



AI-Powered Selection and Classification of Resilient Suppliers: A Hybrid Approach Using Fuzzy DEA and ML Techniques and Its Application in the Textile Industry

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Abstract

A resilient supplier is able to persevere in the face of disruptions and risks. Selecting resilient suppliers is crucial for businesses to receive high-quality services quickly and at a low cost. Clustering resilient suppliers facilitates identifying the most efficient and resilient ones. Mathematical models used to evaluate supplier resilience and cluster suppliers have limitations when addressing large-scale problems and fuzzy data. New techniques, such as Machine Learning (ML) methods, can be used to mitigate these limitations and predict supplier performance accurately. Few studies have used ML methods to cluster suppliers based on resilience criteria in imprecise data environments. To bridge this gap, this study proposes an integrated approach using Fuzzy Data Envelopment Analysis (FDEA) and ML methods to predict efficiency scores and classify suppliers based on resilience criteria. These methods were applied to evaluate a spinning and weaving factory as a real-life case study, based on resilience criteria. The results demonstrated that among five algorithms- Decision Tree (DT), Random Forests (RF), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), and Logistic Regression (LR) - the SVR algorithm had the best performance in predicting the efficiency and resilience of suppliers with the accuracy value of .85. Additionally, the suppliers were classified into weak, medium, and strong classes. Five ML algorithms were used to predict the class of new suppliers. Among the LR, DT, RF, KNN, and SVR algorithms, the DT had the highest accuracy value of 1, while the KNN had the lowest accuracy value of .55.

Keywords:

Supplier Selection and Classification, Resilient Supplier, Machine Learning (ML) Algorithms, Data Envelopment Analysis (DEA), Fuzzy Data.

Introduction

Suppliers are the providers of materials and resources for companies, factories, and customers. Selecting resilient suppliers enhances the efficiency of supply chains. This study presents a robust integrated DEA-ML approach that combines mathematical modeling and ML algorithms to evaluate and classify resilient suppliers, leading to suitable supplier selection. The main topics investigated in this paper will be explained in the following sub-sections.

Resilient Supplier Selection

Supplier selection is the process of choosing suppliers based on a number of criteria that are compatible with a company's conditions. The primary objective of Supply Chain Management

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(SCM) is to identify the most suitable supplier in order to reduce product processing costs, mitigate risks, enhance the quality of the supply chain, and sustain a long-term partnership with suppliers [Khaleie et al., (2012)]. Supplier selection influences various factors, including the reduction of waste and material consumption, which in turn enhances financial advantages. The minimization of waste through sustainable supplier selection can result in economic gains, particularly in terms of cost savings [Doonan et al., (2005)]. In relation to the issue of supplier selection, quantitative approaches primarily address the inquiries regarding which vendors to choose and how to optimally allocate subsequent orders to the selected suppliers. [Mohajeri and Esmaeili, (2023)]. Christopher and Peck (2004) characterized resilience as the capacity of a system to revert to its initial condition or transition to a more favorable state following a disturbance. According to Wieland and Durach (2021) definition, supply chain resilience is the capacity of a supply chain to persist, adapt, or transform in the face of change. Resilient suppliers exhibit the capability to endure and rebound from various disruptions, including natural disasters, geopolitical tensions, or interruptions in the supply chain. They implement comprehensive business continuity strategies, adopt diversified sourcing approaches, and engage in proactive risk management practices [Parkouhi et al., (2019)]. In this study, based on expert' opinion, five criteria - costs, delivery time, material quality, customer satisfaction, and flexibility- have been considered for evaluating the resilience of suppliers. The efficiency scores of suppliers are calculated based on resilience criteria.

Supplier Assessment Based on Resilience Criteria

In this research, the resilience criteria are categorized as inputs and outputs of suppliers to assess their performance and efficiency score. DEA models, as powerful mathematical methods, are used to calculate the efficiency scores of homogeneous Decision Making Units (DMUs) that consume inputs to produce outputs [Charnes et al. (1978)]. Here, we treat suppliers as DMUs and apply DEA models to measure their efficiency scores based on resilience criteria me.

Fuzzy Data

In many situations, precise information is not available, and there is imprecise or qualitative data for input and output values. Fuzzy arithmetic is suitable for handling inexact data. To deal with vague concepts, fuzzy techniques are employed in which the degree of similarity to an adjective is measured by a membership function. The values of the membership function are real and belong to the interval $[0,1]$. A value of 0 means no similarity to a specific adjective, a value of 1 implies full similarity and a value between 0 and 1 indicates partial similarity. In this study [zadeh, (1965)]. In this paper, supplier classification and selection will be conducted in the presence of fuzzy data.

