ARTICLE

doi: https://10.55124/jaim.v3i1.259

SciForce

Journal of Artificial intelligence and Machine Learning

Journal homepage: www.sciforce.org

Evaluating Machine Learning Techniques for Demand Forecasting in Supply Chains Using MOORA Method

Rakesh Mittapally*

*Business Intelligence Architect/AI and ML Engineer, Texas, USA

ARTICLE INFO

Article history:
Received: 20250116
Received in revised form: 20250126
Accepted: 20250220
Available online: 20250308

Keywords:
Machine Learning (ML);
Supply Chain Management (SCM);
Multi-Criteria Decision-Making (MCDM);
Prediction;
Sensitivity Analysis.

ABSTRACT

This study introduces a novel approach that combines Combining Machine Learning methods with Multi-Criteria Decision-Making to help supply chain stakeholders identify the best model for delay prediction. Unlike conventional approaches that integrate MCDM and ML into a single system, this paper uses MCDM to evaluate different ML classifiers to improve decision-making. Additionally includes a sensitivity study to assess the method's resilience to other MCDM approaches, providing a thorough solution for accurate delay prediction in dynamic supply chain settings.

This study is noteworthy for being the first to combine Supply chain support through machine learning and multi-criteria decision-making stakeholders in predicting delays. By evaluating different ML classifiers through MCDM and performing a sensitivity analysis, it provides a robust and interpretable decision-making framework that improves supply chain management efficiency.

The bagging method achieved the highest rank, while the Decision Tree received the lowest rank.

According to the MOORA approach, bagging holds the highest value for machine learning in supply chain applications.

*Corresponding author. e-mail: mittapallyrakesh@gmail.com

1. **Introduction**

This study is novel in that it combines machine learning and multi-criteria decision-making to help supply chain participants choose the best model for forecasting delays. The unique contributions of this paper differ from the more popular strategy of creating a unified prediction method that combines MCDM and ML. These include: a new method that uses MCDM to assess various ML classifiers and a sensitivity analysis to evaluate the approach's robustness across the various MCDM techniques used for evaluating and choosing ML models. [2] Concerns about inadequate data have given way to anxieties about the deluge of data in supply chain management (SCM) in today's dynamic and often changing environment. The enormous amount of data produced throughout the supply chain has changed how SCM analysis is carried out. Traditional procedures have become less effective and efficient as the

Amount of data has grown. The inability of these approaches to handle and comprehend enormous datasets has led academics to create other ways that can analyze and interpret big data. Since one well-known Machine learning (ML) techniques are used in conjunction with artificial intelligence (AI), the main goal of this study is to investigate (SCM). The benefits that machine learning offers to production and inventory management, transportation and distribution, demand and sales forecasting, and supply chain risk prediction, sustainable development (SD), supplier selection and segmentation, and the circular economy (CE) are highlighted in this paper through the creation of a conceptual framework. [3] The creation of medium- to long-term plans for the entire supply chain is supply chain planning's (SCP) goal. SCP's primary goal is to plan production and logistics resources to satisfy customer needs. Resource planning is therefore dependent on anticipated consumer demand.

Demand and network planning are important activities in SCP because they enable available-to-promise and capable-to-promise checks and serve as the basis for planning for production, distribution, and procurement. SCP is supported in the short term by scheduling, sequencing, procurement planning, and short-term distribution planning. [4] Participating companies should aim for complete supply chain collaboration, but there are a number of obstacles that prevent meaningful advancement in this direction. Participants must therefore forecast demand even when they do not have full knowledge of other participants' desire. In order to predict this study explores the use of sophisticated machine learning methods, such as recurrent neural networks and support vector machines, and neural networks, to address the bullwhip effect, or skewed demand at a supply chain's conclusion.

These strategies are contrasted with more traditional approaches like trend analysis and linear regression analysis, naive forecasting, and moving averages. Two datasets, one from actual Canadian foundries and the other from a simulated supply chain orders are used in the study's experiments. [5] Pre-trained models are a relatively new technology, and security procedures pertaining to their application should get better with time. Our goal is to strongly encourage the application of the knowledge gained from software supply chain security to the field of machine learning security. We specifically advise that repositories include digital signatures for models and that pre-trained models be received from reliable sources via channels that provide strong integrity assurances while in transit.

In a broader sense, we think our research highlights the necessity of investigating methods for identifying backdoors in deep neural networks. Given the intrinsic difficulties of understanding the behavior of a trained network, we expect this to be a difficult undertaking, but it might be possible to identify and analyze the activity of network portions that do not operate during validation. [6] As human labor give way to robots and sensor-activated equipment, businesses must modify their operations. It's critical to acknowledge the rapidly expanding trend of global industrial activities powered by machine learning, indicating that machine learning has already taken precedence over other business priorities for many companies across the globe. Machine learning is showing great promise in forecasting and projection.

Along with focusing on supply and demand balance, organizations anticipate better projections for their manufacturing and supply chains. Businesses can get precise and trustworthy forecasts because to machine learning's capacity to automatically store, evaluate, and—most importantly—predict data. These projections aid in the optimization of purchasing and order processing, among other procurement-related tasks. Furthermore, machine learning finds patterns and trends that help create more effective production and retailing plans. Supply chain collaboration has become more information-intensive, particularly given the current corporate environment's instability and dynamism. Researchers and experts alike have found methods to efficiently handle this data and use it to inform stronger, more informed decisions. [7] Combining machine learning techniques with optimization algorithms inspired by natural occurrences can yield useful and efficient solutions for industries and supply networks. Industrial plants frequently utilize simulation techniques to handle internal logistical issues; these models assess warehouse effectiveness and assist in lowering internal logistics expenses. Business continuity and profitability may be at risk if possible risks are not recognized and plans to reduce high-probability hazards are not developed. However, businesses that prioritize risk management are more likely to face actual difficulties with flexibility and responsiveness to unanticipated problems.

