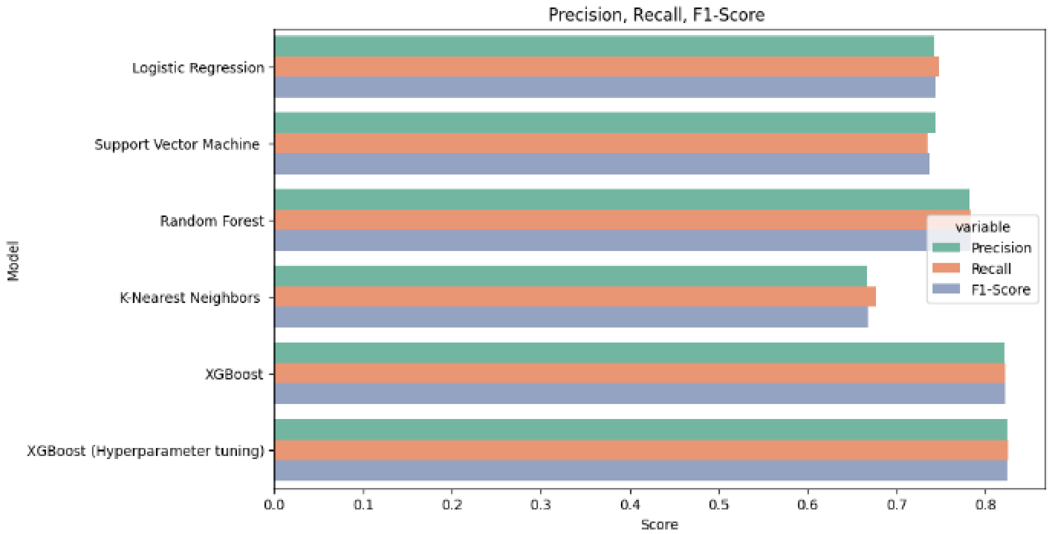


Figure 10. Confusion matrices

A detailed analysis of the confusion matrices reveals that the XGBoost model with hyperparameter optimization achieves the highest number of true positive predictions (272) and the lowest number of false negatives (37) among all evaluated models, indicating an enhanced capability in correctly detecting fake audio samples. Although the default XGBoost model exhibits the lowest false positive count (45), the overall trade-off between false positives and false negatives appears more balanced in the hyperparameter-tuned model. This balance is particularly important in forgery detection tasks, where minimizing both types of errors contributes significantly to the reliability of the classification system. Therefore, the hyperparameter-tuned XGBoost model demonstrates a comparatively more favorable performance profile, suggesting its potential suitability for practical deployment in audio forgery detection scenarios. The results of other metrics calculated based on the confusion matrices are shown in Figure 11.



(a)



(b)

Figure 11. Comparisons of the models (a) accuracy score (b)precision, recall, f1 score

Figure 11(a) presents the overall accuracy scores of the evaluated models, while Figure 11(b) provides a comparative analysis of their Precision, Recall, and F1-Score metrics. As can be observed, the XGBoost and hyperparameter-tuned XGBoost models consistently outperform the other algorithms across all evaluation metrics. Notably, the hyperparameter-tuned XGBoost model achieves the highest F1-Score (0.8247), indicating a balanced and reliable classification performance between precision and recall. In contrast, the K-Nearest Neighbors (KNN) model demonstrates the lowest performance across all metrics, with an accuracy of 67.61% and a corresponding decline in precision (66.69%), recall

(67.61%), and F1-Score (66.82%). This suggests that KNN may not effectively capture the underlying structure of the audio forgery data in this study. The numerical results, summarized in Table 3, further highlight that while Random Forest (RF) and Support Vector Machine (SVM) models show competitive precision values, they lag slightly behind XGBoost-based methods in terms of recall and F1-Score. Considering the relatively high F1-Score values obtained with XGBoost models, it can be inferred that these methods offer a more robust balance between correctly identifying forged audio samples and minimizing false alarms. Overall, these findings reinforce the suitability of ensemble-based approaches, particularly optimized XGBoost models, for the detection of copy-move forgeries in audio data, especially when computational efficiency and interpretability are also prioritized.

Table 3. Test results of the models.

Model	Accuracy	Precision	Recall	F-1 score
LR	0.7470	0.7431	0.7470	0.7439
SVM	0.7348	0.7442	0.7348	0.7376
RF	0.7733	0.7707	0.7733	0.7713
KNN	0.6761	0.6669	0.6761	0.6682
XGBoost	0.8219	0.8215	0.8219	0.8217
XGBoost (tuned)	0.8259	0.8244	0.8259	0.8247

The Receiver Operating Characteristic (ROC) curve is a widely used tool for evaluating the performance of classification models. It shows the trade-off between the true positive rate and the false positive rate across various thresholds. The closer a model's ROC curve is to the upper left corner of the graph, the better the classification performance. Further, the Area Under the Curve (AUC) value provides a scalar metric that gives a single metric summarizing the overall effectiveness of the model, with higher AUC values indicating better performance.

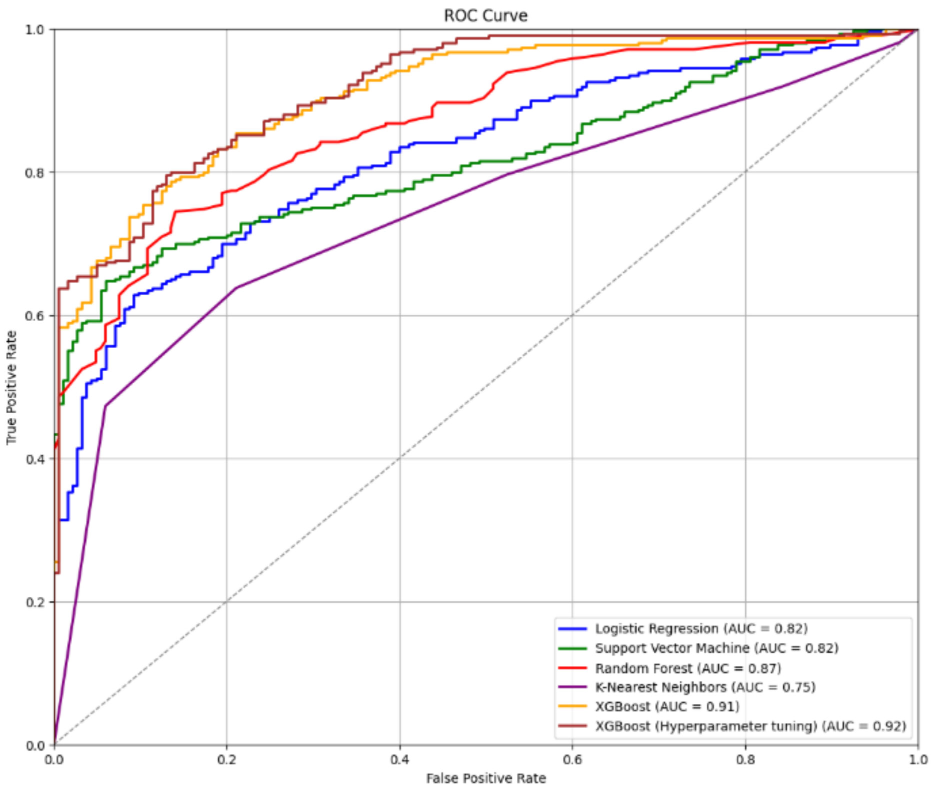


Figure 12. ROC curve

Figure 12 presents the ROC curves for the six classification algorithms used in this study. Analyzing the ROC curves in Figure 12, it can be seen that the XGBoost algorithm with hyperparameter tuning achieves the best performance and its curve is closer to the upper left corner than the others. This observation is supported by the AUC value of 0.92, which is higher than the other models. The standard XGBoost implementation also performs strongly (AUC = 0.91), followed by Random Forest (AUC = 0.87). In contrast, SVM and Logistic Regression models show moderate performance with the same AUC values of 0.82, while KNN shows the lowest AUC value of 0.75, indicating relatively weaker classification ability. The XGBoost (hyperparameter tuning) model stands out as the most successful model, achieving the highest results in all metrics. Random Forest and XGBoost models also show balanced performances. KNN gives the lowest results in all metrics compared to other models. Depending on the application area, the metrics that should be emphasized may change.

These results highlight the effectiveness of hyperparameter tuning in improving model performance, as demonstrated by the significant improvement of XGBoost after tuning. Furthermore, the comparison between the algorithms highlights the importance of choosing not only the right classification method but also the optimal parameter configuration for robust audio forgery detection.

Many studies on audio forgery detection in the literature have been conducted using outdated datasets, which often fail to reflect modern audio manipulation techniques; Table 4 summarizes the information about these studies. The KTUCengAudioForgerySet, with its up-to-date structure, enables more accurate and reliable results in forgery detection. This dataset contains comprehensive and rich examples designed to model contemporary audio forgeries, and its inclusion of both original and forged audio files allows for more reliable analyses.

Table 4. Summary of Studies on Audio Copy-Move Forgery Detection

Study	Methods	Dataset
Akdeniz & Becerikli (2024) [19]	MFCCs, MFCCs, MFCCs, MFCC + MFCC + MFCCs, and LPCs	TIMIT database (1993)
Su et al. (2023) [35]	CQCC, sliding window	Chinese speech and LibriSpeech dataset (2015)
Yan et al. (2019) [36]	Pitch feature and formant feature	Wall Street Journal(WSJ) speech database (1992) TIMIT database (1993)
Imran et al. (2017) [37]	1D LBP	King Saud University Arabic Speech Database (2014)
Our study	**XGBoost (hyperparameters tuned using Random Search) with Mel spectrogram features**	**KTUCengAudioForgerySet (2024)**

5. CONCLUSION

In this study, the results of machine learning based models developed for voice forgery detection are analyzed. Comparisons between different algorithms show that XGBoost provides the highest success rate and has a balanced performance in terms of both precision and recall. In particular, the Random Search method applied for the hyperparameter tuning of XGBoost increased the accuracy of the model. The use of Mel-spectrograms for analyzing audio data within the scope of the study helps to understand the structure of the voice and to make an accurate classification in forgery detection. Audio forgery is a significant threat in the digital age. In this context, techniques such as "copy-move forgery" can be applied to audio files to easily obtain and use fake voices, creating more risk. The results emphasize that XGBoost is more effective in audio forgery detection than other machine learning models. In addition, this study lays the groundwork for future work and research on analyzing audio data. Integration of different feature extraction methods or model development to improve performance for more complex and real-world problems will provide guidance for future studies. The increasing accessibility of audio manipulation tools raises ethical concerns, particularly regarding the potential misuse of forged audio in malicious or deceptive contexts. Moreover, the risk of false positives in detection systems could lead to unintended consequences, especially in sensitive applications such as legal or forensic investigations. Therefore, while developing detection systems, it is crucial to balance technical performance with considerations of fairness, transparency, and responsible use. In future work, the dataset will be expanded to include a wider range of audio samples, enabling the application of more complex models. This extension will allow for the integration of deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which are well-suited to capturing intricate temporal and spectral patterns in audio data. These models are expected to improve forgery detection performance, particularly in more diverse and realistic scenarios.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Merve Arslan: Software, Visualization, Data Curation, Writing – Original Draft, Writing – Review & Editing **Şerif Ali Sadık:** Conceptualization**,** Methodology, Visualization, Writing – Review & Editing.

REFERENCES

[1] Imbwaga JL, Chittaragi NB, Koolagudi SG. Automatic hate speech detection in audio using machine learning algorithms. Int J Speech Technol 2024; 27(2): 447-469.

[2] Salamon J, Jacoby C, Bello JP. A dataset and taxonomy for urban sound research. In: 22nd ACM International Conference on Multimedia; Nov 2014; pp. 1041-1044. Retrieved 14 December 2020 from https://urbansounddataset.weebly.com/urbansound8k.html.

[3] Chathuranga S. Sound Event Dataset. [Online]. Retrieved 14 December 2020 from https://github.com/chathuranga95/SoundEventClassification.

[4] Gourisaria MK, Agrawal R, Sahni M, Singh PK. Comparative analysis of audio classification with MFCC and STFT features using machine learning techniques. Discov Internet Things 2024; 4(1): 1.