Resilient Supplier Classification

Clustering resilient suppliers makes it possible and easy to identify the most efficient and resilient suppliers. Clustering involves the categorization of similar entities, specifically suppliers in this context, according to specific characteristics or attributes [Jain and Singh, (2020)]. The primary objective of clustering is to uncover patterns or segments within a broader dataset, thereby facilitating informed decision-making [Wen et al., (2020)]. Clustering suppliers based on their performance levels leads to selecting the most appropriate suppliers resulting in efficient resource allocation, risk reduction, quality and capacity enhancement, and

ultimately ensuring continuity in supply chains. Additionally, supplier classification allows for the implementation of similar management policies within each group, rather than managing suppliers individually.

Application of ML Techniques

Increasing resilience criteria, along with the presence of fuzzy data, indicates a large number of constraints and variables in models measuring resilience scores. Additionally, adding new suppliers involves recalculating the scores of all suppliers in traditional DEA approaches. It is possible to handle large amounts of data more efficiently by using ML techniques than traditional methods [Batta, (2019)]. ML is a branch of Artificial Intelligence (AI) that enables the efficient selection of suppliers based on their historical performance [Luan et al., (2019), Dogan and Birant, (2021)]. This technology is capable of accommodating inaccuracies, uncertainties, and imprecise data, thereby enhancing its robustness in simulating human decision-making processes. As AI continues to evolve, ML has found applications across various aspects of supply chain management, including the selection, assessment, and development of resilient and sustainable suppliers [Muzahid Khan et al., (2023)]. In this study, the resilience scores of suppliers are measured and then used as training data in ML algorithms to accurately predict performance. Additionally, suppliers are classified based on their efficiency scores using ML methods.

Contributions of This Paper

I. This paper proposes methods for selecting and clustering suppliers with imprecise data assumptions. By employing fuzzy methods, qualitative information can be incorporated in to the mathematical model, allowing for more accurate simulations of real-world situations. Proposed approaches are applicable for managers and policy-makers as exact information is often insufficient or unavailable. Applying fuzzy methods makes it possible to obtain a crisp efficiency score from qualitative data.

II. This study proposes a combined DEA-ML method to assess suppliers based on resilience criteria. This approach offers several advantages. Firstly, it provides an accurate prediction of performance measures. Secondly, it addresses the traditional DEA limitations in handling a large number of computations. Thirdly, DEA-ML methods can predict the resilience score of new suppliers without recalculating the scores of all previous suppliers, unlike traditional DEA-based approaches. Fourthly, assessing suppliers based on resilience criteria leads to making appropriate selections.

III. In this study, suppliers are classified based on their levels of resilience. This classification provides comprehensive information about resilient suppliers, which facilitates appropriate selections. It also allows for the implementation of similar management policies within each group, rather than managing suppliers individually.

The next section presents a review of research studies conducted on the combination of mathematical methods with ML techniques for supplier classification and selection. Section 3 contains the notations and preliminaries necessary to present the fuzzy DEA method. In addition, four ML algorithms and ML classifier methods are explained. In Section 4, a hybrid approach integrating fuzzy DEA and ML methods to predict the efficiency scores and classify suppliers based on resilience criteria will be explained. In Section 5, the combined DEA-ML techniques are applied for evaluation of an Iranian spinning and weaving factory.

Literature Review

Studies have been conducted on merging ML techniques and mathematical methods for supplier segmentation. Cavalcante et al. (2019) developed a hybrid technique as combining simulation and ML and examined its applications to data-driven decision-making support in resilient supplier selection. They considered on-time delivery as an indicator for supplier reliability and utilized a combination of supervised ML and simulation to improve the delivery reliability. Bakhtiari Tavana et al. (2020) presented a hybrid approach for evaluating and ranking suppliers based on sustainability criteria and modeling the problem of selecting a sustainable-resilient supplier and order allocation under disruption risks. The proposed mathematical framework employs a two-stage stochastic programming approach aimed at minimizing overall costs while maximizing sustainability performance in the event of disruptions. This model is solved through the application of the ε -constraint method.