These businesses enhance their operations by taking measured risks. SMBs must develop a thorough risk management strategy that tackles the main risks to their supplier network inventory, including poor supplier quality and implementation, supply chain volatility, complex product and administration mix issues, insufficient outsourcing operations and connections, and a shortage of physical resources. [8] In order to protect supply chains from disruptions by foreseeing their appearance and mitigating their negative effects, supply chain risk management has received more attention in recent years. Concurrently, research into Supply chain risk management has improved thanks to machine learning techniques and their application to the resurgence of artificial intelligence (AI).

The one that majority of research, however, places a strong emphasis on prediction accuracy at the expense of interpretability, which is essential for supply chain experts to comprehend the findings and make choices that can reduce or eliminate hazards. In this paper, we propose a framework for supply chain risk prediction that leverages the collaboration between supply chain experts and AI, utilizing data-driven AI techniques. Next, we investigate how the framework might be used to predict delivery delays in an actual multi-tier industrial supply chain, balancing interpretability and prediction accuracy.

Experimental results indicate that emphasizing interpretability over prediction performance may lead to trade-offs, especially regarding average precision scores. [9]Agriculture is vital for supporting human activities, yet challenges like overpopulation and resource competition pose significant threats to global food security. To tackle the growing complexity of Precision agriculture, smart farming, and agricultural production systems offer effective solutions for enhancing sustainability. Data analytics are critical for securing future food availability, safety, and ecological balance.

Disruptive technologies, including among the challenges that machine learning, big data analytics, cloud computing, and other technologies can help with are raising production and yield, conserving water, preserving soil and plant health, and promoting environmental responsibility block chain may help with. A thorough analysis of machine learning applications in agricultural supply chains is given in this article. Ninety-three research publications in all, focusing on the application of different machine learning algorithms at various phases of the ASC. [10] This disruption offers both possibilities and difficulties for businesses, particularly in supply chain management. As much data becomes more prevalent, data analytics is crucial for converting raw data into actionable insights, which are vital for supply chain operations.

One data analytics technique set the Knowledge job automation, sometimes referred to as machine learning, and has the potential to affect market inequities, employment, and growth. This study highlights the promise of machine learning by offering a thorough review of its applications in demand forecasting to improve supply chain efficiency. [11] They improve supply chain transparency by utilizing machine learning-based systems that integrate IoT and scanning devices to gather a large volume of data. These systems, combined with real-time information such as weather forecasts, traffic conditions, and other critical factors affecting transportation, provide enhanced visibility into the supply chain. This allows for the prediction of delivery delays and route adjustments when needed. [12] The food industry is a complex commercial network that spans the whole value chain, from production to consumption, rather than just being a typical industry.

The industry must continuously incorporate the newest technologies to be sustainable and competitive. Productivity in the food industry can be increased via artificial intelligence (AI). Crop output predictions, irrigation needs, and soil composition analysis are all aided by machine learning. AI can also be used in robotics and video surveillance to track crops, identify weeds, and automate planting and weed control. [13] Using information from executives, managers, and senior managers of SMEs, a structural model that combines AI-driven risk management capabilities, supply chain re-engineering capabilities, and supply chain agility (SCA) was created and evaluated.

Artificial neural networks (ANN) and partial least squares-based structural equation modeling (PLS-SEM) were the main research techniques employed in this study. The findings showed that Agility and supply chain re-engineering capabilities are impacted by AI's involvement in risk management, with re-engineering capabilities impacting and mediating agility. A comparison of the PLS-SEM and ANN results showed consistency between models A and B. Present-day uncertainty in supply chain demand pose challenges for managers who must make difficult trade-off decisions under pressure and with limited resources.

AI allows for modeling various scenarios to address key issues that outdated systems cannot. This study introduces a multi-construct agility concept and emphasizes the identification of non-linear relationships within the model. [14] The first contribution of this study is that our bibliometric analysis offers the research community a clearer insight into the adoption and viability of AI and ML concepts within the supply chain context. This analysis enables scholars to trace the evolution and growth of academic research in this field since 2002. Secondly, researchers exploring AI and ML's function in the supply chain can leverage our findings to guide their own work, addressing the gaps identified in this study and setting targeted research objectives for future investigations. [15] This paper aims to close the gap in the existing literature on humanitarian supply chains, which mostly concentrates on discrete technical applications without offering a thorough framework to examine the problems and potential solutions. The report illustrates solutions that make use of new disruptive technologies using a case study of the 2007 Tabasco flood in Mexico. The paper also makes the case that achieving notable advantages in several technologies must be integrated into humanitarian supply networks.

Thus, it proposes a paradigm for improving the flow of information, products, and financial resources in these supply chains by fusing three emerging disruptive technologies: artificial intelligence, block chain, and 3D printing. [16] However, the study revealed a surprising finding about the connection between cooperation and internal integration in the manufacturing supply chain. The authors suggest that certain firm attributes and outside variables, such laws, may be the cause of these discrepancies. They highlight how complicated industrial supply chain research is and how several factors might affect the results. Notwithstanding this unexpected discovery, the study emphasizes how AI might improve manufacturing's resilience and adaptability. All things considered, AI and cloud adoption are viewed as critical instruments for American manufacturers to thrive in a cutthroat, resource-constrained market. [17] Numerous systems and applications make extensive use of machine learning (ML) techniques, which improve overall efficiency and performance.

In a variety of industries, these methods offer improved services and user experiences. Machine learning (ML) is used in supply chain management (SCM) to avoid problems and failures and guarantee on-time delivery of goods. In SCM, reinforcement learning algorithms are particularly popular since they enhance process performance and dependability. To lower the failure rate during detection, these algorithms make use of particular patterns, parameters, and values. SCM specifically uses reinforcement learning methods to improve the precision of product movement tracking within software.

2. MATERIALS AND METHOD

Decision Tree: One type of supervised machine learning method is decision trees used in classification and regression applications. It models decisions using a structure resembling a tree, where every internal node represents a feature-based selection and every leaf node a continuous value or a class label, while each branch represents the decision's result. It is frequently used for simple prediction tasks because of its ease of interpretation.

Random Forest: To improve accuracy and resilience, Random Forest, an ensemble learning technique, integrates many decision trees. It trains each tree is applied to a random portion of the data, and their predictions are combined using either averaging (for regression) or majority voting (for categorization). This method helps reduce overfitting and improves overall model performance.