[5] Reimao R, Tzerpos V. For: a dataset for synthetic speech detection. In: 2019 International Conference on Speech Technology and Human–Computer Dialogue (SpeD); 2019. IEEE; pp. 1-10.

[6] Evgeniou T, Pontil M. Support vector machines: theory and applications. In: Advanced Course on Artificial Intelligence. Berlin: Springer; 1999. pp. 249-257.

[7] Ke G, Meng Q, Finley T, Wang T, Chen W, Ma W, Ye Q, Liu T-Y. Lightgbm: a highly efficient gradient boosting decision tree. Adv Neural Inf Process Syst 2017; 30: 3146-3154.

[8] Chen T, Guestrin C. Xgboost: a scalable tree boosting system. In: 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; 2016. pp. 785-794.

[9] Guo G, Wang H, Bell D, Bi Y, Greer K. KNN model-based approach in classification. In: OTM Confederated International Conferences on the Move to Meaningful Internet Systems. Berlin: Springer; 2003. pp. 986-996.

[10] Breiman L. Random forests. Mach Learn 2001; 45(1): 5-32.

[11] Khochare J, Joshi C, Yenarkar B, Suratkar S, Kazi F. A deep learning framework for audio deepfake detection. Arab J Sci Eng 2021; 1-12.

[12] Gupta S, Cho S, Kuo CCJ. Current developments and future trends in audio authentication. IEEE Multimedia 2011; 19(1): 50-59.

[13] Ustubioglu B, Tahaoglu G, Ulutas G. Detection of audio copy-move-forgery with novel feature matching on Mel spectrogram. Expert Syst Appl 2023; 213: 118963.

[14] Klapuri A, Davy M. Signal processing methods for music transcription. Springer; 2006. ISBN 978-0-387-30667-4.

[15] Yan Q, Yang R, Huang J. Copy-move detection of audio recording with pitch similarity. In: 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); Apr 2015. IEEE; pp. 1782-1786.

[16] Wang F, Li C, Tian L. An algorithm of detecting audio copy-move forgery based on DCT and SVD. In: 2017 IEEE 17th International Conference on Communication Technology (ICCT); Oct 2017. IEEE; pp. 1652-1657.

[17] Garofolo JS, Lamel LF, Fisher WM, Fiscus JG, Pallett DS. DARPA TIMIT acoustic-phonetic continuous speech corpus CD-ROM. NIST Speech Disc 1-1.1. NASA STI/Recon Tech Rep N 1993; 93: 27403.

[18] Akdeniz F, Becerikli Y. Detection of copy-move forgery in audio signal with mel frequency and delta-mel frequency kepstrum coefficients. In: 2021 Innovations in Intelligent Systems and Applications Conference (ASYU); 2021. IEEE; pp. 1-6.

[19] Akdeniz F, Becerikli Y. Detecting audio copy-move forgery with an artificial neural network. Signal Image Video Process 2024; 18(3): 2117-2133.

[20] Yan Q, Yang R, Huang J. Robust copy-move detection of speech recording using similarities of pitch and formant. IEEE Trans Inf Forensics Secur 2019; 14(9): 2331-2341.

[21] Shah K, Patel H, Sanghvi D, Shah M. A comparative analysis of logistic regression, random forest and KNN models for the text classification. Augment Hum Res 2020; 5(1): 12.

[22] Yang Z, Li D. Application of logistic regression with filter in data classification. In: 2019 Chinese Control Conference (CCC); Jul 2019. IEEE; pp. 3755-3759.

[23] Mondal PK, Foysal KH, Norman BA, Gittner LS. Predicting childhood obesity based on single and multiple well-child visit data using machine learning classifiers. Sensors 2023; 23(2): 759.

[24] Vapnik VN. The Nature of Statistical Learning Theory. 2nd ed. Springer Verlag; 1995. pp. 1-20.

[25] Kotsiantis SB. Supervised machine learning: a review of classification techniques. Informatica 2007; 31: 249-268.

[26] Schnyer DM, Clasen PC, Gonzalez C, Beevers CG. Evaluating the diagnostic utility of applying a machine learning algorithm to diffusion tensor MRI measures in individuals with major depressive disorder. Psychiatry Res Neuroimaging 2017; 264: 1-9.

[27] Biau G, Scornet E. A random forest guided tour. Test 2016; 25: 197-227.

[28] Rigatti SJ. Random forest. J Insur Med 2017; 47(1): 31-39.

[29] Sahour H, Gholami V, Torkaman J, Vazifedan M, Saeedi S. Random forest and extreme gradient boosting algorithms for streamflow modeling using vessel features and tree-rings. Environ Earth Sci 2021; 80: 1-14.

[30] Kiranmai SA, Laxmi AJ. Data mining for classification of power quality problems using WEKA and the effect of attributes on classification accuracy. Prot Control Mod Power Syst 2018; 3(3): 1-12.

[31] Bramer M. Principles of data mining. Springer; 2007.

[32] Ogunleye A, Wang QG. XGBoost model for chronic kidney disease diagnosis. IEEE/ACM Trans Comput Biol Bioinform 2019; 17(6): 2131-2140.

[33] Wang CC, Kuo PH, Chen GY. Machine learning prediction of turning precision using optimized XGBoost model. Appl Sci 2022; 12(15): 7739.

[34] Ustubioglu B, Tahaoglu G, Ayaz GO, Ustubioglu A, Ulutas G, Cosar M, Kılıc M. KTUCengAudioForgerySet: a new audio copy-move forgery dataset. In: 2024 47th International Conference on Telecommunications and Signal Processing (TSP); Jul 2024. IEEE; pp. 123-129.

[35] Su Z, Li M, Zhang G, Wu Q, Wang Y. Robust audio copymove forgery detection on short forged slices using sliding window. Journal of Information Security and Applications, 2023; 75, 103507.

[36] Yan Q, Yang R, Huang J. Robust copy-move detection of speech recording using similarities of pitch and formant. IEEE Trans. Inform. Forensics Secur., 2019;4(9), 2331–2341.

[37] Imran M, Al Z, Bakhsh ST, Akram S. Blind detection of copy-move forgery in digital audio forensics. IEEE Access, 2017; 5, 12843–12855.

ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2025, 26 (2) pp. 150-160, DOI: 10.18038/estubtda.1635458

RESEARCH ARTICLE

INTEGRATION OF TRIGONOMETRIC QUARTIC B-SPLINE COLLOCATION APPROACH AND ADAMS-MOULTON SCHEME TO SOLVE THE EQUAL WIDTH EQUATION

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Abstract

This study focuses on the development of a novel numerical technique used to solve Equal Width (EW) equation. The spatial discretization of the EW equation is accomplished using a trigonometric quartic B-spline collocation technique. To achieve a fully discretized formulation of the EW equation, the third-order implicit Adams-Moulton method is employed. The efficiency and applicability of the recommended computational scheme are validated through numerical experiments, which include the analysis of single solitary wave propagation and the interaction of two solitary waves. The results obtained are compared with those from existing methods documented in the literature. These comparisons demonstrate that the proposed numerical scheme outperforms other methods in terms of accuracy.

Keywords

Quartic trigonometric B-spline,
Solitary wave,
Collocation method,
Adams-Moulton method

Time Scale of Article

Received :07 February 2025
Accepted : 16 May 2025
Online date : 25 June 2025

1. INTRODUCTION

Nonlinear dispersive wave equations play an important role in modeling many physical phenomena, such as the movement of shallow water waves. One of these equations is the Equal Width (EW) equation, introduced by Peregrine [1], which is considered a valuable replacement for the well-established Korteweg–de Vries (KdV) equation. The EW equation is written in the following form of

$$w_t + ww_x - \mu w_{xxt} = 0, \qquad x \in [\alpha, \beta] \tag{1}$$

with the boundary conditions (BCs)

$$\begin{array}{ll} w(\alpha,t) = 0 & w(\beta,t) = 0 \\ w_x(\alpha,t) = 0 & w_x(\beta,t) = 0 \end{array}, \qquad t \in (0,T] \tag{2}$$

and the initial condition (IC)

$$w(x,0) = f(x), \qquad x \in [\alpha, \beta] \tag{3}$$

where w describes the wave amplitude and the parameter μ is a positive constant.

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Because of the nonlinear term in the EW equation, its exact solution can only be found under limited boundary and initial conditions. As a result, recent researches has mainly focused on computational methods, leading to the development of various numerical techniques for solving the EW equation. These techniques include the Petrov-Galerkin method [2, 3], lumped Galerkin method [4], B-spline Galerkin methods [5–9], B-spline collocation methods [10–14], the least-squares method [15], finite difference methods [16, 17], the RBF-PS scheme [18], meshless kernel-based methods [19], multiquadric quasi-interpolation [20], the Haar wavelet method [21], and a numerical method using polynomial scaling functions [22].

In this study, a novel numerical scheme is developed to derive approximate solutions for the EW equation. This scheme combines the trigonometric quartic B-spline collocation technique with the Adams-Moulton method. This work aims primarily to show how using the Adams-Moulton method for time integration affects the results. The paper is organized as follows: Section 2 discusses the time and space discretization of the EW equation. Section 3 examines the behavior and interaction of two solitary waves to test the impact and validity of the suggested method. The results are shown in tables, and a comparison is made between the proposed method and existing approaches. Finally, Section 4 provides an outline of the method's key discoveries and contributions of the method.

2. DISCRETIZATION SCHEME

To establish the temporal and spatial discretization of the EW equation, the domain $[\alpha, \beta] \times (0, T]$ is first discretized using uniformly distributed grid points (x_r, t_n), where $x_r = \alpha + rh$, $r = 0,1, \dots, M$ and $t_n = n\Delta t$, $n = 0,1, \dots, N$. Here, h and Δt represent the spatial and temporal step sizes, respectively.

2.1. Temporal Discretization

Considering the EW equation of the form

$$v_t = (w - \mu w_{xx})_t = -w w_x \tag{4}$$

and utilizing the following one and two-step methods

$$v^{n+1} = v^n + \frac{\Delta t}{2}(v_t^{n+1} + v_t^n) + O(\Delta t^3) \tag{5}$$

$$v^{n+1} = v^n + \Delta t\left(\frac{5}{12}v_t^{n+1} + \frac{2}{3}v_t^n - \frac{1}{12}v_t^{n-1}\right) + O(\Delta t^4) \tag{6}$$

we set up the temporal integration of the Equation (4). The methods given in Equation (5) and Equation (6) can be rewritten in the general form as

$$v^{n+1} = v^n + \Delta t(\theta_1 v_t^{n+1} + \theta_2 v_t^n + \theta_3 v_t^{n-1}) \tag{7}$$

Selecting the coefficients in Equation (7) as $\theta_1 = \frac{1}{2}, \theta_2 = \frac{1}{2}, \theta_3 = 0$ provides Crank - Nicolson (CN) method which is second order in time and substituting the coefficients in Equation (7) as $\theta_1 = \frac{5}{12}, \theta_2 = \frac{2}{3}, \theta_3 = -\frac{1}{12}$ yields the two-step implicit Adams Moulton scheme. Using Equation (7), the temporal integration of the Equation (4) is achieved as

$$w^{n+1} - \mu w_{xx}^{n+1} + \theta_1 \Delta t w^{n+1} w_x^{n+1} = w^n - \mu w_{xx}^n - \theta_2 \Delta t w^n w_x^n - \theta_3 \Delta t w^{n-1} w_x^{n-1} \tag{8}$$