Aggarwal et al. (2021) utilized ML algorithms to analyze the results of DEA for classification purposes, subsequently evaluating their accuracy through the use of a confusion matrix. Their research indicated that the DT algorithm significantly outperformed both the Kernel Support Vector Machines (SVM) and LR in terms of accuracy. Wahyudi and Asrol (2022) created two ML models, namely DT and Artificial Neural Network (ANN), to evaluate supplier performance. Additionally, Eyika Gaida et al. (2022) introduced an optimization strategy aimed at enhancing the supplier selection process. This strategy involved the selection of commonly utilized variables for supplier assessment and employed a logistic regression algorithm to develop an optimization model that learns from customer requirements and supplier data, ultimately generating predictions and recommendations for best suppliers. Asrol et al. (2023) proposed ensemble and SVM methods accuracy for analyzing and evaluating suppliers in the food industry and demonstrated that the ensemble method - Gradient Boosting (GB) model outperforms other ensemble methods and SVM. Ramjan Ali et al. (2023) proposed integrated framework comprises four widely used supervised ML models of RF classifier and RF-based feature selection algorithm to identify a comprehensive list of supplier selection criteria and their performance measures. Muzahid Khan et al. (2023) implemented the Supply Chain Occupational Reference (SCOR) 4.0 model with the integration of Best Worst Method (BWM) to develop the framework of customer satisfaction and to identify the critical elements of the suppliers. Then, they implemented the GB-ML model to classify the supplier as well as rank the suppliers from best to worst based on the acceptability score. Kiani Mavi et al. (2023) utilized fuzzy equivalence relations to cluster sustainable suppliers by creating a detailed taxonomy of criteria for selecting sustainable suppliers, which encompasses supply chain risk. Esmaeili et al. (2023) employed two clustering algorithms to generate labels grounded in the concept of resilience capacity. Subsequently, they utilized a DT to classify suppliers according to their performance, based on the expert labeling of the clusters. Abdel Aal (2024) presented a comprehensive overview of the requirements and criteria for selecting and managing resilient and sustainable suppliers, employing Multi-Criteria Decision-Making (MCDM) to address various criteria and ranking alternatives using the Double Normalization-Based Multi-Aggregation (DNMA) method. Abdulla and Baryannis (2024) combined MCDM methods with ML algorithms- DT, LR, KNN, ANN, SVM, and RF- for supplier selection based on price, technical quality, delivery time, offer validity duration, delivery mode, delivery terms, and payment terms. A classification of previous studies that have combined mathematical and AI approaches for supplier performance evaluation, supplier selection, and supplier classification is provided in Table 1.

Table 1. A classification of mathematical-AI approaches for supplier performance evaluation, supplier selection, and supplier classification

Article	Approach	Supplier Performance Evaluation	Supplier Selection	Supplier Classification
Aggarwal et al. (2021)	DT, Kernel SVM, LR		✓	
Wahyudi and Asrol (2022)	DT, ANN	✓		
Asrol et al. (2023)	GB, SVM	✓		
Muzahid Khan et al. (2023)	GB, BWM			✓
Esmaili et al. (2023)	DT			✓
Abdel Aal (2024)	MCDM, DNMA		✓	
Abdulla and Baryannis (2024)	MCDM, DT, LR, KNN, ANN, SVM, RF	✓	✓	
Gabellini et al. (2024)	GB		✓	
Husna et al. (2024)	K-means		✓	
Liu et al. (2024)	NN			
Pap et al. (2025)	DT		✓	

Notations and Preliminaries

Fuzzy Arithmetic

In many real-world situations, there is imprecise or qualitative information. Fuzzy arithmetic is a suitable method to deal with inexact qualitative data. Let U represent universe of discourse and $A \subseteq U$. function $\mu_A : U \rightarrow [0,1]$ is called membership function and $\mu_A(x)$ is termed the grade of membership of x in A . The fuzzy subset of A is defined as $\{(x, \mu_A(x)) \mid x \in U\}$. The α -cut set of A is defined as $A^\alpha = \{x \mid \mu_A(x) \geq \alpha, \alpha \in [0,1]\}$. The support set of A is defined as $S(A) = \{x \mid \mu_A(x) > 0\}$. A triangular fuzzy number represented as $A = (a, b, c)$, is a fuzzy number with a membership function as follows:

$$\mu_A(x) = \begin{cases} \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & \text{otherwise.} \end{cases}$$

Fuzzy DEA (FDEA)

In this context, a supplier is denoted by DMU . Consider DMU_j ($j = 1, \dots, n$). Let X_j and Y_j be the input and output vectors, respectively. The framework utilized to assess the efficiency score of DMU_o , which focuses on the reduction of input values, is referred to as the input-oriented CCR model. The primary and its corresponding dual (input-oriented) CCR models are defined as Models (1) and (2) [Charnes et al. (1978)]:

$$\begin{aligned} \theta^* &= \min \theta - \varepsilon(S^- + S^+) \\ \text{s.t.} \sum_{j=1}^n \lambda_j X_j &= \theta X_o - S^-, \sum_{j=1}^n \lambda_j Y_j = Y_o + S^+, \lambda, S^-, S^+ \geq 0 \end{aligned} \quad (1)$$

$$\begin{aligned} \gamma^* &= \max \sum_{r=1}^s u_r y_{ro} \\ \text{s.t.} \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} &\leq 0 \quad \forall j, \sum_{i=1}^m v_i x_{io} = 1, u_r, v_i \geq 0 \quad \forall i, r \end{aligned} \quad (2)$$