Ada Boost: Ada Boost (Adaptive Boosting) is an ensemble technique that builds a stronger classifier by combining several weak classifiers, typically decision trees classifier. It iteratively adjusts the weight of misclassified instances, placing more emphasis on the difficult cases in each successive iteration. This approach enhances the model's accuracy by giving greater weight to harder-to-predict samples.

Bagging: Bagging (Bootstrap Aggregating) is an ensemble technique that creates several models by training them on various random data subsets, generated through sampling with an alternative. The ultimate result is produced by combining each model's predictions, either by averaging (for regression) or majority voting (for classification). Bagging aids in reducing variance and enhancing the stability of the model.

Accuracy: Accuracy represents the proportion of accurate predictions a model makes, computed as the proportion of instances that were accurately predicted to every situation. Despite offering an exhaustive evaluation of the model's effectiveness, it may not be ideal for datasets with imbalanced classes.

Precision: The percentage of accurately identified positive observations among all expected positive instances of observations is known as precision. It gauges the precision of positive forecasts and is particularly important when erroneous positives are costly.

Recall: Recall, also referred to termed the real positive rate or sensitivity determined by the model, is the proportion of true positive cases that are accurately reported. It is essential when a positive event (false positive) is missed.

Log Loss: Log Loss, sometimes referred to as Logarithmic Loss or Cross-Entropy Loss, assesses a classification model that outputs probability values between 0 and 1. It imposes a heavier penalty when the model is confident but wrong in its predictions. A lower log loss signifies better model performance.

Method: This approach uses a matrix representing the responses of alternatives to different objectives, using ratios for these responses. To demonstrate its effectiveness, the MOORA method is compared with the established alternative reference point method and is shown to outperform other techniques. A unique feature of MOORA is the use of ratios, where the denominator it is the sum of the squared replies divided by the square root. These dimensionless ratios are either subtracted for minimization or added for maximizing. They have a range of zero to one, allowing for the ranking of alternatives.

In addition, the method enables prioritization of specific objectives by replacing them with sub-objectives or by assigning importance coefficients. [19] This paper examines six decision-making scenarios, including the selection process involves Choosing a computerized numerical control (CNC) system, a flexible manufacturing system, or an industrial robot machine, a fast prototyping, non-traditional machining, and an automated inspection system designed for a particular mix of shape and material. In each case, the outcomes derived using the MOORA method closely align with those from earlier studies, demonstrating its relevance, efficiency, and versatility in tackling complex decision-making challenges in modern manufacturing systems. [20] These interpretations were evaluated through their application in the Lithuanian facilities sector. The multi-objective analysis considered factors such as costs, experience, and efficiency from the contractors' perspective, as well as quality, project duration, and cost from the owners' perspective. Since these objectives are expressed in different units, the MOORA method's dimensionless ratios effectively resolved normalization challenges. In the first MOORA stage, in the second step, these ratios were evaluated as distances from a reference point after being aggregated.

The consistency of the outcomes from both phases supported their dependability. Furthermore, MOORA outperformed other multi-objective optimization techniques in terms of reliability. In the facilities industry in Lithuania, both MOORA stages produced similar rankings, further confirming the robustness of the findings. [21] It should be noted that in order to address both advantageous and non-beneficial factors in decision-making teams, special normalization equations are occasionally needed. Nevertheless, a number of contemporary approaches are intricate and challenging to apply, frequently necessitating a high level of mathematical expertise.

This intricacy emphasizes the necessity of a straightforward, rational, and organized method for resolving material selection issues. Multi-objective optimization is one of three straightforward techniques that are used this paper relies on ratio analysis (MOORA), reference point method, and integer multiplication MOORA. These methods facilitate more accurate ranking of material alternatives while minimizing the impact of criterion weights and normalization processes. [22] Using the Multi-Objective Optimization by Ratio Analysis (MOORA) method, the first six requirements are all met. Furthermore, by merging two distinct multi-objective optimization techniques, it partially satisfies the seventh criteriastands out as a very robust approach, as no other method has been proven to satisfy all seven conditions so effectively. [23] This research paper presents an analysis of a maintenance system using the MOORA method.

The evaluation provides valuable insights that will help maintenance managers identify the most effective strategies to reduce operational costs due to machine failures and production line downtime. Ultimately, a complete evaluation of the maintenance system helps identify the best performing machines and guides the development of action plans to improve the performance of the underperforming machines. The MOORA method is mathematically simple, systematic, easy to understand, and well suited for maintenance system evaluation, providing a more objective and rational approach.

For future research, it is recommended to explore other MCDM techniques to confirm the findings and compare the results under varying levels of decision-making uncertainty. [24] The following outcomes were obtained using the MOORA method: three contractors were placed in the top three, and the fourth contractor also received a favorable ranking. One contractor was placed in the lowest category, and the remaining ten contractors were ranked lower, although their exact positions were not specified. Interestingly, the top performing contractors were not the most cost-effective, which was somewhat surprising. However, company size significantly affected the rating.

Consequently, initial concerns about excluding small companies from consideration were found to be unfounded. [25] The MOORA method that decision-makers or management can use effectively to make precise and timely decisions on various elements of the manufacturing environment, including product design, materials, manufacturing systems, facility location and organization, technology, and suppliers selection. However, since this method requires manual mathematical calculations, there is a need for a computer program to streamline the process and cut down on the computation time. Such a program can be created in the future using programming languages such as C++. [26] The ranking of performance factors is determined by six variables that influence three key aspects key components of a flexible manufacturing system (FMS): Productivity, flexibility, and quality are the key factors considered.

The MOORA method is applied in three variations: ratio-based, reference point, and integer multiplication approaches. The rankings are made with and without considering attribute weights. In addition, the PSI method is employed to determine the most significant variable among the factors. The results from both the MOORA and PSI methods align, confirming that the production system's most important component is productivity. These rankings are further validated considering how consistently the outcomes from the various approaches used in this study. [27] The study utilized the Fuzzy MOORA and fuzzy AHP techniques to analyze survey data gathered from industrial engineers and students aspiring to join the field.