2.1. Spatial Discretization

Consider subdividing the spatial domain $[a, b]$ into M uniformly spaced finite elements at the specified points

$$\alpha = x_0 < x_1 < \cdots < x_M = \beta \tag{9}$$

Then, the quartic trigonometric B-splines $T_r^4(x),\ r = -2, \ldots, M+1$, at these knots are derived by the recurrence relation given in [23] as

$$T_r^4(x) = \frac{1}{\theta}\begin{cases} \rho^4(x_{r-2}), & x_{r-2} \leq x < x_{r-1}, \\ \begin{array}{c} -\rho^3(x_{r-2})\rho(x_r) - \rho^2(x_{r-2})\rho(x_{r+1})\rho(x_{r-1}) \\ -\rho(x_{r-2})\rho(x_{r+2})\rho^2(x_{r-1}) - \rho(x_{r+3})\rho^3(x_{r-1}), \end{array} & x_{r-1} \leq x < x_r, \\ \begin{array}{c} \rho^2(x_{r-2})\rho^2(x_{r+1}) + \rho(x_{r-2})\rho(x_{r+2})\rho(x_{r-1})\rho(x_{r+1}) \\ +\rho(x_{r-2})\rho^2(x_{r+2})\rho(x_r) + \rho(x_{r+3})\rho^2(x_{r-1})\rho(x_{r+1}) \\ +\rho(x_{r+3})\rho(x_{r-1})\rho(x_{r+2})\rho(x_r) + \rho^2(x_{r+3})\rho^2(x_r), \end{array} & x_r \leq x < x_{r+1}, \\ \begin{array}{c} -\rho(x_{r-2})\rho^3(x_{r+2}) - \rho(x_{r+3})\rho(x_{r-1})\rho^2(x_{r+2}) \\ -\rho^2(x_{r+3})\rho(x_r)\rho(x_{r+2}) - \rho^3(x_{r+3})\rho(x_{r+1}), \end{array} & x_{r+1} \leq x < x_{r+2}, \\ \rho^4(x_{r+3}), & x_{r+2} \leq x < x_{r+3}, \\ 0, & otherwise \end{cases} \tag{10}$$

where

$$\theta = \sin\left(\frac{h}{2}\right)\sin(h)\sin\left(\frac{3h}{2}\right)\sin(2h)$$
$$\rho(x_r) = \sin\left(\frac{x - x_r}{2}\right)$$

The collection of the quartic trigonometric B-spline functions $\{T_{-2}^4(x), T_{-1}^4(x), \ldots, T_M^4(x), T_{M+1}^4(x)\}$ creates a basis for the smooth functions defined across the spatial domain.

To perform the spatial integration of Equation (1), we begin by assuming that $W(x,t)$ is the quartic trigonometric B-spline approximation to the exact solution $w(x,t)$ to the problem. Following that form $W(x,t)$ in terms of the trigonometric B-splines T_j^4 and the temporal terms $\delta_j(t)$ as

$$W(x,t) = \sum_{j=-2}^{M+1} \delta_j T_j^4 \tag{11}$$

where the temporal terms $\delta_j(t)$ will be calculated using the BCs and collocation method. Since each subinterval $[x_{r-1}, x_r]$ is represented by five quartic trigonometric B-spline functions, the unknown function W and its first two spatial derivatives at the knots x_r are calculated in terms of the temporal terms as

$$\begin{aligned} W_r &= a_1\delta_{r-2} + a_2\delta_{r-1} + a_2\delta_r + a_1\delta_{r+1} \\ W_r' &= b_1\delta_{r-2} + b_2\delta_{r-1} - b_2\delta_r - b_1\delta_{r+1} \\ W_r'' &= c_1\delta_{r-2} - c_1\delta_{r-1} - c_1\delta_r + c_1\delta_{r+1} \end{aligned} \tag{12}$$

where

$$a_1 = \frac{\sin^4\left(\frac{h}{2}\right)}{\theta}, \qquad a_2 = \frac{\sin^4\left(\frac{h}{2}\right)\left(12\cos^2\left(\frac{h}{2}\right) - 1\right)}{\theta},$$
$$b_1 = -\frac{2\sin^3\left(\frac{h}{2}\right)\cos\left(\frac{h}{2}\right)}{\theta}, \qquad b_2 = -\frac{2\sin^3\left(\frac{h}{2}\right)\cos\left(\frac{h}{2}\right)\left(4\cos^2\left(\frac{h}{2}\right) - 1\right)}{\theta},$$
$$c_1 = \frac{\sin^2\left(\frac{h}{2}\right)\left(4\cos^2\left(\frac{h}{2}\right) - 1\right)}{\theta}.$$

Using (12) in (8), the fully-discretized form of EW equation is obtained as

$$\begin{aligned} &\delta_{r-2}^{n+1}(\alpha_1 - \mu c_1 + \Delta t W_r^{n+1} b_1) + \delta_{r-1}^{n+1}(\alpha_2 + \mu c_1 + \theta_1 \Delta t W_r^{n+1} b_2) \\ &+\delta_r^{n+1}(\alpha_2 + \mu c_1 - \theta_1 \Delta t W_r^{n+1} b_2) + \delta_{r+1}^{n+1}(\alpha_1 - \mu c_1 - \theta_1 \Delta t W_r^{n+1} b_1) \\ &= W_r^n - \mu (W_{xx})_r^n - \theta_2 \Delta t W_r^n (W_x)_r^n - \theta_3 \Delta t W_r^{n-1}(W_x)_r^{n-1}, \qquad 0 \le r \le M. \end{aligned} \tag{13}$$

Hence, we achieve a system (13) involving $M+1$ equations and $M+4$ unknowns. Using the BCs (3) enables to equalize the number of equations and unknowns and the variables

$$\delta_{-2}^{n+1}, \delta_{-1}^{n+1} \; and \; \delta_{M+1}^{n+1}$$

are eliminated from the system (13), simplifying it into a solvable $(M+1) \times (M+1)$ matrix system. So as to commence the iterative procedure, the initial vectors $\delta^0 = (\delta_{-2}^0, \delta_{-1}^0, \dots, \delta_{M+1}^0)^T$ and $\delta^1 = (\delta_{-2}^1, \delta_{-1}^1, \dots, \delta_{M+1}^1)^T$ need to be computed. The initial vector δ^0 is first calculated by the use of IC and BCs as follows :

$$\begin{aligned} W'(\alpha, 0) &= 0 \\ W''(\alpha, 0) &= 0 \\ W(x_r, 0) &= f(x_r) \\ W'(\beta, 0) &= 0 \end{aligned}$$

where $r = 0,1,\dots,M$. Then, the other initial vector $\boldsymbol{\delta}^1$ is achieved by using CN technique. Therefore, the unknown vector $\boldsymbol{\delta}^{n+1} = (\delta_{-2}^{n+1}, \delta_{-1}^{n+1}, \dots, \delta_{M+1}^{n+1})^T$ $(n = 1,2,\dots)$ can be computed iteratively at any desired time by using two previous $\boldsymbol{\delta}^n$ and $\boldsymbol{\delta}^{n-1}$ unknown vectors. Since we have an implicit system (13) with respect to the term δ, an inner iterative algorithm is used three times at all-time steps to obtain better accuracy.

3. NUMERICAL RESULTS

This section presents two test problems to demonstrate the efficiency and applicability of the proposed scheme. The accuracy of the solution is assessed by calculating the error norm L_∞

$$L_\infty = \max_m |w_m - W_m|, \tag{14}$$

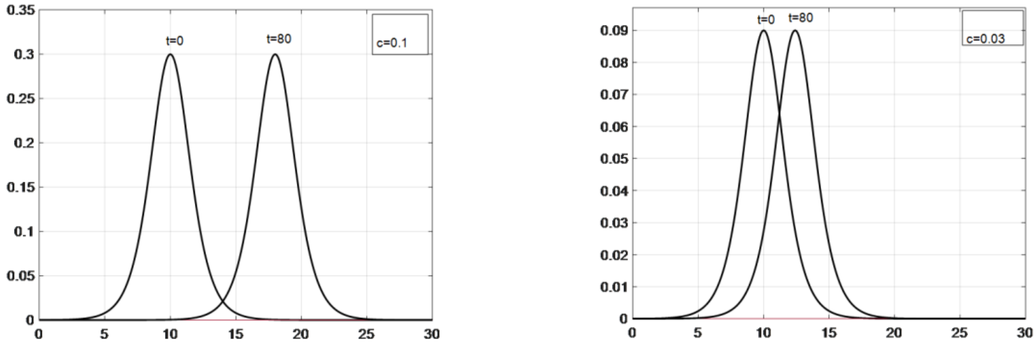
and the following formulae is used to calculate the order of the temporal-convergence

$$order = \frac{\log\left|\frac{(L_\infty)_{\Delta t_i}}{(L_\infty)_{\Delta t_{i+1}}}\right|}{\log\left|\frac{\Delta t_i}{\Delta t_{i+1}}\right|} \tag{15}$$

where $(L_\infty)_{\Delta t_i}$ represents the error norm L_∞ for temporal step Δt_i. The three invariants corresponding to mass I_1, momentum I_2 and energy I_3 are worked out by means of the following formulae [24]

$$\begin{aligned} I_1 &= \int_{-\infty}^{\infty} w dx \approx \int_{\alpha}^{\beta} W dx \\ I_2 &= \int_{-\infty}^{\infty} (w^2 + \mu(w_x)^2) dx \approx \int_{\alpha}^{\beta} (W^2 + \mu(W_x)^2) dx \\ I_3 &= \int_{-\infty}^{\infty} w^3 dx \approx \int_{\alpha}^{\beta} W^3 dx \end{aligned}$$

The trapezoidal rule for the spatial domain $[\alpha, \beta]$ is employed to evaluate approximately the above integrals at all-time steps.



(a) (b)

Figure 1. $W(x,t)$ for $h = 0.1$ and $\Delta t = 0.1$

3.1. Motion of a Single Solitary Wave

In the first test problem, the analytical single solitary wave solution of the EW equation is expressed with equation:

$$w(x,t) = 3c \sec h^2 \left(k[x - \tilde{x}_0 - vt]\right) \tag{16}$$

in which the velocity of the solitary wave $v = c$, amplitude of the solitary wave is $3c$, $k = \sqrt{\frac{c}{4\mu v}}$ represents the width of the solitary wave and $\tilde{x}_0$ denotes the initial wave peak position. The BCs are set to zero at both ends. By taking $t = 0$ in the analytical solution (16), the IC is obtained as

$$w(x,0) = 3c \sec h^2 \left(k[x - \tilde{x}_0]\right) \tag{17}$$

Using IC (16) in the integrals I_1, I_2, I_3, the analytical values of three invariants are calculated for the first problem as follows

$$I_1 = \frac{6c}{k},\ I_2 = \frac{12c^2}{k} + \frac{48k\mu c^2}{5}, I_3 = \frac{144c^3}{5k}$$

The calculations are done with the parameters $\mu = 1$, $\tilde{x}_0 = 10$, amplitudes $3c = 0.3$, $3c = 0.09$. The graphs of the simulations of the single solitary wave for various values of c at $t = 0$ and $t = 80$ are displayed in Figure 1. It is obvious from Figure 1 that the solitary wave maintains its initial shape, velocity and amplitude during the simulation. The algorithm is run up to $t = 80$ over various spatial domains with different temporal and spatial step widths. The error norm L_∞ and three invariants are reported in Table 1a and Table 1b to compare the present method with existing methods. The comparison demonstrates that the proposed method yields significantly more accurate results than the existing techniques outlined in $[2, 3, 4, 5, 6, 14, 21]$. Additionally, the invariants computed using the present method align closely with the analytical values, as illustrated in Table 1a and Table 1b. Table 2a and Table 2b present the conservation invariants, temporal rate of convergence, and error norms, which confirm that for a fixed spatial step size, reducing the temporal step size from 2 to 0.25 results in a numerical convergence rate approaching three. Furthermore, the computed invariants remain consistent with their analytical counterparts. Figure 2 displays the absolute error plot for the parameters $c = 0.1, h = 0.05$, and $\Delta t = 0.25$.