in the case that input and output values are triangular fuzzy numbers as $\tilde{x}_{ij} = (x_{ij}^l, x_{ij}^m, x_{ij}^u)$ and $\tilde{y}_{rj} = (y_{rj}^l, y_{rj}^m, y_{rj}^u)$, and $\alpha \in (0, 1]$, let $(\tilde{x}_{ij})_\alpha^L = \min \{x_{ij} \in S(\tilde{x}_{ij}) \mid \mu_{\tilde{x}_{ij}}(x_{ij}) \geq \alpha\}$ and $(\tilde{x}_{ij})_\alpha^U = \max \{x_{ij} \in S(\tilde{x}_{ij}) \mid \mu_{\tilde{x}_{ij}}(x_{ij}) \geq \alpha\}$. Therefore, a crisp interval $[\alpha x_{ij}^m + (1 - \alpha)x_{ij}^l, \alpha x_{ij}^m + (1 - \alpha)x_{ij}^u]$ obtained for a fuzzy input value. Crisp intervals related to $\tilde{y}_{rj}$ can be obtained by similar methods. Saati et al. (2002) proposed the following parametric linear programming when the input and output values are triangular fuzzy numbers.

$$\begin{aligned} \hat{\gamma} &= \max \sum_{r=1}^s \hat{y}_{ro} \\ \text{s.t. } \sum_{r=1}^s \hat{y}_{rj} - \sum_{i=1}^m \hat{x}_{ij} &\leq 0 \quad \forall j, \quad \sum_{i=1}^m \hat{x}_{io} = 1, \quad v_i((1 - \alpha)x_{ij}^l + \alpha x_{ij}^m) \leq \hat{x}_{ij} \leq v_i((1 - \alpha)x_{ij}^u + \alpha x_{ij}^m) \quad \forall i, j, \\ u_r((1 - \alpha)y_{rj}^l + \alpha y_{rj}^m) &\leq \hat{y}_{ij} \leq u_r((1 - \alpha)y_{rj}^u + \alpha y_{rj}^m) \quad \forall r, j, \quad u_r, v_i \geq 0 \quad \forall i, r \end{aligned} \quad (3)$$

Model (3) is a development of Model (2) in a fuzzy environment and is referred to as the FDEA model in this paper.

Summary of ML Algorithms

ML is a powerful technique for data analysis that integrates mathematics, statistics, computer science, and artificial intelligence to derive insights from input data and autonomously make predictions [Naghdehforoushha et al. (2022)]. The ML algorithms LR, DT, RF, KNN, and SVR utilized in this paper are described below.

1) LR is robust supervised ML algorithm that is commonly utilized for predictive tasks or for classifying data into separate categories. In its basic configuration, LR employs a logistic function, to model a binary dependent variable; however, it can be modified to handle multiple classes. This function adeptly converts any real number into a value that ranges between 0 and 1. The logistic function can be formulated as $P(Y|X = x) = \frac{1}{1 + e^{-\alpha - \beta x}}$, where x is the input variable, β is the regression coefficient, and α is the bias term, often referred to as the intercept [Peng et al. (2002)].

2) KNN algorithm is another supervised ML technique that takes into account the K nearest neighbors (data points) to forecast the class or continuous value for new data. The predicted value is determined by the average of the values of the nearest neighbors [Rehman et al. (2022)].

3) DT is a supervised ML method utilized for predictive purposes in regression and classification [Guggari et al. (2018)]. The tree's nodes represent the features of the training dataset and each branch stemming from a node signifies one of the possible values of that feature. To classify a new instance, one begins at the tree's root, evaluates the value of its features, and proceeds along the branch that corresponds to the feature value of the instance [Comito and Pizzuti (2022)].

4) RF is an ensemble learning approach that employs bagging to create multiple decision trees during the training process, ultimately providing the mean prediction from the individual trees [Comito and Pizzuti (2022)].

5) SVR addresses binary classification problem using the concept of separation hyperplane and determining the maximum separation margin that accurately classifies the training data as much as possible. The optimal hyperplane is denoted by the support vectors. SVR extends this concept by introducing a region, referred to as a tube, around the function to be optimized

[Comito and Pizzuti (2022)].

A Hybrid FDEA-ML Approach for Performance Prediction and Classification

The resilience criteria are categorized as inputs and outputs of suppliers to assess their performance. Qualitative values for resilience criteria are considered and represented as triangular fuzzy numbers. Crisp efficiency scores of suppliers are calculated based on resilience criteria by solving model (3). The efficiency scores are used to train ML algorithms, which are then used to accurately predict the future performance and resilience of suppliers. During model training, it is identified which combination of input and output values results in the efficiency score of a DMU. The combined FDEA-ML framework is shown in Figure1. We also use ML methods to classify the suppliers based on their resilience scores. Since the efficiency scores are measured based on resilience criteria, suppliers with higher scores are considered more resilient. Suppliers are classified into weak, medium, and strong levels based on their resilience scores using ML methods. Supplier classification provides businesses with comprehensive information to identify and select the most appropriate suppliers.