The aim was to prioritize and rank job sectors in manufacturing, logistics, finance/banking, healthcare, technology, software/information, and education based on ten criteria: salary, job satisfaction, career growth opportunities, productivity, goal alignment, professional status, guidance/pressure, social interaction opportunities, job demand, and ease of work. Among different approaches to multi-criteria decision-making (MCDM) approaches, MOORA was chosen for its effectiveness for three main reasons. First, as a new MCDM approach, it was designed to improve the performance of older techniques and get around its drawbacks. Second, it reduces the computational time required for problem-solving, as noted in MCDM literature. Lastly, MOORA has minimal setup time and is widely recognized for its robustness, making it an appealing choice for this study. [28] A shaft material selection challenge was investigated in order to confirm the efficacy of the suggested approach.

Alloy steel was determined to be the best material for the shaft using the fuzzy MOORA approach. This method was compared to the fuzzy VIKOR, fuzzy GRA, and fuzzy TOPSIS approaches to make sure it was reliable for AHM material selection. The suggested method's dependability as a tool for choosing AHM materials was validated by the consistent outcomes obtained from all four approaches. Subsequently, the main AHM components were designed and analyzed, leading to the fabrication and testing of the AHM to assess its performance. [29] Of the application concepts based on GRA, TM, PCA, GA, MOSA, MOPSO, and Taguchi, the MOORA method stands out for its simplicity, ease of use, and straightforward implementation.

According to various researchers, MOORA provides solutions with accuracy comparable to or nearly identical to those obtained by more complex MODM techniques. By focusing only on direct ratio analysis, it requires minimal manual effort and basic mathematical calculations, which significantly reduces the computational time typically associated with more complex methods. Furthermore, while other techniques often require specialized software such as Minitab, Design Expert, or MATLAB, and advanced technical skills, the MOORA method can be effectively implemented using MS Excel.

Its simplicity makes it an accessible and practical tool for both researchers and decision makers. [30] Selecting the most suitable ERP software from available market alternatives should be guided by a reliable MCDM approach. By using an MCDM-based approach improves the selection process by ensuring justification, accountability, and rationality, which are key factors for addressing complex and high-stakes decisions. This study introduces the to identify the optimal ERP systems for two manufacturing organizations, the fuzzy multi-objective optimization (MOORA) method—which is based on ratio analysis—was employed. The results show that the fuzzy MOORA approach is a straightforward, intuitive, and dependable tool for tackling decision-making challenges involving uncertain and imprecise valuation data.

3. ANALYSIS AND DISCUSSION

TABLE 1. Machine learning with supply chain

	DATA SET			
	Accuracy	Precision	Recall	Log Loss
Decision Tree	0.65	0.4	0.65	0.67
Random Forest	0.75	0.52	0.59	0.54
AdaBoost	0.69	0.43	0.5	0.69
Bagging	0.77	0.58	0.5	0.55

The table 1 presents the performance of four machine learning models—Decision Tree, Random Forest, Ada Boost, and Bagging applied to supply chain data. The evaluation metrics consist of log loss, recall, accuracy, and precision, offering a comprehensive overview of their effectiveness. Decision Tree achieves an accuracy of 0.65, indicating moderate performance in predicting outcomes. Its precision (0.4) and recall (0.65) reveal a trade-off between correctly identifying true positives and minimizing false negatives. However, its log loss value of 0.67 suggests a relatively high level of uncertainty in its predictions. Random Forest outperforms Decision Tree with an accuracy of 0.75. Its precision (0.52) is higher, indicating better performance in identifying relevant results. However, its recall (0.59) slightly lags, showing some limitations in detecting true positives. With a lower log loss of 0.54, Random Forest demonstrates greater reliability and confidence in predictions. Ada Boost delivers an accuracy of 0.69, slightly below Random Forest. While it’s precision (0.43) and recall (0.5) are modest, the log loss of 0.69 indicates higher prediction uncertainty in contrast to the alternative models. The maximum accuracy in bagging is attained at 0.77 and precision at 0.58. Although its recall (0.5) is the same as Ada Boost, it has a lower log loss (0.55), making it the most balanced and reliable model among the four.

