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# Using DEMATEL, clustering, and fuzzy logic for supply chain evaluation of electric vehicles: A SCOR model

**Mehrbakhsh Nilashi[1,2,*], Rabab Ali Abumalloh[3], Hossein Ahmadi[4], Mesfer Alrizq[5,6], Hamad Abosaq[6,7], Abdullah Alghamdi[6,8], Murtaza Farooque[9] and Syed Salman Mahmood[10]**

[1] UCSI Graduate Business School, UCSI University, 56000, Cheras, Kuala Lumpur, Malaysia
[2] Centre for Global Sustainability Studies (CGSS), Universiti Sains Malaysia, 11800 Penang, Malaysia
[3] Department of Computer Science and Engineering, Qatar University, Doha 2713, Qatar
[4] Centre for Health Technology, Faculty of Health, University of Plymouth, Plymouth PL4 8AA, UK
[5] Information Systems Dept., College of Computer Science and Information Systems, Najran University, Najran, Saudi Arabia
[6] Scientific and Engineering Research Center (SERC), Najran University, Najran, Saudi Arabia
[7] Computer Science Dept. College of Computer Science and Information Systems, Najran University, Najran, Saudi Arabia
[8] Information Systems Dept., College of Computer Science and Information Systems, Najran Univesity, Najran, Saudi Arabia
[9] Department of MIS, Dhofar University, Salalah, Oman
[10] Department of Mathematics & Statistics, Colleges of Arts & Sciences, Abu Dhabi University, United Arab Emirates

* **Correspondence:** Email: nilashidotnet@hotmail.com.

**Abstract:** The transportation sector is considered among the major sources of greenhouse gas emissions. Given advancements in transportation technology, customers' willingness to reduce carbon footprints, as well as policy incentives, Electric Vehicles (EVs) are becoming an increasingly important part of the passenger vehicle industry. Evaluation of Supply Chain (SC) performance in the EV industry seems to contribute significantly to the enhancement of the operational consequences across the supply chain tiers. The SCOR (Supply Chain Operations Reference) model was designed to help businesses optimize their supply chain operations, reduce costs, and improve customer satisfaction. Although many performance measurement models have been developed in the context of SC, there is no performance measurement model in relation to the EV supply chain based on indicators of customer perceived value (Reliability, Responsiveness and Agility) in the SCOR model. Therefore, we aimed to develop a new method to evaluate the performance of the EV supply chain using a set of critical SC performance evaluation indicators. Multi-criteria decision-making along with machine learning was used in order to develop a new method for evaluating SC performance. We used k-means clustering and fuzzy logic approaches in the development of the new method. An assessment of indicators' importance level was performed using the fuzzy logic approach. The results of the method evaluation show that the proposed method is capable of predicting the performance of the EV supply chain accurately. According to the results, by optimizing their supply chain, companies can improve their ability to deliver products and services that meet or exceed customer expectations, resulting in higher customer perceived value and customer satisfaction.

**Keywords:** fuzzy logic; DEMATEL; electric vehicles; supply chain performance; SCOR metrics

## 1. Introduction

Transportation is one of the major sources of greenhouse gas emissions [1]. Sustainable transportation is essential for reducing greenhouse gas emissions, mitigating climate change, and promoting a healthier and cleaner environment. Sustainable transportation recently gained the attention of many researchers [2,3]. Currently, significant 2 learning are used in order to develop a new method for evauating SC performance. We used *k*-means clustering and fuzzy logic approaches in the development of the new method. An assessment of the indicators' importance level is performed using fuzzy logic through fuzzy inference system. This method can help to achieve accurate prediction of supply chain performance in uncertain conditions with learning abilities as well as better interpretable results.