Results and Discussion

Predicting the Efficiency Scores of Suppliers Using ML Algorithms and Comparison Predicted Scores with FDEA Model Results

Data preparation

Fallahpour et al. (2018) conducted a study to determine supplier resilience criteria for an Iranian spinning and weaving factory that produces cotton and cotton-polyester blended spun yarn. Based on the expert' opinion, five criteria - costs, delivery time, material quality, customer satisfaction, and flexibility- were selected for evaluating suppliers. Qualitative values for resilience criteria were received and represented as triangular fuzzy numbers. The criteria were categorized as inputs and outputs of suppliers to assess their performance. Costs and delivery time are considered as inputs, and material quality, customer satisfaction, and flexibility are considered as outputs. By increasing output values and decreasing input values, the efficiency score increases. Therefore, lower input values and higher output values are preferred. For example, fuzzy number $(7,9,10)$ for output value and fuzzy number $(1,1,3)$ for input value is preferred. These relationships are explained in Table 2.

Table 2. Fuzzy representations for qualitative data

Fuzzy values	Outputs	Inputs
Very low	$(1,1,3)$	$(7,9,10)$
Low	$(1,3,5)$	$(5,7,9)$
Medium	$(3,5,7)$	$(3,5,7)$
High	$(5,7,9)$	$(1,3,5)$
Very high	$(7,9,10)$	$(1,1,3)$

Parameter Selection for ML Algorithms

Tables 3 to 7 show the important parameters of the LR, DT, RF, KNN, and SVR algorithms.

Table 3. LR parameters

fit_intercept	copy_X	positive
True	True	False

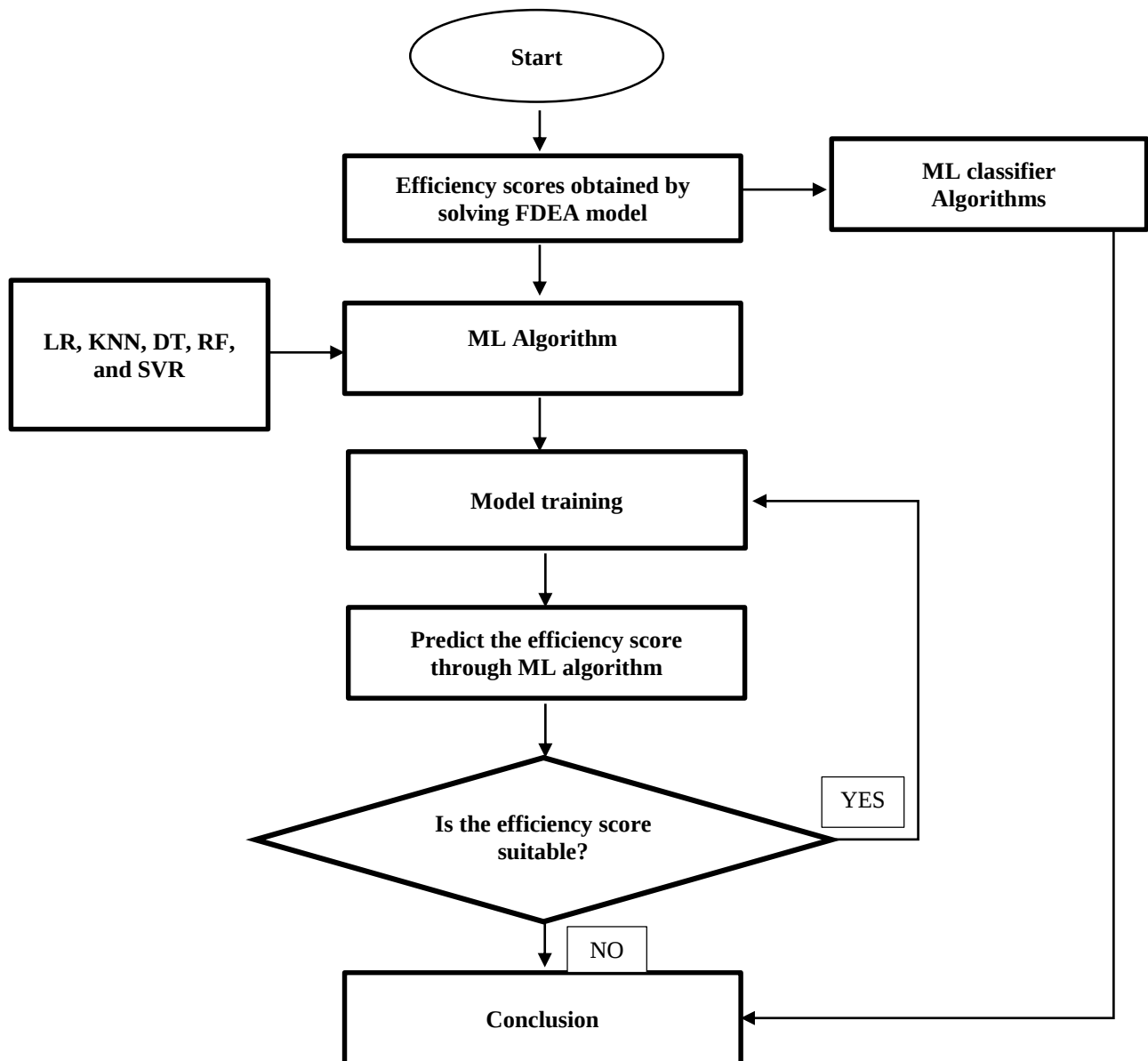


Figure. 1. The combined FDEA-ML framework

In the LR model, the `fit_intercept` parameter is used to calculate the intercept for the model. This means that if it is set to `False`, no intercept will be used in calculations. `Copy_X` is another parameter that, when set to `True`, `X` will be copied; otherwise, it may be overwritten. When the `positive` parameter is set to `False`, it enforces that the coefficients must be negative.