Table 1a. Error norms and invariants of single solitary wave for $c = 0.1, h = 0.03,\ \Delta t = 0.05, 0 \leq x \leq 30$ at t=80

Method	I_1	I_2	I_3	L_∞
Present Method	1.19999	0.28800	0.05760	7.37×10^{-6}
[2]	1.19100	0.28550	0.05582	2.64×10^{-3}
[5]	1.23387	0.29915	0.06097	1.64×10^{-2}
[4]	1.19995	0.28798	0.05759	2.10×10^{-5}
[3]	1.20004	0.28880	0.05760	5.15×10^{-5}
[14]	1.19999	0.28800	0.05760	9.60×10^{-6}
[21]	1.19999	0.28799	0.05759	1.26×10^{-5}
Analytical	1.2	0.288	0.0576	–

Table 1b. Error norms and invariants of single solitary wave for $c = 0.03, h = 0.1,\ \Delta t = 0.1, 0 \leq x \leq 30$ at t=80

Method	I_1	I_2	I_3	L_∞
Present Method	0.3599970	0.0259200	0.0015552	1.48×10^{-6}
[6] QBGM	0.3599964	0.0259252	0.0015525	2.09×10^{-6}
Analytical	0.36	0.02592	0.00155520	–

Table 2a. Error norms, invariants and order of convergence with $c = 0.1, h = 0.05, -10 \leq x \leq 40$ at t=80

Δt	I_1	I_2	I_3	L_∞	order
2	1.199050	0.288127	0.057365	2.96×10^{-4}	–
1	1.199882	0.288016	0.057605	3.64×10^{-5}	3.02
0.5	1.199998	0.288002	0.576001	4.50×10^{-6}	3.02
0.25	1.199999	0.288000	0.576001	5.47×10^{-7}	3.04

Table 2b. Error norms, invariants and order of convergence with $c = 0.03, h = 0.05, -10 \leq x \leq 40$ at t=80

Δt	I_1	I_2	I_3	L_∞	order
2	0.359998	0.025920	0.001555	1.24×10^{-6}	–
1	0.360000	0.025920	0.001555	1.54×10^{-7}	3.00
0.5	0.360000	0.025920	0.001555	1.89×10^{-8}	3.03
0.25	0.360000	0.025920	0.001555	2.53×10^{-9}	2.90

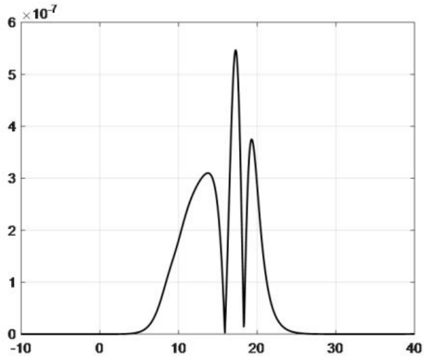


Figure 2. Absolute error at $t = 80$

3.1. Interaction of Two Solitary Waves

In the problem of interaction of two solitary waves, the following IC is tackled

$$w(x,0) = 3c_1 \sec h^2\left(\frac{1}{2}[x - \tilde{x}_1 - c_1]\right) + 3c_2 \sec h^2\left(\frac{1}{2}[x - \tilde{x}_2 - c_2]\right) \tag{18}$$

where the parameters $\mu = 1, c_1 = 1.5, c_2 = 0.75, \tilde{x}_1 = 10$ and $\tilde{x}_2 = 25$ are selected.

These parameters yield two well-separated solitary waves initially situated at $\tilde{x}_1$ and $\tilde{x}_2$ and moving in the same directions. To make a comparison our results with the results of the method given in [18], the algorithm is run on the spatial domain $[0, 80]$ with time step $\Delta t = 0.05$ and space step $h = 0.2$ until $t = 30$. Simulation of the interaction process is given in Figure 3. As shown in Figure 3, the interaction takes place at nearly $t = 15$ and then two waves proceed without change their original shape. The values of analytical invariants are determined as

$$\begin{aligned} I_1 &= 12(c_1 + c_2) = 27, \\ I_2 &= 28.8({c_1}^2 + {c_2}^2) = 81, \\ I_3 &= 57.6({c_1}^3 + {c_2}^3) = 218.7. \end{aligned}$$

The comparison of the computed invariants with invariants presented by the method [18] is given in Table 3. It can obviously be seen that the three invariants computed by the present method are closer to the analytical values of the invariants. Also, the calculated invariants are reported in Table 4 at various time levels. When Table 4 is examined, the calculated invariants are observed to align with the analytical values throughout the interaction process

Table 3. Comparison of the invariants for the interaction of two solitary waves at $t = 30$

	Present Method	**[18]**(RK4)
I_1	26.99643	26.92975
I_1	81.00892	80.79845
I_1	218.73882	218.15719

Table 4. Invariants for the interaction of two solitary waves with $h = 0.2, \Delta t = 0.05$ at various time levels

t	I_1	I_2	I_3
1	26.99948	81.00053	218.70239
5	26.99928	81.00173	218.70778
10	26.99858	81.00322	218.71455
15	26.99810	81.00457	218.71992
20	26.99778	81.00560	218.72461
25	26.99714	81.00739	218.73210
30	26.99643	81.00892	218.73882
Exact	27	81	218.7

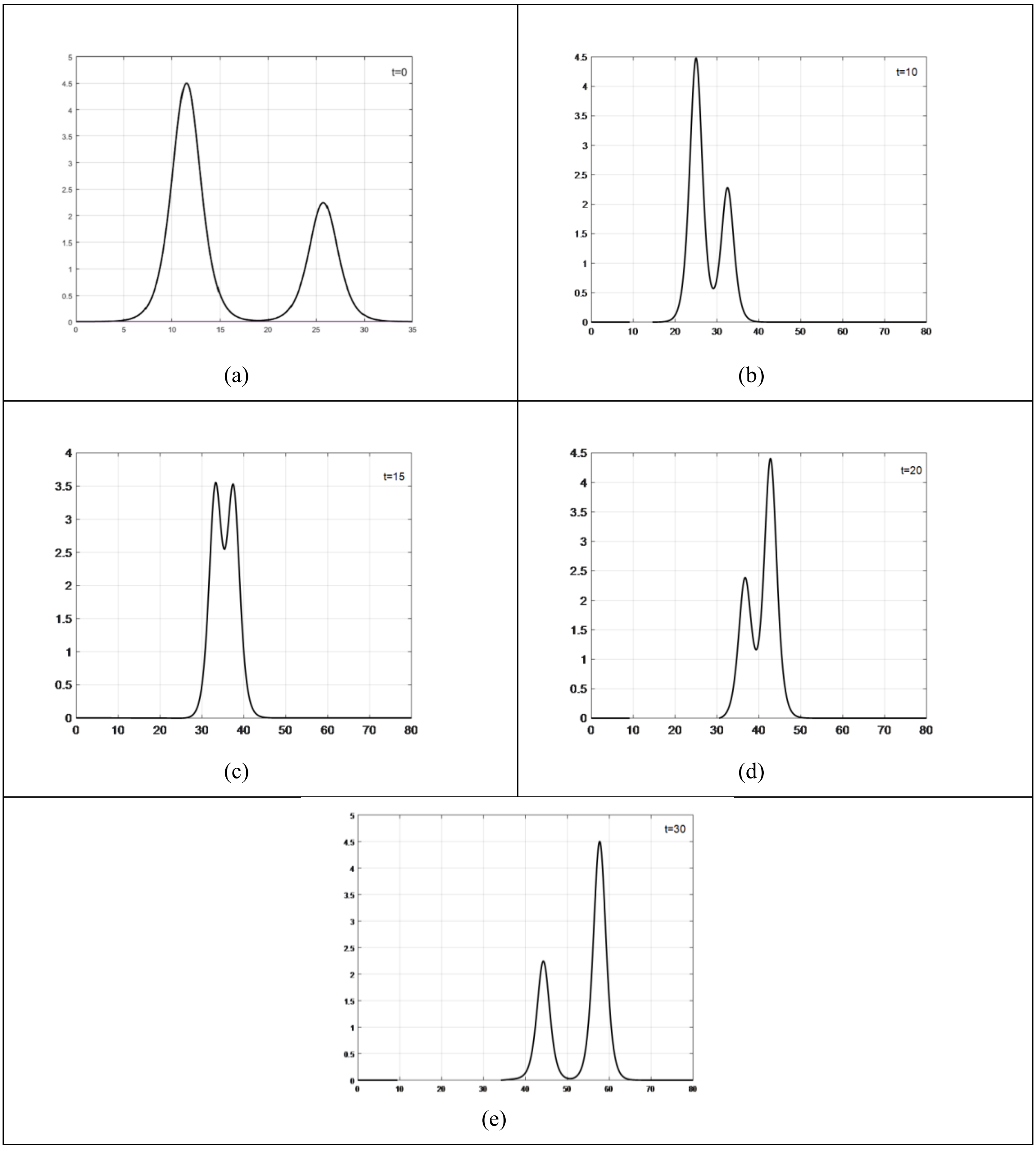


Figure 3. The simulation of interaction process

4. CONCLUSION

In the present work, a novel numerical scheme is introduced to derive approximate solutions for the EW equation. This scheme is developed by integrating the trigonometric quartic B-spline collocation technique with the third-order implicit Adams-Moulton method. To evaluate the performance and efficiency of the proposed approach, two test problems are investigated, focusing on the behavior of a solitary wave and the interaction between two solitary waves. The results demonstrate that the error norms produced by the present method are significantly smaller than studies of [2, 3, 4, 5, 6,14, 21]. The invariant constants are computed numerically and compared with their analytical values, revealing that the invariants remain well-preserved throughout the simulation. This indicates an accurate representation of soliton propagation and interaction. Additionally, the calculated temporal rate of convergence aligns closely with the theoretical value. In conclusion, the proposed numerical scheme offers notable advantages in terms of both accuracy and computational efficiency, making it a highly suitable method for addressing problems that model physical phenomena in engineering and scientific applications.

ACKNOWLEDGEMENTS

Acknowledgments of people, grants, funds, etc. should be placed in a separate section before the reference list. The names of funding organizations should be written in full.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Emre Kırlı: Methodology, Supervision, Software, Conceptualization, **Mehmet Ali Mersin:** Writing-Original Draft, Visualization, Writing-Review& Editing, Supervision

REFERENCES

[1] Morrison PJ, Meiss JD, Carey JR. Scattering of RLW solitary waves. Physica D 1984; 11(3): 324-336.

[2] Gardner LRT, Gardner GA, Ayoub FA, Amein NK. Simulations of the EW undular bore. Commun Numer Methods Eng 1997; 13(7): 583-592.

[3] Roshan T. A Petrov-Galerkin method for equal width equation. Appl Math Comput 2011; 218(6): 2730-2739.

[4] Esen A. A numerical solution of the equal width wave equation by a lumped Galerkin method. Appl Math Comput 2005; 168(1): 270-282.

[5] Doğan A. Application of Galerkin's method to equal width wave equation. Appl Math Comput 2005; 160(1): 65-76.

[6] Irk D. B-Spline Galerkin solutions for the equal width equation. Phys Wave Phenom 2012; 20(2): 122-130.

[7] Saka B. A finite element method for equal width equation. Appl Math Comput 2006; 175(1): 730-747.

[8] Saka B, Dağ I, Dereli Y, Korkmaz A. Three different methods for numerical solution of the EW equation. Eng Anal Bound Elem 2008; 32(7): 556-566.

[9] Dağ I, Irk D, Boz A. Simulation of EW wave generation via quadratic B-spline finite element method. Int J Math Stat 2007; 1(A07): 46-59.

[10] Zorşahin Görgülü M. A new algorithm based on the dedic (tenth degree) B-spline functions for numerical solution of the equal width equation. J Eng Technol Appl Sci (In press): DOI: 10.30931/jetas.1072151.

[11] Raslan KR. Collocation method using quartic B-spline for the equal width (EW) equation. Appl Math Comput 2005; 168(2): 795-805.

[12] Dağ I, Saka B. A cubic B-spline collocation method for the EW equation. Math Comput Appl 2004; 9(3): 381-392.

[13] Dağ I, Ersoy Ö. The exponential cubic B-spline algorithm for equal width equation. Adv Stud Contemp Math 2015; 25(4): 525-535.

[14] Yağmurlu NM, Karakaş AS. Numerical solutions of the equal width equation by trigonometric cubic B-spline collocation method based on Rubin-Graves type linearization. Numer Methods Partial Differ Equ 2020; 36(5): 1170-1183.

[15] Zaki SI. A least-squares finite element scheme for the EW equation. Commun Numer Methods Eng 2000; 16(3): 177-190.

[16] Banaja MA, Bakodah HO. Runge-Kutta integration of the equal width wave equation using the method of lines. Math Probl Eng 2015; 2015: Article ID 274579.

[17] İnan B, Bahadır AR. A numerical solution of the equal width wave equation using a fully implicit finite difference method. Turk J Math Comput Sci 2014; 2(1): 1-14.