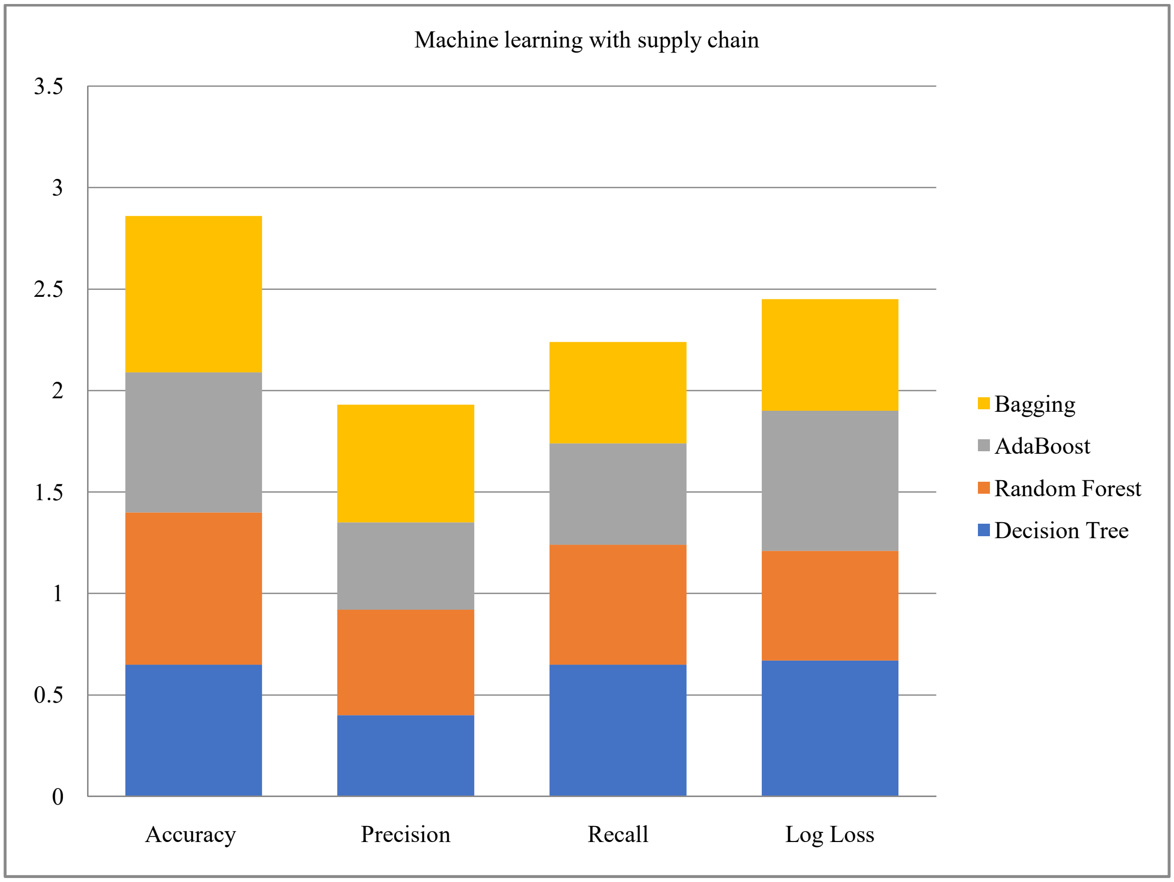

FIGURE 1. Machine learning with supply chain

Figure 1 illustrates the performance of four machine learning models—Decision Tree, Random Forest, Ada Boost, and Bagging applied to supply chain data. Bagging stands out with the highest accuracy (0.77) and precision (0.58), indicating its strong capability to make reliable predictions with fewer false positives. Random Forest follows closely, achieving an accuracy of 0.75 and a precision of 0.52, with a low log loss (0.54), suggesting good model confidence. Ada Boost and Decision Tree perform moderately, with accuracies of 0.69 and 0.65, respectively. However, their higher log loss values (0.69 and 0.67) highlight greater uncertainty in predictions compared to Bagging and Random Forest.

TABLE 2. Normalized Data

	Normalized Data			
	Accuracy	Precision	Recall	Log Loss
Decision Tree	0.4535	0.4100	0.5766	0.5436
Random Forest	0.5233	0.5330	0.5234	0.4381
AdaBoost	0.4814	0.4408	0.4436	0.5598
Bagging	0.5373	0.5945	0.4436	0.4462

Table 2 provides the normalized performance metrics—accuracy, precision, recall, and log loss—of four machine learning models: Decision Tree, Random Forest, Ada Boost, and Bagging. These metrics evaluate the models' effectiveness in handling supply chain data. Bagging achieves the highest normalized accuracy (0.5373) and precision (0.5945), demonstrating its capability to produce accurate predictions with fewer false positives. Its log loss (0.4462) is low, indicating higher confidence in its predictions despite a recall of 0.4436, which suggests room for improvement in identifying true positives. Random Forest follows closely, with a normalized accuracy of 0.5233 and precision of 0.5330. Notably, it records the lowest log loss (0.4381), showcasing its strong reliability in predicting outcomes. Its recall (0.5234) reflects a balanced ability to detect true positives.AdaBoost and Decision Tree exhibit moderate performance. AdaBoost has a normalized accuracy of 0.4814 and precision of 0.4408, with a relatively higher log loss (0.5598), suggesting more uncertainty in its predictions. Decision Tree has the lowest normalized accuracy (0.4535) and precision (0.4100), though its recall (0.5766) is the highest among the models, highlighting its strength in identifying true positives despite a higher log loss (0.5436).

TABLE 3. Weight

	Weight			
Decision Tree	0.25	0.25	0.25	0.25
Random Forest	0.25	0.25	0.25	0.25
AdaBoost	0.25	0.25	0.25	0.25
Bagging	0.25	0.25	0.25	0.25

Table 3 displays the weight distribution for four machine learning models Decision Tree, Random Forest, Ada Boost, and baggingassessed according to log loss, recall, accuracy, and precision metrics. Each model is assigned an equal weight of 0.25 across all criteria, indicating that no single metric is prioritized over the others in the evaluation process. This uniform weighting suggests a balanced approach to assessing model performance, emphasizing the importance of each metric equally. Accuracy reflects the overall correctness of predictions, precision measures the ability to minimize false positives, recall evaluates the detection of true positives, and log loss assesses the confidence and uncertainty of predictions. By assigning equal importance to these metrics, the analysis ensures that each model's strengths and weaknesses are considered fairly. The equal weights imply that no individual model has an advantage due to metric prioritization. Instead, their performance is evaluated holistically, fostering an unbiased comparison. This method is particularly beneficial when no specific criterion is deemed more critical in the context of supply chain data. Ultimately, the results from this approach help provide a fair and comprehensive assessment of the models, guiding decision-making in selecting the most effective one for the task at hand.

TABLE 4. Weighted normalized DM

	Weighted normalized DM			
Decision Tree	0.1134	0.1025	0.1442	0.1359
Random Forest	0.1308	0.1333	0.1309	0.1095
AdaBoost	0.1204	0.1102	0.1109	0.1400
Bagging	0.1343	0.1486	0.1109	0.1116

Table 4 presents the weighted normalized decision matrix (DM) for four machine learning models—Decision Tree, Random Forest, Ada Boost, and Bagging—evaluated on accuracy, precision, recall, and log loss. The weighted normalized values reflect each model's performance after accounting for the equal weight distribution across all criteria, as shown in Table 3. Bagging emerges as the top-performing model, with the highest scores in accuracy (0.1343) and precision (0.1486). These values indicate its superior ability to produce reliable and accurate predictions. However, its recall (0.1109) and log loss (0.1116) are relatively moderate, suggesting some trade-offs in identifying true positives and predictive confidence. Random Forest performs consistently, with scores of 0.1308 in accuracy and 0.1333 in precision, indicating strong reliability. While its recall (0.1309) is slightly higher than Banging's, its log loss (0.1095) is the lowest, reflecting excellent prediction certainty. Ada Boost shows moderate performance, with values of 0.1204 in accuracy and 0.1102 in precision. Although its log loss (0.1400) is higher than others, it demonstrates balanced but less effective performance compared to Bagging and Random Forest. Decision Tree has the lowest overall values in accuracy (0.1134) and precision (0.1025). Despite a relatively higher recall (0.1442), its log loss (0.1359) suggests less reliable predictions.