Table 4. DT parameters

critierion	splitter	max_depth
squared_error	best	5

Table 5. RF parameters

critierion	n_estimators	max_depth
squared_error	100	5

In both DT and RF models, the `criterion` refers to the function used to assess the quality of a split, while `max_depth` indicates the maximum depth of a decision tree. In the DT model, the `splitter` determines the splitting strategy at each node, and in particular, the “best” splitter strategy is used to identify the optimal split. In the RF model, `n_estimators` is the number of trees used in the random forest.

Table 6. KNN parameters

n_neighbors	weights	algorithm	p	Metric
5	uniform	auto	2	Minkowski

In the KNN model, the most important parameter is the number of neighbors used, denoted by `n_neighbors`. It's essential to emphasize that selecting a small number of neighbors, such as one or two, may lead to overfitting in the model. Weight refers to the function used in prediction. In particular, in the “uniform” weights, all points in each neighborhood are weighted equally. The algorithm parameter is used to compute the nearest neighbors, and in particular, the “auto” algorithm will attempt to determine the most suitable algorithm. `p` is the power parameter for the Minkowski metric used for distance computation. When $p=2$, this is equivalent to using the standard Euclidean distance.

Table 7. SVR parameters

kernel	degree	c	Epsilon
rbf	3	1	0.1

In the SVR model, the type of kernel to be used is specified by the kernel parameter, which defaults to “rbf”. The degree parameter specifies the degree of the polynomial kernel function. The parameter `c` is a regularization parameter. Additionally, epsilon defines the epsilon-tube, which is a range where predictions within a distance of epsilon from the actual value do not incur penalties in the training loss function.

Results of the hybrid FDEA-ML approach

Model (3) was solved for $\alpha = .9$ to calculate the efficiency score of spinning and weaving factory over 248 periods, based on the resilience criteria explained in Section 5.1.1. The data, presented as crisp intervals discussed in Section 3.2, and efficiency scores are provided in the **Supplementary Material**. 80% of the resilience scores were allocated for training and the remaining 20% were used for testing in five ML algorithms: LR, KNN, DT, RF, and SVR. The efficiency scores of the testing dataset and their predicted values by ML algorithms are shown in Table 8.

Table 8. Efficiency scores as the test data, obtained by solving model (3) for $\alpha = .9$, and their predicted values by FDEA-ML algorithms

Supplier	FDEA	FDEA-KNN	FDEA-LR	FDEA-SVR	FDEA-RF	FDEA-DT
1	1	0.21	0.73	0.90	0.97	1
2	0.40	0.65	0.44	0.53	0.35	0.24
3	1	0.36	0.83	0.70	1	1
4	0.83	0.86	0.83	0.92	1	1
5	0.71	0.84	0.73	0.70	0.56	0.24
6	1	0.86	0.78	0.89	1	1
7	0.83	0.39	0.63	0.72	1	1
8	1	0.70	1.25	0.90	1	1
9	0.37	0.33	0.31	0.39	0.39	0.31
10	0.	0.	0.	0.	0.	0.
11	1	0.72	0.79	0.92	1	1
12	1	0.72	0.79	0.92	1	1
13	0.40	0.65	0.44	0.53	0.35	0.24
14	0.62	0.84	0.64	0.70	0.53	0.24
15	1	1	0.60	0.74	1	1
16	0.35	0.34	0.34	0.39	0.34	0.34
17	0.62	0.84	0.64	0.67	0.51	0.24
18	0.34	0.33	0.31	0.42	0.34	0.34
19	0.34	0.33	0.36	0.42	0.33	0.34
20	0.26	0.25	0.32	0.35	0.28	0.26