[18] Uddin M. RBF-PS scheme for solving the equal width equation. Appl Math Comput 2013; 222: 619-631.

[19] Dereli Y, Schaback R. The meshless kernel-based method of lines for solving the equal width equation. Appl Math Comput 2013; 219(10): 5224-5232.

[20] Dhawan S, Ak T, Apaydın G. Algorithms for numerical solution of the equal width wave equation using multi-quadric quasi-interpolation method. Int J Mod Phys C 2019; 30(11): 1950087.

[21] Ghafoor A, Haq S. An efficient numerical scheme for the study of equal width equation. Results Phys 2018; 9: 1411-1416.

[22] Oruç Ö, Esen A, Bulut F. Highly accurate numerical scheme based on polynomial scaling functions for equal width equation. Wave Motion 2021; 105: 102760.

[23] Lyche T, Winther R. A stable recurrence relation for trigonometric B-splines. J Approx Theory 1979; 25(3): 266-279.

[24] Olver PJ. Euler operators and conservation laws of the BBM equation. Math Proc Camb Philos Soc 1979; 85(1): 143-159.

ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2025, 26 (2) pp.161-178, DOI: 10.18038/estubtda.1674259

RESEARCH ARTICLE

AIRCRAFT SEQUENCING WITH FUZZY LOGIC METHOD

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Abstract

The growth in the demand for air transport causes an increase in air traffic. In this case, more air traffic needs to be carried out safely, regularly and quickly. It is important to correctly and fairly order the landing traffic in order to reduce the delaying, especially in the air due to heavy traffic.

In this study, it is aimed to sequence the arrival traffic with fuzzy logic method. Speed, distance, altitude parameters were used for sequencing. Traffic data was collected from the Air Traffic Simulation Laboratory at Eskişehir Technical University's Air Traffic Control Department.

A comparative analysis was conducted between the current arrival traffic sequencing within the simulation area and the sequencing results derived from the fuzzy logic method. The findings indicate a significant overlap between both traffic ranking outcomes. This research contributes to the existing literature by demonstrating the application of the fuzzy logic method in the field of air traffic control.

Keywords

Aircraft,
Sequencing,
Fuzzy Logic,
Real Time Simulation

Time Scale of Article

Received : 11 April 2025
Accepted : 14 June 2025
Online date : 25 June 2025

1. INTRODUCTION

The demand for air transportation is continuously increasing due to technological advancements and globalization. According to estimates by the European Organization for the Safety of Air Navigation (EUROCONTROL), the number of daily Instrument Flight Rules (IFR) flights in European airspace is projected to reach 53,600 in the high scenario by 2050 (EUROCONTROL, 2023). This increase results in the concentration of air traffic within the Terminal Control Area (TMA) and issues such as delays, conflicts, and disruptions in flight operations. To address these challenges, air traffic controllers provide instructions and recommendations to ensure the safe, orderly, and efficient management of traffic. However, there is an increasing need for automation systems to reduce the workload of controllers and provide more effective sequencing under heavy traffic conditions.

Sequencing arrival traffic within the TMA is crucial for minimizing airborne waiting times, optimizing fuel consumption, and reducing environmental impacts such as emissions and noise pollution. One of the traditional sequencing methods, the First Come, First Served (FCFS) approach, although simple to apply, is insufficient in heavy traffic scenarios and can lead to delays. In this context, the fuzzy logic method emerges as an effective tool for modeling complex systems that involve uncertainty.

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The aim of this study is to present a new approach for sequencing arrival traffic within the TMA using the fuzzy logic method. In the study, the traffic was ordered by considering the distance, altitude, and speed from the entry points of the TMA to the final approach point using the fuzzy logic method. The traffic sequencing derived from the fuzzy logic method was comparatively assessed against the sequencing executed within a real-time simulation (RTS) environment at the Department of Air Traffic Control, Eskişehir Technical University. The findings demonstrate a strong consistency between the aircraft arrival sequencing determined by real-time simulation's estimated arrival times and the sequencing generated via the fuzzy logic method.

2. LITERATURE REVIEW

The aircraft sequencing problem is one of the fundamental research areas of air traffic control and has been studied for a long time in order to increase operational efficiency and reduce delays. Numerous methods have been developed in the literature for this problem; these methods can be generally classified as deterministic, stochastic and metaheuristic approaches. While deterministic methods include static and dynamic models, stochastic methods include techniques such as genetic algorithms and tabu search. Metaheuristic approaches include innovative solutions such as ant colony optimization, particle swarm optimization and artificial bee colony algorithms.

Studies on single-runway landing problems have formed the basis of sequencing models. Moser developed a hybrid algorithm combining stochastic and deterministic elements to solve the single-runway aircraft landing problem and showed that this method is effective even in chaotic scenarios with up to 24 aircraft [1].

Brentnall and Cheng compared the scheduling algorithms using discrete event simulation at a single-runway airport; they analyzed the effects of delay sharing strategy, arrival rate and turbulence category mix with statistical methods [2]. Çeçen et al. managed to minimize the total aircraft delay by proposing a stochastic model for mixed aircraft operations and demonstrated the superiority of this model over deterministic approaches [3]. For multi-runway scenarios, Dönmez (2022) developed a stochastic model that takes into account the runway exit point and occupancy period uncertainties; they proved the applicability and robustness of this model on runways with multiple exits [4].

The First Come, First Served (FCFS) approach, one of the traditional sorting strategies, is widely used in the world due to its simplicity and applicability. However, Liang stated that FCFS does not produce optimum results in high-density operations and can lead to excessive delays [5]. To overcome this problem, the Constrained Position Shift (CPS) method proposed by Dear aims to shorten the sorting time by optimizing the positions of the aircraft according to operational constraints [6]. Ikli et al. showed that CPS significantly reduces the total landing time compared to FCFS through an example scenario; for example, the total landing time, which is 452 seconds in a four-aircraft FCFS sorting, decreases to 238 seconds with CPS [7].

Fuzzy logic is increasingly gaining attention in air traffic control as a powerful tool for modeling systems with uncertainty. Ören and Koçyiğit successfully applied the fuzzy logic model to the landing sequence of unmanned aerial vehicles and proved the effectiveness of the system in real-time scenarios [8]. Pratiwi used the fuzzy logic method to automate the landing decision processes of Boeing aircraft; reliable results were obtained by processing parameters such as speed, distance and altitude with fuzzy rules [9]. Ntakolia and Lyridis presented an n-dimensional optimization model by integrating fuzzy logic with ant colony optimization in air traffic flow management and reported that this approach was successful in managing traffic density [10]. Bongo and Seva used fuzzy DEMATEL and fuzzy BWM methods to examine the factors affecting the performance of air traffic controllers. The case study conducted at the Mactan Control Tower determined the cause-effect relationships and priority ranking of the factors;

While communication stood out as the highest priority factor, factors such as situation awareness were included in the effect factors group [11].

Chikha and Skorupski developed a fuzzy logic-based expert system to assess the risk of accidents in airport ground traffic. The study focused on the performance and training level of ground handling personnel (GSE operators) and emphasized the importance of human factors in preventing accidents. Using fuzzy inference systems, personnel reactions and the severity of possible consequences were modeled [12].

Kolotusha et al. proposed fuzzy logic methods together with expert evaluation methods to evaluate the conformity of air traffic control (ATC) simulators to the real system. Fuzzy logic was used in processing uncertain and imprecise data, quantitatively classifying the adequacy of simulators (e.g. 'low conformity', 'medium conformity', 'best fit') and formalizing expert opinions through membership functions in the analysis of practical tasks such as 'Vectoring'. This approach provided reliable results in evaluating the accuracy of simulators in reproducing the professional environment (high, typical, basic, low) [13]. Chang and Wong used the fuzzy Delphi method to assess human-induced risk factors in runway incursion incidents [14]. Pacheco et al. presented a fuzzy logic methodology to determine the risk of airport accidents [15] and considered the perceptions of pilots operating in airport traffic [12].

A review of the literature reveals that research in the field of air traffic control remains limited. Also, existing efforts often lack integration with real-time simulation (RTS) environments, which are essential for assessing the practical applicability and operational performance of sequencing models. To address this gap, this study proposes a fuzzy logic-based sequencing approach for arrival traffic. Moreover, the proposed model, which relies on speed, distance, and altitude parameters, is validated in real-time air traffic simulation and offers an alternative approach to existing sequencing methods.

3. METHODOLOGY

The generic TMA and scenario required for the fuzzy logic-based model were provided through the real-time simulator which supports the basic training of air traffic controllers. Moreover, it plays a significant role in airspace and procedural development. The design and implementation of the proposed fuzzy model were carried out systematically by taking into account the basic components of fuzzy logic. The details of the method are presented in the following parts.

3.1. Fuzzy Logic

Fuzzy logic, in contrast to classical (binary) logic, is a mathematical approach that handles uncertainty and gradation rather than relying on strict boundaries. Introduced by Lotfi Zadeh in 1965, this methodology is specifically designed to address complex and imprecise data encountered in real-world systems [16]. While classical logic dictates that an element either fully belongs to a set (1) or does not belong at all (0), fuzzy logic allows for degrees of membership, represented by continuous values within the interval [0, 1]. This characteristic makes fuzzy logic particularly suitable for dynamic and uncertain systems such as air traffic control. For instance, an aircraft's speed is not rigidly categorized as "slow" or "fast"; instead, a specific speed value may simultaneously belong to multiple fuzzy sets to varying degrees [17].

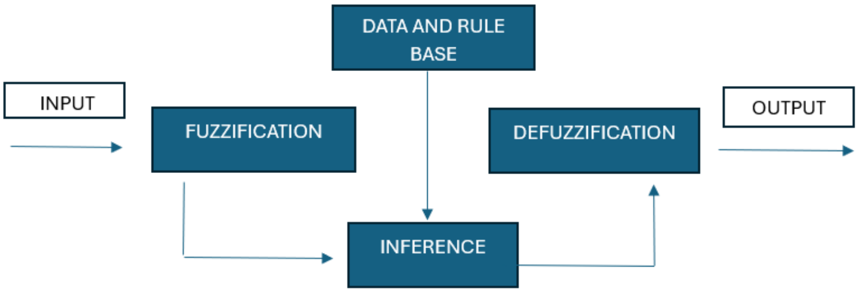

Figure 1. Fuzzy Logic System. [18].

3.2. Fuzzy Set

A fuzzy set is a concept that defines the degree of belonging of elements to a set in the range [0, 1]. Unlike classical sets, the belonging of an element in fuzzy sets is determined not by sharp boundaries but by a continuous function. In fuzzy logic; the graph that changes with the values of the set members is called a membership function. The x-axis of this graph indicates the member values, and the y-axis indicates the membership degrees [19].

3.3. Membership Functions

Membership functions mathematically express the degree of belonging of an element to a certain fuzzy set. The most commonly used membership functions are triangular, trapezoidal and Gaussian types.
Triangle Membership Function: Triangle membership function can be explained with three parameters, a left side point, b center point, c right side point, the graphic of the triangle membership function is shown in Figure 2 and Equation 1 [20].

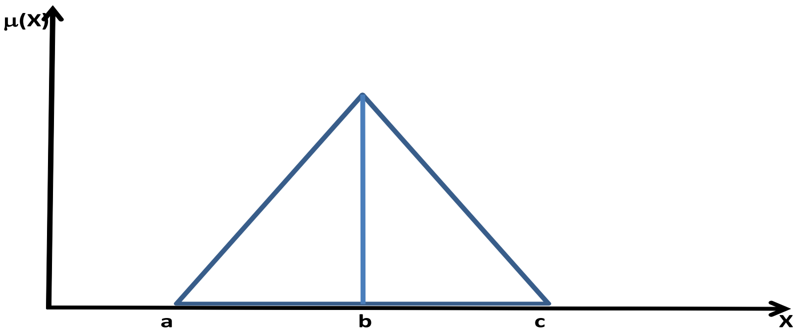

Figure 2. Triangle Membership Function. [20].

$$\text{Triangle } \mu A(x;,a,b,c,) = \begin{cases} (x-a)/(b-a) & a \le x \le b \\ (c-x)/(c-b) & b \le x \le c \\ 0 & x > c \text{ veya } x < a \end{cases} \quad (1)$$

Trapezoidal Membership Function is defined by four parameters a, b, c and d, the distance between b and c represents the highest membership value that the element can have. And if x is between (a, b) or (c, d), then it will have a membership value between 0 and 1. The trapezoidal membership function is shown in Figure 3 and the equations belonging to this membership function are shown equation 2, 3. [21].