TABLE 5. Assesment value

Assesment value	
Decision Tree	-0.0642
Random Forest	0.0237
AdaBoost	-0.0203
Bagging	0.0605

Table 5 provides the assessment values for four machine learning models decision Tree, Random Forest, Ada Boost, and bagging based on their weighted normalized performance across key evaluation metrics. These values represent the overall effectiveness of each model, with positive values indicating better performance and negative values highlighting areas for improvement. Bagging achieves the highest assessment value (0.0605), solidifying its position as the most effective model among the four. This positive score reflects its superior performance in key metrics like accuracy and precision, as well as its balanced reliability in other criteria. Random Forest follows with an assessment value of 0.0237, demonstrating consistent and reliable performance. Although slightly lower than Bagging, this positive value underscores its strength as a competitive model, particularly due to its low log loss, which indicates high confidence in predictions. Ada Boost has a negative assessment value (-0.0203), indicating room for improvement. While it performs moderately across certain metrics, the overall effectiveness is slightly undermined by higher log loss and less favorable precision. Decision Tree records the lowest assessment value (-0.0642), highlighting it as the least effective model in this comparison. Despite a relatively higher recall, its lower scores in accuracy, precision, and log loss contribute to this negative assessment, emphasizing its limitations in achieving balanced performance.

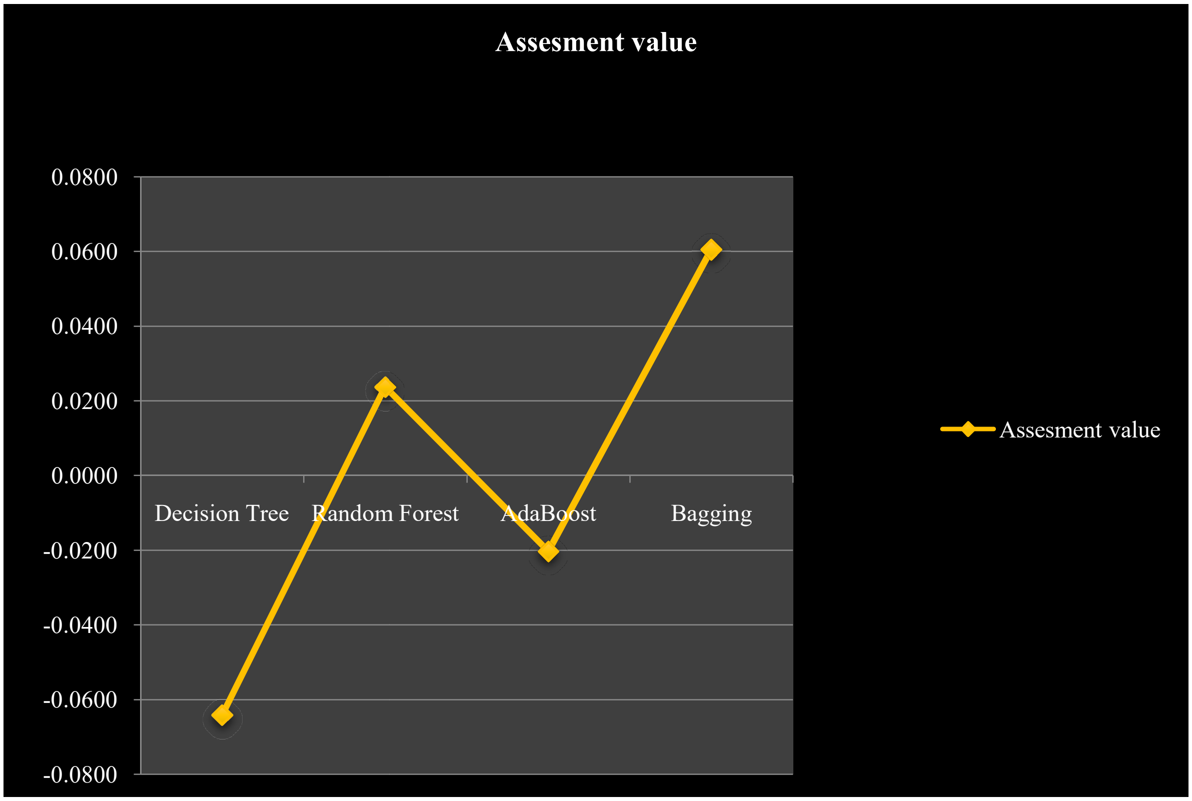

FIGURE 2. Assesment value

Figure 2 illustrates the assessment values of four machine learning models decision Tree, Random Forest, Ada Boost, and bagging evaluated based on their overall performance. Bagging achieves the highest assessment value (0.0605), confirming its position as the most effective model, with strong performance across key metrics. Random Forest follows with a positive value (0.0237), showcasing its reliability and balanced outcomes, particularly in accuracy and log loss. In contrast, Ada Boost has a slightly negative assessment value (-0.0203), reflecting moderate performance but some shortcomings, particularly in precision and log loss. Decision Tree records the lowest value (-0.0642), indicating it is the least effective model due to lower accuracy and precision.

TABLE 5. Rank

Rank	
Decision Tree	4
Random Forest	2
Ada Boost	3
Bagging	1

Table 5 presents the ranks assigned to four machine learning models Decision Tree, Random Forest, Ada Boost, and Bagging based on their overall assessment values. The ranking reflects each model's relative performance, with lower rank numbers indicating better results. Bagging is ranked first, highlighting its superior effectiveness across all evaluation criteria. This aligns with its highest assessment value and top scores in metrics like accuracy and precision, making it the most reliable choice for predictive tasks within the given context. Random Forest secures the second rank, demonstrating strong and consistent performance. While it slightly lags behind Bagging in overall assessment value, it exhibits balanced outcomes, particularly with a low log loss, which indicates high confidence in its predictions. Ada Boost is ranked third, reflecting its moderate performance. Although it achieves reasonable results in some metrics, its higher log loss and lower precision contribute to its middle-tier placement, making it less effective compared to Bagging and Random Forest. Decision Tree is ranked fourth, indicating the least effective performance among the models. Despite showing strength in recall, its lower accuracy, precision, and higher uncertainty in predictions result in its lower position. This suggests that Decision Tree is less suitable for achieving optimal outcomes in this context.