21	1	1	0.83	0.92	1	1
22	0.24	0.24	0.17	0.21	0.25	0.25
23	0.71	0.84	0.73	0.61	0.56	0.41
24	0.29	0.29	0.29	0.44	0.32	0.31
25	1	1	0.74	0.89	1	1
26	0.31	0.28	0.34	0.37	0.31	0.31
27	1	1	0.84	0.90	1	1
28	0.62	0.84	0.64	0.70	0.53	0.24
29	1	1	0.83	0.89	1	1
30	1	1	0.79	0.89	1	1
31	0.31	0.28	0.21	0.28	0.30	0.31
32	0.23	0.24	0.25	0.22	0.23	0.23
33	1	1	0.89	0.91	1	1
34	0.63	0.84	0.53	0.59	0.37	0.24
35	0.71	0.84	0.75	0.61	0.56	0.24
36	0.37	0.33	0.31	0.39	0.39	0.31
37	0.35	0.34	0.34	0.39	0.34	0.34
38	0.61	0.32	0.41	0.36	0.28	0.26
39	1	1	0.78	0.90	1	1
40	0.64	0.39	0.57	0.45	0.56	0.32
41	0.37	0.33	0.31	0.39	0.39	0.31
42	1	1	0.84	0.97	1	1
43	0.34	0.32	0.36	0.40	0.34	0.34
44	1	1	0.84	0.97	1	1
45	0.72	1	0.87	1	0.98	1
46	0.29	0.29	0.29	0.44	0.32	0.31
47	1	1	0.84	0.83	0.64	1
48	0.62	0.70	0.64	0.51	0.40	0.32
49	0.71	0.56	0.64	0.66	0.53	1
50	1	1	0.76	0.93	1	0.23
Average	0.6754	0.6324	0.6022	0.6398	0.6384	0.5710

Figure 2 displays the accuracy values and errors, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) for five DEA-ML algorithms predicting the training and testing data.

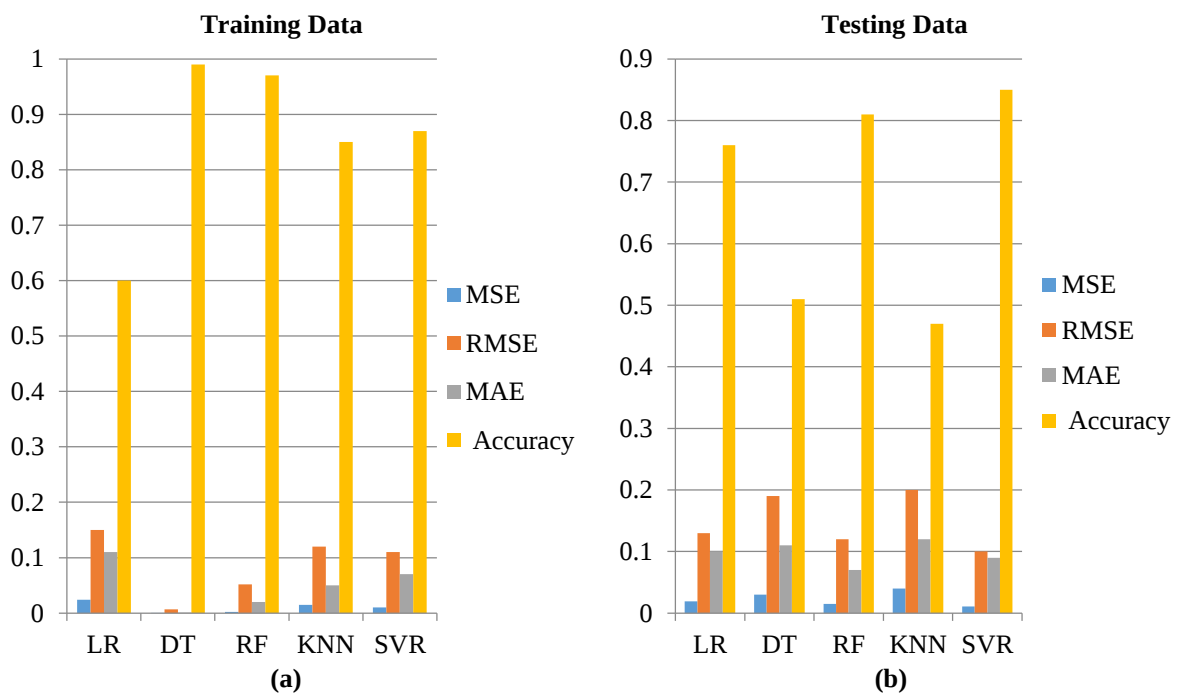


Figure 2. Comparison of error and accuracy values of DEA-ML algorithms: (a) for training data and (b) for

testing data

As shown in Figure2, in the test dataset, the FDEA-SVR algorithm has the lowest MSE value of .011 when predicting the efficiency score and resilience of spinning and weaving factory. The order of MSE values related to the testing data set is $MSE_{SVR} = .011 < MSE_{RF} = .015 < MSE_{LR} = .019 < MSE_{DT} = .03 < MSE_{KNN} = .04$. This result is consistent with the data presented in Table3, where the predicted values by FDEA-SVR have the smallest deviation from the actual FDEA scores. The order of prediction accuracy values related to the testing data set is $Accuracy_{SVR} = .85 > Accuracy_{RF} = .81 > Accuracy_{LR} = .76 > Accuracy_{DT} = .51 > Accuracy_{KNN} = .47$.