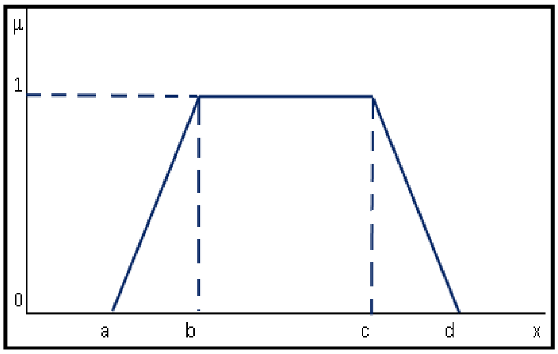

Figure 3. Trapezoidal Membership Function [21].

$$\text{Trapezoid } \mu(x) = (x; , a, b, c, d) = \begin{cases} 0, & x < a \\ (x-a)/(b-a) & a \leq x \leq b \\ 1 & b \leq x \leq c \\ (d-x)/(d-c) & c \leq x \leq d \end{cases} \quad (2)$$

$$\mu(x) = \text{Max}(\min(x-a)/(b-a),\ 1, (d-x)/(d-c)\quad, 0) \quad (3)$$

Gaussian Membership Function:

The Gauss membership function, σ, consists of two parameters, the function is shown in Figure 4 and Equation 4.

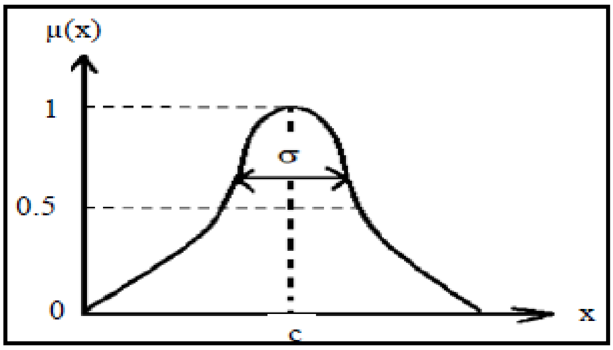

Figure 4. Gaussian Membership Function [22].

$$\text{Gauss } \mu(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (4)$$

In this function, c represents the mean, center, of the Gaussian curve and σ represents the distribution of the curve. This is a natural way to represent the distribution of data, but is not often used in fuzzification methods due to its mathematical complexity [22].

3.4. Fuzzification

The stage of converting the data input, which is taken from the outside world to the computer through measurement and has a definite numerical value, into verbal expressions by the membership functions in the knowledge base and into membership degrees that show to what extent the input data supports this expression is called fuzzification. The verbal expressions obtained at the end of fuzzification are compared with the propositions in the rule base, as in the decision-making process of humans, and verbal judgment results are reached, and the extent to which these results are valid is determined by the membership degrees in the input [19].

3.5. Data and Rule Base

Data base is where the membership functions of the fuzzy system are located. All the rules that transform the inputs obtained from here into output variables, which can be written in the if-then type, are located in the knowledge base. Thus, each rule logically connects a part of the input space to the output space. All of these contexts constitute the rule base [18].

VSlow: Very Slow, Slow: Slow, M: Medium, F: Fast, VF: Very Fast, VFar: Very Far, Far: Far, C: Close, VC: Very Close, VL: Very Low, L: Low, H: High, VH: Very High, VVL: Very Very Low, VL: Very Low, L: Low, VVH: Very Very High are expressed as and are given in Table 1.

Table 1. Rule Matrix

Speed	Distance	Altitude				
		Very Low	Low	Medium	High	Very High
VSlow	VFar	VL	VL	VVL	VVL	VVL
VSlow	Far	L	VL	VL	VVL	VVL
VSlow	M	L	L	VL	VL	VVL
VSlow	C	M	L	L	VL	VL
VSlow	VC	H	M	L	VL	VL
Slow	VFar	L	VL	VL	VVL	VVL
Slow	Far	L	L	VL	VL	VVL
Slow	M	M	L	L	VL	VL
Slow	C	H	M	L	L	VL
Slow	VC	VH	VH	H	H	M
M	VFar	L	L	VL	VL	VVL
M	Far	M	L	L	L	VL
M	M	H	H	M	M	L
M	C	VH	VH	H	H	M
M	VC	VVH	VH	VH	H	H
H	VFar	M	L	VL	VL	VL
H	Far	H	H	H	H	L
H	M	VH	H	H	H	M
H	C	VVH	VH	VH	H	H
H	VC	VVH	VVH	VH	VH	H
VH	VFar	VH	H	H	M	L
VH	Far	VH	VH	H	H	M
VH	M	VVH	VH	VH	H	H
VH	C	VVH	VVH	VH	VH	H
VH	VC	VVH	VVH	VVH	VH	VH

3.6. Inference Procedures

Inference is the process of deriving fuzzy outputs from fuzzy inputs. In this study, the Mamdani inference method is preferred (Figure 5). The Mamdani method combines the fuzzy outputs obtained from the "If-Then" statements in the rule base and produces intuitive results.
The connection between linguistic variables (x, y and z) is defined using max. and min. operators based on generalized fuzzy connection. The min. operator is used in the condition (If) section of the rules, and the max. operator is used to bring two rules together [23].

Rule 1: If x = A1 and y = B1 then z = C1
Rule 2: If x = A2 and y = B2 then z = C2

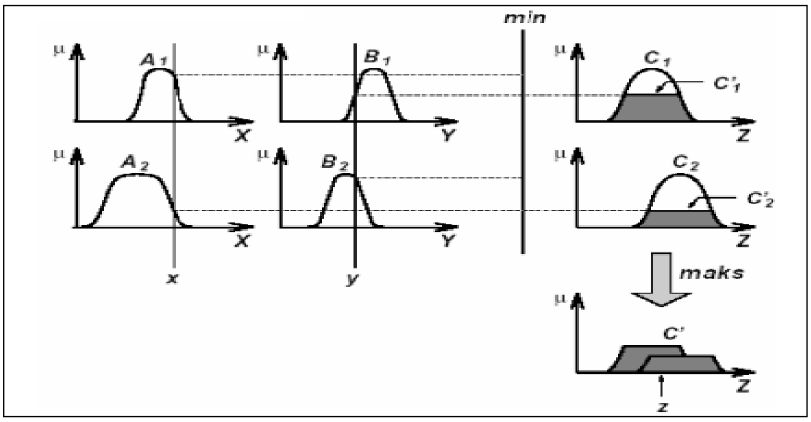

Figure 5. Mamdani Inference Method [23]

Alternative methods are Takagi-Sugeno and Tsukamoto Figure 5 among inference methods. While Takagi-Sugeno produces linear outputs with mathematical functions, Tsukamoto works with monotonic membership functions. However, in this study, the Mamdani method was chosen due to its interpretability and suitability for intuitive requirements in air traffic control [23].

3.7 Defuzzification and Methods

The results obtained as a result of the inference process are a fuzzy set containing linguistic expressions. Defuzzification process is required to transform this set system into the required numerical data [17]. For defuzzification, the centroid method, the largest membership (maximum) method, the weight average method, the Mean-Max membership method, the smallest of the largest method, the largest of the largest method are among the most commonly used methods.

In center of gravity method, the center of gravity of the areas obtained as a result of the inference process is found and calculated as a defuzzification process as a definite value. In this method, the integral process is applied in the conversion of fuzzy numbers to classical numbers. The centre of gravity is shown in Figure 6 and Equation 5 [24].

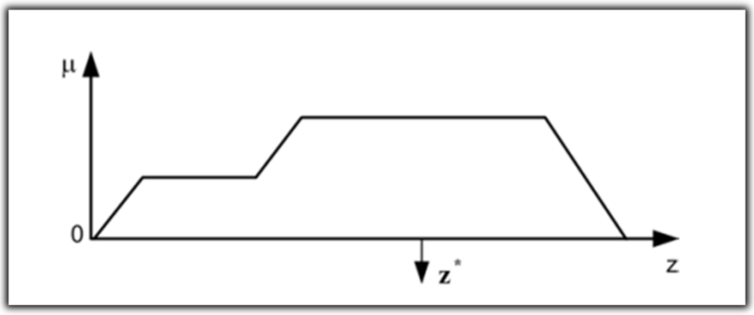

Figure 6. Center of Gravity Method [25]

$$z^{*}=\frac{\int \mu_z z\,dz}{\int \mu_z z\,dz} \quad (5)$$

4. APPLICATION OF THE FUZZY LOGIC METHOD TO THE AIRCRAFT SEQUENCING PROBLEM

In this study, the membership functions, inference method and defuzzification processes used in fuzzy logic are modeled with the MATLAB program.

The assumptions made in the fuzzy logic modeling in the study can be listed as follows:

• All aircraft entering TMA follow their current arrival routes and perform point-to-point navigation.

• Meteorological conditions (wind etc.) are not taken into account.

• Longitudinal separation is not used between traffics.

• Speed restriction is not applied.

•No delay method (waiting, vector etc.) is used in sequencing traffics.

• Ground speed is used in the model.

• The altitude range of traffics in TMA is 4000 ft-10000ft.

• Traffic entering TMA will complete their landing sequence based on the specified report point (called as Imren) at a distance of 23 NM on the final approach route and it is assumed that they will land according to the determined landing sequence.

In this study, the fuzzification, rule base and inference, defuzzification and system integration stages of the fuzzy logic system are systematically applied to model the traffic sequence in TMA as follows, respectively.

4.1. Fuzzification

In this phase, numerical inputs such as speed, distance and altitude are converted to fuzzy values by means of defined membership functions. For example, 180 kt speed is fuzzified with a degree of belonging to the “Medium” cluster of 0.6 and to the “Fast” cluster of 0.4. In this study, real-time data obtained from the simulator (for example, Speed: 200 kt, Distance: 10 NM, Altitude: 3000 ft) are fuzzified in the MATLAB/FIS interface and provided as input to the model.

In this study, fuzzy sets are defined for speed, distance and altitude parameters. MATLAB/FIS is used. Triangular membership functions are mainly used; this choice was made to increase the computational efficiency of the system and to facilitate the interpretability of the results. It is converted to fuzzy values by means of defined membership functions.

The parameters of the membership functions are given below:
Speed (knot-kt): Speed consists of five membership functions between 220-340 kt: Very slow, slow, medium, fast, very fast.
Distance (NM): It consists of five membership functions between 0-65 NM: Very close, close, medium, far and very far.
Altitude (feet-ft): It consists of five membership functions between 4000 ft-16000 ft: Very low, low, medium, high, very high.
Output: It consists of seven membership functions between 0-100 points under the name of score: Very very low, very low, low, medium, high, very high, very very high.

4.1.1. Speed membership function

Speed parameters are made according to the speed values of the aircraft in the scenarios run in the RTS environment. Speed values are given in terms of ground speed. Lower and upper limits and related ranges are determined according to the speed values observed at the moment of entry of each aircraft in the scenario to the TMA. The reason for taking speed values from the scenarios used in the simulator environment is to compare the traffic rankings in the scenario with the ranking values obtained with fuzzy logic. Figure 7 shows the speed ranges used in this study and the corresponding linguistic expressions.

The speed parameters between 220 kt and 340 kt are shown on the x-axis for aircraft speed, and the membership degree between 0-1 is on the y-axis. Speeds are shown as

220-245 kt very slow,
225-275 kt is slow,
255-305 kt is medium,
285-335 kt is fast,
315-340 kt is very fast.