### *1.1. Research problems and contributions*

Although many performance measurement models have been developed in the context of SC, there is no performance measurement model in relation to the EV supply chain based on indicators of customer perceived value (Reliability, Responsiveness, and Agility) in the SCOR model. Customer perceived value is an essential concept in transportation, as it represents the customer's perception of the benefits and costs associated with a transportation service. In transportation, CPV plays a critical role in determining customer satisfaction and loyalty. For example, if a customer perceives that a transportation service provides high customer perceived value, they are more likely to use that service again and recommend it to others. Furthermore, transportation providers should continuously monitor and analyze customer feedback to identify areas for improvement and adjust their services accordingly. This can help to maintain high levels of customer perceived value, which is critical for long-term success in the transportation industry. High customer perceived value can also lead to improved collaboration and communication within the supply chain. When customers perceive that the supply chain provides high-quality products or services, they are more likely to engage with the supply chain and provide feedback, which can help the supply chain to identify areas for improvement and optimize its operations accordingly.

We develop an expert system for supply chain performance evaluation using multi-criteria and machine learning approaches. Computational tools assist organizations to discover suitable knowledge required by assessment systems for SC performance to address serious managerial challenges and supply them with proper decision support platforms. These systems have become more popular in recent years because of their potential to apply human expert knowledge as rules to solve complicated problems in a determined field. Besides this important role in the research on the measurement of SC performance, the present work has also provided useful guidelines to develop, train, and validate computational models according to machine learning strategies. Thus, it has a significant role in the enhancement of measurement tools that assist managers in decision-making in the area of SC management.

Multiple-Criteria Decision-Making (MCDM) techniques have been effective in the development of models and systems based on several criteria. MCDM methods provide a comprehensive framework for evaluating and optimizing transportation systems and enable transportation planners and policymakers to prioritize and allocate resources efficiently. MCDM techniques such as the Analytic Hierarchy Process (AHP) [4], Analytic Network Process (ANP) [5,6], Decision Making Trial and Evaluation Laboratory (DEMATEL) [7,8], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [9,10] and fuzzy MCDM [11] are widely used in the transportation context. This paper develops a new hybrid method to identify the weights of SCOR model criteria for SC performance evaluation. The method uses the DEMATEL which is widely used in decision-making problems [8,12]. We use fuzzy logic approach for SC performance evaluation. Since performance measurement is a complicated process, it is inevitable to use qualitative linguistic terms. Moreover, subjectivity and uncertainty are the typical features of the respondents' perceptions regarding the likelihood and effects of performance indicators. It is possible to address the problem of subjective judgments through fuzzy logic. Expressing fuzzy variables in a mathematical logic becomes possible using fuzzy evaluation. Such systems can address quantitative and qualitative information in an effective way. They are promising for SC performance applications since the incorporation of qualitative expert heuristic knowledge in the process of constructing the model is facilitated through them. Fine-tuning of the model is possible using quantitative historical/experimental data. Accordingly, more robustness and accuracy of the model is obtained along with easier interpretability. Interpretability of the model is critical in the assessment of SC performance.

The proposed system is based on the SCOR model which combines the performance metrics with modeling and simulation strategies to support management actions, including assessment of SC performance, assessment of risk, evaluation of suppliers, and benchmarking. Nevertheless, applications based on SCOR introduced in previous studies mostly concentrated on the measurement of SC performance through multi-criteria decision-making approaches. We, however, take advantage of the SCOR model for the SC performance evaluation in the EV supply chain using machine learning and multi-criteria decision-making approaches.

Finally, we use decision trees to implement fuzzy logic approach. The decision trees technique is widely used in prediction tasks in transportation studies [13,14]. We use Classification and Regression Tree (CART) approach to automatically discover the decision rules from the data for SC performance evaluation. These rules are used in the fuzzy logic approach to identify the associations of the input and output variables, with no requirement to make parameters of variables as well as decision rules manually. This can be a positive point of the suggested method compared to those that are merely dependent on fuzzy inference as the problems in providing a definition for appropriate linguistic terms and relative fuzzy numbers can be an important weakness of these systems. Besides, the exponential growth of the decision rules is possible according to the number of indicators and linguistic terms which make the rule base system design more complicated. Therefore, adjustment of the inference system seems to be a learning process, involving a team of experts in the area of SC performance and fuzzy inference in the real application.