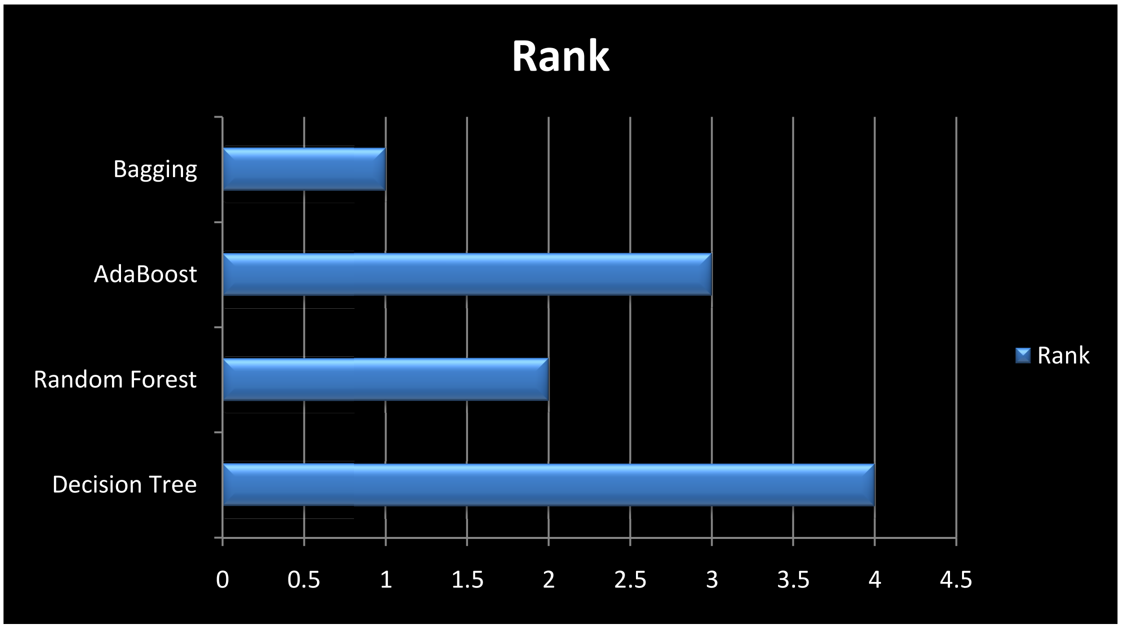

FIGURE 3. Rank

Figure 3 presents the ranking among four models for machine learning Random Forest and Decision Tree, AdaBoost, and Bagging based on their overall performance. Bagging is ranked first, reflecting its superior results in important parameters including precision and accuracy, making it the most reliable model. Random Forest follows in second place, showing strong consistency and reliability, particularly in log loss. Ada Boost is ranked third, with moderate performance. While it performs reasonably well, its lower precision and higher log loss contribute to a middle-tier rank. Decision Tree is ranked fourth, indicating it is the least effective model in this evaluation due to lower accuracy and precision.

4. Conclusion

In conclusion, this study introduces a comprehensive and innovative approach to improving decision-making in supply chain management (SCM) through the integration of machine learning with multi-criteria decision-making. In contrast to conventional techniques that rely on merging predictive models, the study presents a unique technique that uses MCDM to evaluate various ML classifiers for delay prediction in the supply chain. This method provides a more precise framework for selecting the best predictive model and incorporates sensitivity analysis to examine the system's robustness across different MCDM techniques.

As supply chains generate more data and grow in complexity, the need for advanced tools like machine learning becomes increasingly clear. The research highlights the broad applications of ML in SCM, including demand forecasts, risk assessment, supplier selection, and inventory management. The integration of big data analytics with machine learning facilitates more efficient processing and interpretation of large datasets, helping businesses make informed decisions to enhance supply chain performance. Additionally, the study emphasizes the importance of balancing prediction accuracy with interpretability, especially in supply chain risk management. The proposed framework for forecasting supply chain risks highlights machine learning's capacity to forecast disruptions, including delivery delays, while offering actionable insights for supply chain professionals. As the industry moves towards automation and machine learning-based systems, it brings both opportunities and challenges. Predicting demand and optimizing procurement activities improve operational efficiency, enabling businesses to more effectively control supply and demand. Moreover, the increasing use of machine learning in sectors like agriculture and manufacturing strengthens its role in boosting productivity and sustainability. Ultimately, this research presents a solid approach for decision-making and forecasting in supply chains, with future studies encouraged to validate the findings and explore other MCDM techniques to address decision-making uncertainties. As industries continue to adopt machine learning, ongoing advancements will promote further innovation and efficiency in supply chain operations, helping businesses navigate the complexities of a fast-evolving global market. The results showed that bagging achieved the highest rank, while the Decision Tree model received the lowest rank.