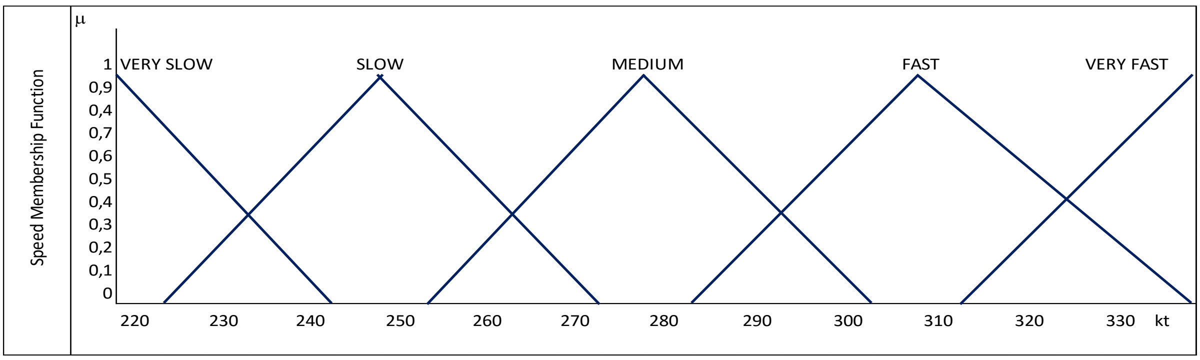

Figure 7. Airspeed triangle membership function

4.1.2. Distance membership function

In the sequencing of arrival traffics, the distance membership function is assumed that the traffics flying within the TMA will fly on the determined routes and the distance is determined between 0-65 NM. Since the study will be compared with the scenarios created in the Istanbul Terminal area where the old Ataturk Airport is located, the distance including the area where the Imren report and waiting point are located, which is 23 NM away before entering the final approach route, is taken as the basis.

The speed ranges corresponding to the verbal expressions given regarding the distance membership function shown in Figure 8 are as follows;

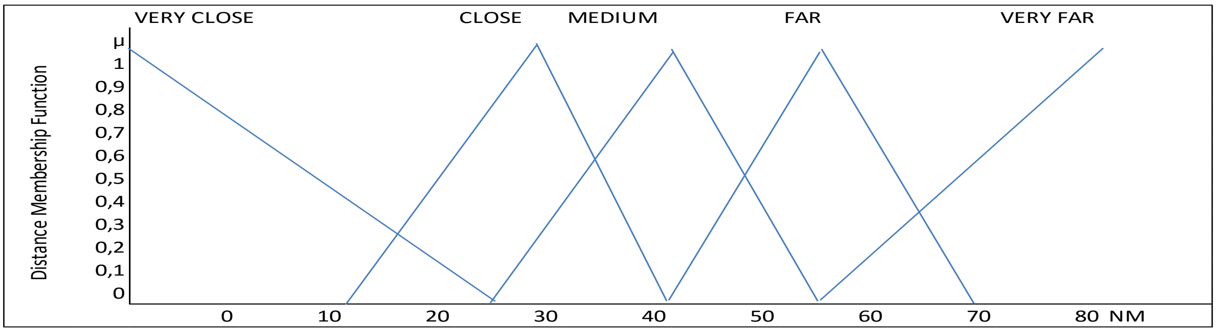

Figure 8. Distance membership function

The distance membership function is determined according to the following values:
Very close between 0-25 NM,
10-40 NM is near,
25-55 NM is medium,
40-70 NM is far,
55-85 NM is very far.

4.1.3. Altitude membership function

The altitude membership function is determined according to the values between 4000 ft-16000 ft. The altitude membership function is shown in Figure 9. The altitude membership function is determined according to the following values:
4000-9000 ft is very low,
6000-12000 ft is low,
9000-15000 ft is medium,
12000-18000 ft is high,
15000-20000 ft is very high.

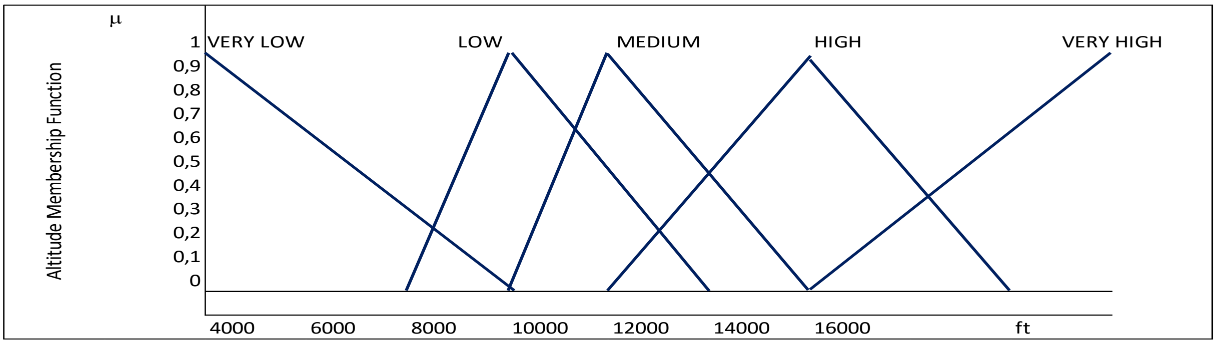

Figure 9. Altitude membership function

4.1.4. Output membership function

Based on the rule base of speed, distance, altitude membership functions, values between 0-100 points for the output membership function are shown in Figure 10. with verbal expressions.
0-20 point is very very low,
10-30 point is very low,
20-50 point is low,
40-60 point is medium,
50-80 point is high,
70-90 point is very high,
80-100 point is very very high.

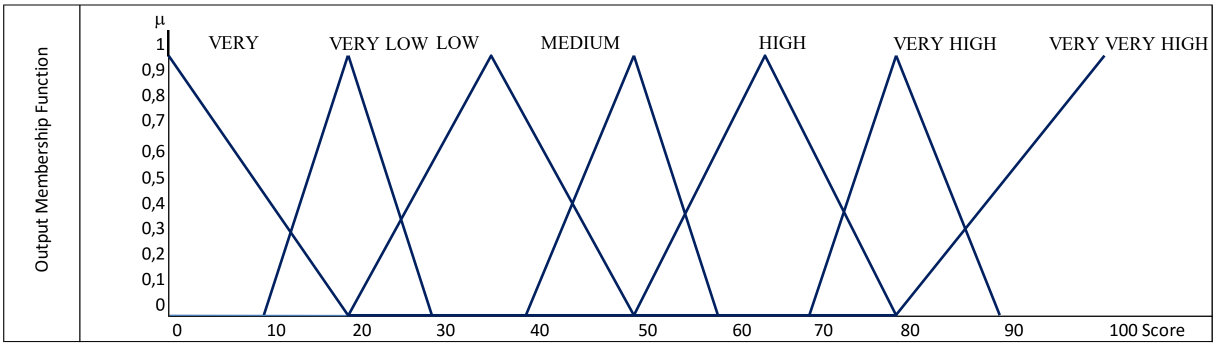

Figure 10. Output membership function

4.2. Fuzzy Database and Rule Base

Traffic data are collected from scenarios developed using aircraft performance data derived from BADA. These scenarios are implemented in the Air Traffic Simulation Laboratory of the Air Traffic Control Department at Eskişehir Technical University. The simulator is capable of running radar-free air traffic control scenarios and provides real-time data on aircraft speed, distance, and altitude at TMA reporting points. A total of ten distinct scenarios were developed based on this data.

4.3. Rule Base

The model is designed with a rule base consisting of 125 rules. The rules are defined in an "If-Then" format based on expert opinions and simulator data. It is demonstrated that when the input values of speed (280 kt), distance (32.5 NM), and altitude (10,000 ft) are entered, the resulting score is 43.7. Scores are calculated separately for each aircraft using the MATLAB.
For example, the rule base can be created according to the speed, distance and altitude of an aircraft coming in for an approach as follows;
If the aircraft is fast, the distance is medium and the altitude is very low, the score is very very high.
If the aircraft speed is slow, the distance is very close and the altitude is high, the score is high.
If the aircraft speed is fast, the distance is very far and the altitude is very low, the score is medium.
After the rule base is created, the inference process is applied.

4.4. Inference

The Mamdani fuzzy inference method is easily created and is widely used in the literature because it is closer to human behavior. In this study, since the researcher worked as an air traffic controller in active working conditions, fuzzy logic modeling was created based on his knowledge and experience and the Mamdani inference method was applied in this modeling.

4.5. Defuzzification

The centroid method was preferred in this study because the ranking scores needed to be expressed continuously and precisely, and this method provided the most accurate results.
This method produces a single numerical value by calculating the weighted average of the fuzzy output. For example, a fuzzy output consisting of the sets “High” and “Very High” was converted to a score of 0.78 by the centroid method.

5. FINDINGS

In this study, a fuzzy logic model was developed for sequencing arrival traffic within TMA, based on ten exercises conducted in the Real-Time Simulation (RTS) environment at the Air Traffic Control Simulation Laboratory of Eskişehir Technical University. Each exercise involved six aircraft, and performance data were obtained from the Base of Aircraft Data (BADA). The aircraft, all of type B738, were simultaneously displayed on the pilot screen of the simulator, with distance, speed, and altitude values provided as part of the exercise setup. The aircraft altitudes ranged between 4,000 ft and 10,000 ft, and the speeds used were those observed in the simulator. The distance values represented the aircraft’s distance to the designated holding point.

The model was tested across ten distinct traffic scenarios. In each scenario, the sequence generated by the fuzzy logic model was compared with the current sequence produced by the procedural (baseline) approach. The analysis evaluated the impact of speed (kt), distance (NM), and altitude (ft) parameters on sequencing outcomes. The results were supported by quantitative outputs derived from both the MATLAB/Fuzzy Inference System (FIS) interface and the simulator data.

5.1. Scenario Analyses

10 scenarios were created based on the distances at the TMA report points and traffic data obtained from the simulation environment. In each scenario, the speed, distance and altitude values of more than one aircraft were given as input to the fuzzy logic model; the sequencing score (SCORE), which is the output of the model, was used to determine the landing priority of the aircraft. Detailed analyses of some selected scenarios are presented below:
The starting time of the scenarios was accepted as 00:00, and the estimated arrival time represents the time in minutes added to this hour. The traffic sequencing was designed based on Imren report point. 10 scenarios were created. The data for the traffics created in the first scenario are shown in Table 2.

Table 2. First scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
A1	293	61	8000	13	6	47,79	5
A2	262	51	6000	13	5	46,50	6
A3	292	66	7000	12	4	48,15	4
A4	292	53	7000	11	3	48,66	3
A5	260	17	5000	5	1	72,9	1
A6	292	44	9000	10	2	53,73	2

An analysis of the estimated arrival times to the Imren point in the traffic scenarios derived from the RTS reveals that the first aircraft in the traffic sequence is A5, followed by A6, A4, and A3, respectively. It is observed that aircraft A1 and A2 share the same estimated arrival time.

From the controller's perspective, when evaluating the traffic in terms of landing sequence, an aircraft at a lower altitude may be prioritized and brought forward to land earlier. Accordingly, in this example, A2 is assigned the fifth landing position, while A1 is positioned last.

When the traffic is ranked based on the scores generated by the proposed fuzzy logic method, it is observed that A5, having the highest score, is ranked first. According to the fuzzy logic-based ranking, the sequence is A6, A4, A3, A1, and A2. A comparison between the results of the simulator scenario and the traffic sequencing determined by the fuzzy logic method indicates a comparable order. In the simulator-based scenario, A1 and A2 are assigned the same rank due to their identical estimated arrival times; however, the fuzzy logic method differentiates between them based on their respective scores, thus altering the estimated ranking. The data related to the second scenario are presented in Table 3.

Table 3. Second scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
B1	262	22	6000	5	1	70,95	1
B2	292	50	9000	10	4	47,58	4
B3	293	47	8000	9	2	53,03	2
B4	293	54	8000	10	3	49,00	3
B5	292	60	9000	12	5	46,54	5
B6	288	65	7000	13	6	45,15	6

In the second scenario, the aircraft B1, B3, B4, B2, B5, and B6 arrive in the same order according to both the estimated arrival times and the fuzzy logic-based ranking. The RTS estimated arrival times for B2 and B4 are identical; therefore, it is expected that the controller would prioritize B4, which is at a lower altitude.