Therefore, the FDEA-SVR algorithm with the lowest MSE and the highest accuracy values demonstrates superior performance and is used to predict the efficiency score and resilience of new suppliers.

Clustering the Suppliers Using ML Algorithms

ML algorithms are used to classify the 248 suppliers based on their resilience scores calculated in the previous section. The suppliers are classified into three classes weak, medium, and strong, based on their resilience scores being less than .6, between .6 and .9, and above .9 to 1. 80% of the 248 resilience scores are used for training and the remaining 20% are used for testing in five ML methods: LR, DT, RF, KNN, and SVR. The accuracy and error values for predicting the classes of the training and testing datasets are shown in Figure 3.

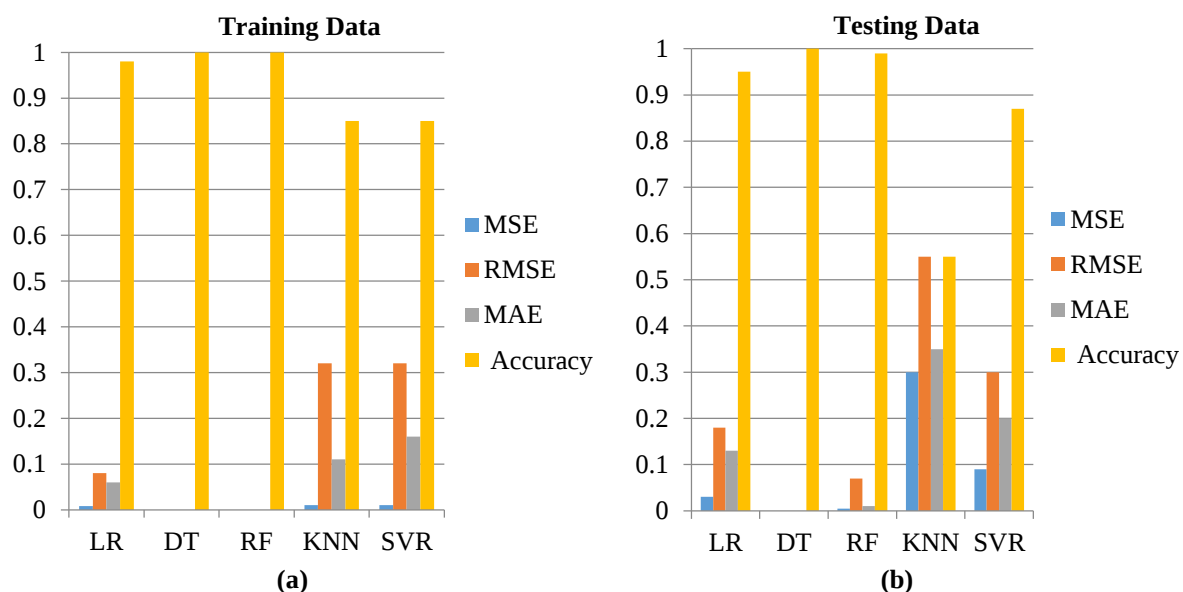


Figure3. Comparison of error and accuracy values of ML algorithms for predicting the classes of (a) the training data and (b) the testing data

As inferred from Figure3, the DT algorithm has the highest accuracy value of 1 and an MSE value of 0 when predicting the class of new suppliers in test data, indicating the superior performance. The RF algorithm is the closest in ranking with an accuracy of .99 and an MSE value of .005. On the other hand, the KNN algorithm shows the worst performance with an accuracy of .55 and an MSE of .3.

Conclusion and Directions for Future Research

A resilient supplier can persevere in the face of disruptions and risks. Clustering suppliers according to their resilience levels provides businesses with thorough information and aids in appropriate supplier selection. In many real-world situations, sufficient and precise data is not available. Fuzzy arithmetic provides policy-makers with methods to interpret qualitative values

as instrumental information.

DEA methods were utilized to measure the efficiency scores of suppliers based on resilience criteria when input and output values are triangular fuzzy numbers. The scores obtained were then prepared for use as training and testing data in ML algorithms. Five ML algorithms were applied to predict the efficiency scores of an Iranian spinning and weaving factory over 248 periods, representing 248 suppliers. The results for the testing dataset showed that the FDEA-SVR algorithm performed the best in predicting the efficiency and resilience of suppliers. Subsequently, five ML algorithms were utilized to classify the suppliers into weak, medium, and strong classes. The DT algorithm demonstrated the best performance, while the KNN algorithm had the worst performance in predicting the class of the testing data.

In this paper, suppliers have been considered as black-box systems, without taking into account their internal activities. However, evaluating suppliers with multi-stage structures involves using network models that are based on the internal relationships between the sub-divisions. Developing DEA models to evaluate resilient suppliers with network structures and combining these network DEA models with ML and deep learning techniques to predict future demands could be considered for future studies.

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