## 2. Supply chain management and evaluation

The supply chain has brought competitive advantages [15–17] toward achieving time to market with the highest efficiency and effectiveness while considering meeting the customers' expectations [18–20]. Therefore, supply change management has changed into a critical component of successful firms. According to [21], supply chain management is systematic which includes the complicated issue of management of all the processes associated with the supply chain in a range of raw materials sourcing to the provision of post-purchase customer services.

All companies that seek to grow and gain profits at the global level need to consider supply chain management as a vital issue [22–24]. The supply chain is regarded as a series of integrated business processes which consist of all actions related to the goods flow and change, including different stages of raw materials to the transfer of finished products to the final consumers [25]. The establishment of the tactical association with suppliers as well as consumers, long-term relations, information sharing, and working together to promote products and processes are included in the supply chain management [26]. Consequently, different benefits, including reducing the inventory, improving resource usage, and higher customer satisfaction are only a few examples [27]. Thus, measurement of SC performance focused on the assessment of how effective supply chain management techniques and methods work seems of extreme importance. Evaluation problems of supply chain performance are associated with a broad scope of measuring independent organizations' performance within supply chains for the measurement of the performance of the overall supply chain system. These problems are among the most extensive strategic decision problems which should be taken into account in long-term effective operations of the total supply chain. Conventionally, independent operation of marketing, distribution, planning, manufacturing and purchasing organizations has been common. Previous research in the area of SC performance measurement consists of a broad scope of studies such as conceptual frameworks of metrics [28], research on the identification of most frequently applied metrics [29], case studies [30] as well as quantitative research models to support performance measurement processes [31].

## 3. SCOR model

The Model of SCOR developed by the Supply Chain Council (SCC) is an effective approach for supply chain management [32,33]. The Supply Chain Council as a non-profit institution developed this reference model for implementation of a standard to model thorough internal as well as external supply chains. A four-level hierarchical pyramid structure is designed for the SCOR model, indicating a plan to improve the performance of the supply chain. Three levels of the processes are addressed by the model and each level continuously increases in terms of process details as well as specificity [34]. Functional and organizational tasks than processes are addressed at level 4, in which supply chain changes are implemented according to the design generated by the SCOR model. Level 1 which is at the top, helps to define the SCOR model's range and contents, while five management processes are determined, including planning, sourcing, making, delivery, and return. The domain and parameters of the overall sub-processes in the supply chain are set by these main management processes. Moreover, five performance characteristics of the supply chain are identified at level 1 by the SCOR model. The first three features, including reliability, responsiveness, and flexibility, are adjusted toward the customer. Attributes of cost and assets are considered with internal focus. Ten metrics of level 1, which can be used by the organizations in the measurement of organizational goal achievement and success, are associated with these features. It is worth noting that organizations are not likely to obtain the best practices in all of the desired metrics. Thus, metrics selected by the organizations as the focus, need to represent the customers' demands.

The process element level is included in Level 3 which practices in-depth exploration of the organizational detailed works along with information flow across the organizational supply chain. Accordingly, chief transactions of input and output look at goals, metrics of performance, the best methods, and the infrastructures of the systems, as well as their supporting potentials, are at the center of focus. Validation of the effects of promotions across the supply chain can be performed at this level. Levels 2 and 3 are aligned to relative performance standards as well as organizational systems and interactions. Implementation of supply management methods is performed at the next level whose activities is unique for each organization and is concentrated on the implementation of tasks. The activities of level 4 consist of concentration on organizational design, processes, systems, as well as individuals across the organization. However, given that every organization has its implementation process, these activities have not been incorporated in the SCOR model. According to the SCOR® model, a series of performance standards are proposed in three hierarchical layers. Figure 1 indicates the SCOR model's organizational structure. Performance attributes of Level 1 and Level 2 indicators are presented in Table 1.