Table 4. Third scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
C1	282	31	7000	6	2	70,47	2
C2	260	20	6000	5	1	71,33	1
C3	291	48	9000	10	4	49,33	4
C4	292	40	8000	9	3	67,88	3
C5	285	60	8000	11	5	37,54	5
C6	280	55	9000	12	6	35	6

In the third scenario, the arrival sequence of the aircraft according to the estimated arrival times and the fuzzy logic method is as follows: C2, C1, C4, C3, C5, and C6 (Table 4). As in the previous scenario, the results indicate that the RTS and fuzzy logic methods align.

Table 5. Fourth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
D1	283	55	7000	11	6	41,03	6
D2	260	20	5000	5	1	71,33	1
D3	260	27	5000	6	2	65,82	2
D4	288	43	8000	9	4	57,83	4
D5	287	50	9000	10	5	46,53	5
D6	260	37	6000	8	3	60	3

In the fourth scenario, the estimated arrival times and the fuzzy logic method resulted in the sequence D2, D3, D6, D4, D5, and D1, with the arrival order being identical (Table 5).

Table 6. Fifth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
E1	293	60	7000	13	6	48,31	6
E2	293	61	7000	12	5	49,78	5
E3	260	20	5000	5	1	71,33	1
E4	298	47	8000	8	3	56,32	3
E5	262	30	6000	7	2	64,45	2
E6	297	54	9000	11	4	52,27	4

In the fifth scenario, the estimated arrival times and the sequencing of the aircraft according to the fuzzy logic method are the same and with the order being E3, E5, E4, E6 and E1, respectively (Table 6).

Table 7. Sixth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
F1	260	21	6000	5	1	70,66	1
F2	262	31	6000	6	2	63,82	2
F3	298	54	8000	11	5	54,38	5
F4	298	47	8000	8	3	56,32	3
F5	297	60	9000	12	6	52,27	6
F6	293	50	7000	10	4	55,02	4

According to the data presented in Table 7, the estimated arrival times of the aircraft and the arrival sequence determined by the fuzzy logic method are identical, with the order being F1, F2, F4, F6, F3, and F5, respectively.

Table 8. Seventh scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
G1	292	54	9000	10	5	46,54	5
G2	293	50	8000	9	4	51,44	4
G3	298	44	8000	9	3	56,60	3
G4	262	34	6000	9	2	62,73	2
G5	262	16	6000	4	1	73,56	1
G6	292	60	9000	12	6	46,54	6

In Table 8, which presents the seventh scenario, the aircraft arrival sequence based on the estimated arrival times is as follows: G5 is ranked first, followed by G2, G3, and G4, which share the same estimated arrival time. Subsequently, G1 and G6 follow. According to the fuzzy logic method, the ranking is G5, G4, G3, and G2. G1 and G6 receive the same score; however, G1 is ranked ahead due to its shorter distance.

Table 9. Eighth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
H1	260	20	5000	5	1	71,33	1
H2	262	30	6000	7	2	64,45	2
H3	293	50	8000	10	4	51,44	4
H4	292	60	9000	12	6	46,54	6
H5	293	57	8000	10	5	47,79	5
H6	288	45	7000	8	3	52,93	3

In the eighth scenario, based on the estimated arrival times, the sequence is H1, H2, H6, followed by H3 and H5, which share the same estimated arrival time (Table 9). According to the fuzzy logic method, the resulting order is H1, H2, H6, H3, H5, and H4. In the fuzzy logic approach, the relatively short distance of H3 is the primary factor contributing to its higher score.

Table 10. Ninth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
I1	293	60	8000	12	5	47,79	5
I2	292	60	9000	12	6	46,54	6
I3	293	50	8000	11	4	51,44	4
I4	288	45	7000	8	3	52,93	3
I5	262	35	6000	7	1	62,53	2
I6	288	35	7000	7	2	72,17	1

In the ninth scenario, according to the estimated arrival times in the RTS, I5 and I6 are ranked first, followed by I4, I3, and then I1 and I2, which share the same estimated arrival time. In contrast, the ranking determined by the fuzzy logic method is I6, I5, I4, I3, I1, and I2, respectively, as shown in Table 10. In the fuzzy logic method, the higher score assigned to I6 is attributed to its higher altitude in combination with a higher speed compared to I5. Similarly, I1 receives a higher score than I2 due to its lower altitude.

Table 11. Tenth scenario

Aircraft Code	Speed (kt)	Distance (NM)	Altitude (ft)	Estimated Time of Arrival (Min)	RTS Sequencing	Fuzzy Logic Score	Fuzzy Logic Sequencing
J1	293	55	8000	11	6	47,79	6
J2	288	48	7000	10	4	52,80	4
J3	262	40	6000	9	2	57,53	2
J4	262	35	6000	9	1	62,53	1
J5	288	45	7000	9	3	52,93	3
J6	293	49	8000	11	5	52,18	5

In the tenth scenario, based on the RTS estimated arrival times, the sequence is J3, J4, and J5—each with the same estimated time—followed by J2, and subsequently J1 and J6, which also share the same estimated arrival time. According to the fuzzy logic method, however, the arrival sequence is determined as J4, J3, J5, J2, J6, and J1, as presented in Table 11.

6. CONCLUSION

In air traffic management, decision making is very important for air traffic to be managed safely, quickly and regularly. Decision making must be done in a timely and most accurate way. It is especially important to be able to make a fair approach order among the traffic coming from different directions for landing within the terminal area. Controllers make decisions according to distance, level or speed parameters among multiple traffics moving within a limited time. Even in normal situations, the traffic order problem, which is very important for controllers to make decisions, leads to an increase in research every day due to the increasing traffic density in the world. In this study, the fuzzy logic method was used to determine the order of arrival traffics in order to help with decision making. The purpose of using this method is to better display human behavior compared to mathematical models and to provide an approach closer to reality by benefiting from the experience and ideas of experts.

Among the results presented by the study, the arrival order made according to the estimated arrival time in the real-time simulator can show the same time or order. However, the arrival order made according to the fuzzy logic method can give a more precise order. It is seen that the fuzzy logic method gives more accurate information, especially in cases where there is closeness or similarity in the values of parameters such as distance, speed or altitude.

In the exercises performed in the real-time simulator environment, the number of aircraft with the same estimated arrival time was 14 and constituted 23.3% of the total traffic, while the number of aircraft with the same score with the fuzzy logic method was 2 and constituted 3.3% of the total traffic. Again, no contradiction was observed between the aircraft with the same estimated arrival time and the arrival order score according to the fuzzy logic method. It was observed that the aircraft with the same estimate came after each other when the arrival order was made with the fuzzy logic score. For this reason, parallelism was observed between the data obtained in the simulator environment and the fuzzy logic method.

The findings showed that the fuzzy logic model produced consistent and reliable results in the ordering of arrival traffics in TMA. It was determined that the model provided higher accuracy in cases where speed and distance were dominant, while altitude had a secondary effect. The high agreement with the simulator supports the validity of the method for real-time applications. The study is a static model in that all data are known in advance and there are no situations that will cause changes later. In future studies, it is thought that this study will be useful in the development of ground support systems for terminal airspace optimization, aircraft ordering and aircraft landing problems by creating a dynamic model.

ACKNOWLEDGEMENTS

This study was derived from the master's thesis titled "A Fuzzy Logic Approach to Sequencing Arrival Traffic," completed at the Graduate Education Institute, Eskişehir Technical University, 2023

This study was supported by Eskişehir Technical University Scientific Research Project Commission under grant no: 23ADP077.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Gülseren Yeşil: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Funding acquisition. **Özlem Şahin:** Supervision, Visualization, Conceptualization, Writing – Review & Editing.

REFERENCES

[1] Moser I. Scheduling aircraft landings dynamically using stochastic and deterministic elements. Int J Inf Technol Intell Comput 2007; 2: 1-21.

[2] Brentnall AR, Cheng RC. Some effects of aircraft arrival sequence algorithms. J Oper Res Soc 2009; 60: 962-972.

[3] Çeçen RK, Cetek C, Kaya O. Aircraft sequencing and scheduling in TMAs under wind direction uncertainties. Aeronaut J 2020; 124: 1896-1912.

[4] Dönmez K. A stochastic sequence planning model for the runways with multiple exits. Akıllı Ulaşım Sist Uyg Derg 2022; 5: 89-101.

[5] Liang M. Aircraft route network optimization in terminal maneuvering area. Univ Paul Sabatier Toulouse 3 2018.

[6] Dear RG. The dynamic scheduling of aircraft in the near terminal area. Cambridge, Mass: Flight Transportation Laboratory, Massachusetts Institute of Technology, 1976.

[7] Ikli S, Mancel C, Mongeau M, Olive X, Rachelson E. The aircraft runway scheduling problem: A survey. Comput Oper Res 2021; 132: 105336.

[8] Ören A, Koçyiğit Y. Unmanned aerial vehicles landing sequencing modelling via fuzzy logic/ İnsansız hava araçları iniş sıralamasının bulanık mantık modellemesi. Celal Bayar Univ J Sci 2016; 12: 1-21.

[9] Pratiwi W, Sofwan A, Setiawan I. Implementation of fuzzy logic method for automation of decision making of Boeing aircraft landing. IAES Int J Artif Intell 2021; 10: 545-555.

[10] Ntakolia C, Lyridis DV. A n− D ant colony optimization with fuzzy logic for air traffic flow management. Oper Res 2022; 22: 5035-5053.

[11] Bongo MF, Seva RR. Evaluating the performance-shaping factors of air traffic controllers using fuzzy DEMATEL and fuzzy BWM approach. Aerospace 2023; 10: 252-262.

[12] Chikha P, Skorupski J. The risk of an airport traffic accident in the context of the ground handling personnel performance. J Air Transp Manag 2022; 105: 102295.

[13] Kolotusha V, Shmelova T, Bondarev D. Multi-criterion evaluation of the criteria of the information model conformity of the air traffic controller simulator to the real system. Int Workshop Adv Civ Aviat Syst Dev 2024; 364-384.

[14] Lee WK. Risk assessment modeling in aviation safety management. J Air Transp Manag 2006; 12: 267-273.

[15] Siergiejczyk M, Krzykowska K, Rosiński A. Reliability assessment of cooperation and replacement of surveillance systems in air traffic. Adv Intell Syst Comput 2014; 286: 403-411.

[16] Ross TJ. Fuzzy logic with engineering applications. (Second Edition), England: John Wiley and Sons, 2004.

[17] Ali OAM, Ali AY, Sumait BS. Comparison between the effects of different types of membership functions on fuzzy logic controller performance. Int J 2015; 76: 76-83.

[18] Dumitrescu C, Ciotirnae P, Vizitiu C. Fuzzy logic for intelligent control system using soft computing applications. Sensors 2021; 21(8): 2617.

[19] Yahia NB, Bellamine N, Ghezala HB. Integrating fuzzy case-based reasoning and particle swarm optimization to support decision making. Int J Comput Sci Issues 2012; 9(3): 117.

[20] Kıyak E. Flight Control Using Fuzzy Logic Method. Eskişehir: Anadolu Üniv Fen Bil Enst, 2003.

[21] Ceruto T, Lapeira O, Tonch A, Plant C, Espin R, Rosete A. Mining medical data to obtain fuzzy predicates. In: Information Technology in Bio-and Medical Informatics: 5th International Conference, ITBAM 2014, Munich, Germany, September 2, 2014; Proceedings 5. Springer International Publishing; 2014. p. 103-117.

[22] Katircioglu F, Sen MOY, Kelek MM, Koyuncu I. FPGA-Based Design of Gaussian Membership Function for Real-Time Fuzzy Logic Applications. In: International Multidisciplinary Congress of Eurasia 2018; 2018. p. 33-39.

[23] Sabri N, Aljunid SA, Salim MS, Badlishah RB, Kamaruddin R, Malek MA. Fuzzy inference system: Short review and design. Int Rev Autom Control 2013; 6(4): 441-449.

[24] Khademi Hamidi J, Shahriar K, Rezai B, Bejari H. Application of fuzzy set theory to rock engineering classification systems: an illustration of the rock mass excavability index. Rock Mech Rock Eng 2010; 43: 335-350.

[25] Karasakal O. Online rule weighting methods for fuzzy pid controllers. İstanbul Tek Üniv Fen Bil Enst 2012.