REFERENCE

1. Wyrembek, Mateusz, and George Baryannis. "USING MCDM METHODS TO OPTIMISE MACHINE LEARNING DECISIONS FOR SUPPLY CHAIN DELAY PREDICTION: A STAKEHOLDER-CENTRIC APPROACH." Logforum 20, no. 2 (2024).
2. Tirkolaee, ErfanBabaee, SaeidSadeghi, Farzaneh Mansoori Mooseloo, HadiRezaei Vandchali, and Samira Aeini. "Application of machine learning in supply chain management: a comprehensive overview of the main areas." Mathematical problems in engineering 2021, no. 1 (2021): 1476043.
3. Wenzel, Hannah, Daniel Smit, and Saskia Sardesai. "A literature review on machine learning in supply chain management." In Artificial Intelligence and Digital Transformation in Supply Chain Management: Innovative Approaches for Supply Chains. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol. 27, pp. 413-441. Berlin: epubli GmbH, 2019.
4. Carbonneau, Real, Kevin Laframboise, and RustamVahidov. "Application of machine learning techniques for supply chain demand forecasting." European journal of operational research 184, no. 3 (2008): 1140-1154.
5. Gu, Tianyu, Brendan Dolan-Gavitt, and SiddharthGarg. "Badnets: Identifying vulnerabilities in the machine learning model supply chain." arXiv preprint arXiv:1708.06733 (2017).
6. Ghazal, T. M., and H. M. Alzoubi. "Modelling supply chain information collaboration empowered with machine learning technique." Intelligent Automation & Soft Computing 29, no. 3 (2021): 243-257.
7. Ghazal, T. M., and H. M. Alzoubi. "Fusion-based supply chain collaboration using machine learning techniques." Intelligent Automation & Soft Computing 31, no. 3 (2022): 1671-1687.
8. Baryannis, George, Samir Dani, and Grigoris Antoniou. "Predicting supply chain risks using machine learning: The trade-off between performance and interpretability." Future Generation Computer Systems 101 (2019): 993-1004.
9. Sharma, Rohit, Sachin S. Kamble, Angappa Gunasekaran, Vikas Kumar, and Anil Kumar. "A systematic literature review on machine learning applications for sustainable agriculture supply chain performance." Computers & Operations Research 119 (2020): 104926.
10. Aamer, Ammar, LuhPutuEkaYani, and IMade Alan Priyatna. "Data analytics in the supply chain management: Review of machine learning applications in demand forecasting." Operations and Supply Chain Management: An International Journal 14, no. 1 (2020): 1-13.
11. Schroeder, Meike, and Sebastian Lodemann. "A systematic investigation of the integration of machine learning into supply chain risk management." Logistics 5, no. 3 (2021): 62.
12. Bačiulienė, Vaida, YuriyBilan, ValentinasNavickas, and LubomirCivín. "The aspects of artificial intelligence in different phases of the food value and supply chain." Foods 12, no. 8 (2023): 1654.
13. Wong, Lai-Wan, Garry Wei-Han Tan, Keng-Boon Ooi, Binshan Lin, and Yogesh K. Dwivedi. "Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis." International Journal of Production Research 62, no. 15 (2024): 5535-5555.
14. Rana, Jeetu, and YashDaultani. "Mapping the role and impact of artificial intelligence and machine learning applications in supply chain digital transformation: a bibliometric analysis." Operations Management Research 16, no. 4 (2023): 1641-1666.
15. Rodríguez-Espíndola, Oscar, SoumyadebChowdhury, Ahmad Beltagui, and PavelAlbores. "The potential of emergent disruptive technologies for humanitarian supply chains: the integration of blockchain, Artificial Intelligence and 3D printing." International Journal of Production Research 58, no. 15 (2020): 4610-4630.
16. Rashid, Aamir, RizwanaRasheed, Abdul HafazNgah, and Noor AinaAmirah. "Unleashing the power of cloud adoption and artificial intelligence in optimizing resilience and sustainable manufacturing supply chain in the USA." Journal of Manufacturing Technology Management ahead-of-print (2024).
17. Zeng, Xiao, and Jing Yi. "Analysis of the Impact of Big Data and Artificial Intelligence Technology on Supply Chain Management." Symmetry 15, no. 9 (2023): 1801.
18. Brauers, Willem Karel, and EdmundasKazimierasZavadskas. "The MOORA method and its application to privatization in a transition economy." Control and cybernetics 35, no. 2 (2006): 445-469.
19. Chakraborty, Shankar. "Applications of the MOORA method for decision making in manufacturing

environment." The International Journal of Advanced Manufacturing Technology 54 (2011): 1155-1166.
20. Brauers, Willem K., and Edmundas K. Zavadskas. "Robustness of the multi objective MOORA method with a test for the facilities sector." Technological and economic development of economy 15, no. 2 (2009): 352-375.
21. Karande, Prasad, and Shankar Chakraborty. "Application of multi-objective optimization on the basis of ratio analysis (MOORA) method for materials selection." Materials & Design 37 (2012): 317-324.
22. Brauers, Willem Karel M., RomualdasGinevičius, and ValentinasPodvezko. "Regional development in Lithuania considering multiple objectives by the MOORA method." Technological and economic development of economy 16, no. 4 (2010): 613-640.
23. Pérez-Domínguez, Luis, KY Sánchez Mojica, LC OvallesPabón, and MC Cordero Diáz. "Application of the MOORA method for the evaluation of the industrial maintenance system." In Journal of Physics: Conference Series, vol. 1126, no. 1, p. 012018. IOP Publishing, 2018.
24. Brauers, Willem Karel M. "Multi-objective contractor's ranking by applying the MOORA method." Journal of Business Economics and management 4 (2008): 245-255.
25. Attri, Rajesh, and Sandeep Grover. "Decision making over the production system life cycle: MOORA method." International Journal of System Assurance Engineering and Management 5 (2014): 320-328.
26. Jain, Vineet. "Application of combined MADM methods as MOORA and PSI for ranking of FMS performance factors." Benchmarking: an international journal 25, no. 6 (2018): 1903-1920.
27. Akkaya, Gökay, BetülTuranoğlu, and SinanÖztaş. "An integrated fuzzy AHP and fuzzy MOORA approach to the problem of industrial engineering sector choosing." Expert Systems with Applications 42, no. 24 (2015): 9565-9573.
28. Emovon, Ikuobase, Oghenenyerovwho Stephen Okpako, and Edith Edjokpa. "Application of fuzzy MOORA method in the design and fabrication of an automated hammering machine." World Journal of Engineering 18, no. 1 (2021): 37-49.
29. Khan, Akhtar, and Kali PadaMaity. "Parametric optimization of some non-conventional machining processes using MOORA method." International journal of engineering research in Africa 20 (2016): 19-40.
30. Karande, Prasad, and Shankar Chakraborty. "A Fuzzy-MOORA approach for ERP system selection." Decision Science Letters 1, no. 1 (2012): 11-21.