## 4. Method

A new method is developed in the present work to evaluate the performance of the EV supply chain using a set of significant measurement indicators in the SCOR model (see Figure 2). Development of the method was carried out by application of multi-criteria decision making as well as machine learning techniques. In the first step of the method, we employed a multi-criteria decision-making approach, DEMATEL, to reveal the importance level of measurement indicators. Then, fuzzy logic was utilized to assess the significance level of indicators for measuring SC performance. To do so, we applied the decision trees method to discover the decision rules to be used in the fuzzy logic approach. The present research concentrates on customer-focused indicators that have been supplied in the SCOR model. The indicators are presented in Table 2 [35]. An introduction to the methods is presented in the following sections.

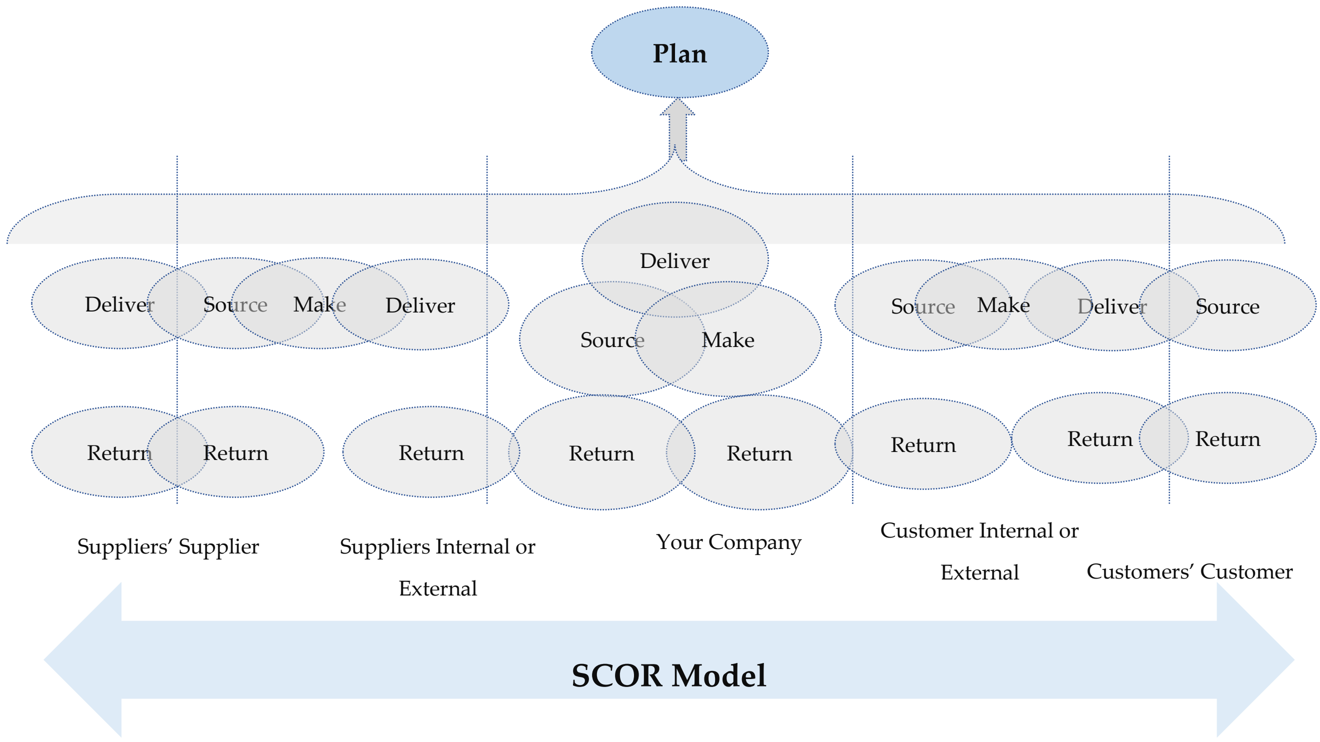



**Figure 1.** The organizational structure of the SCOR model.

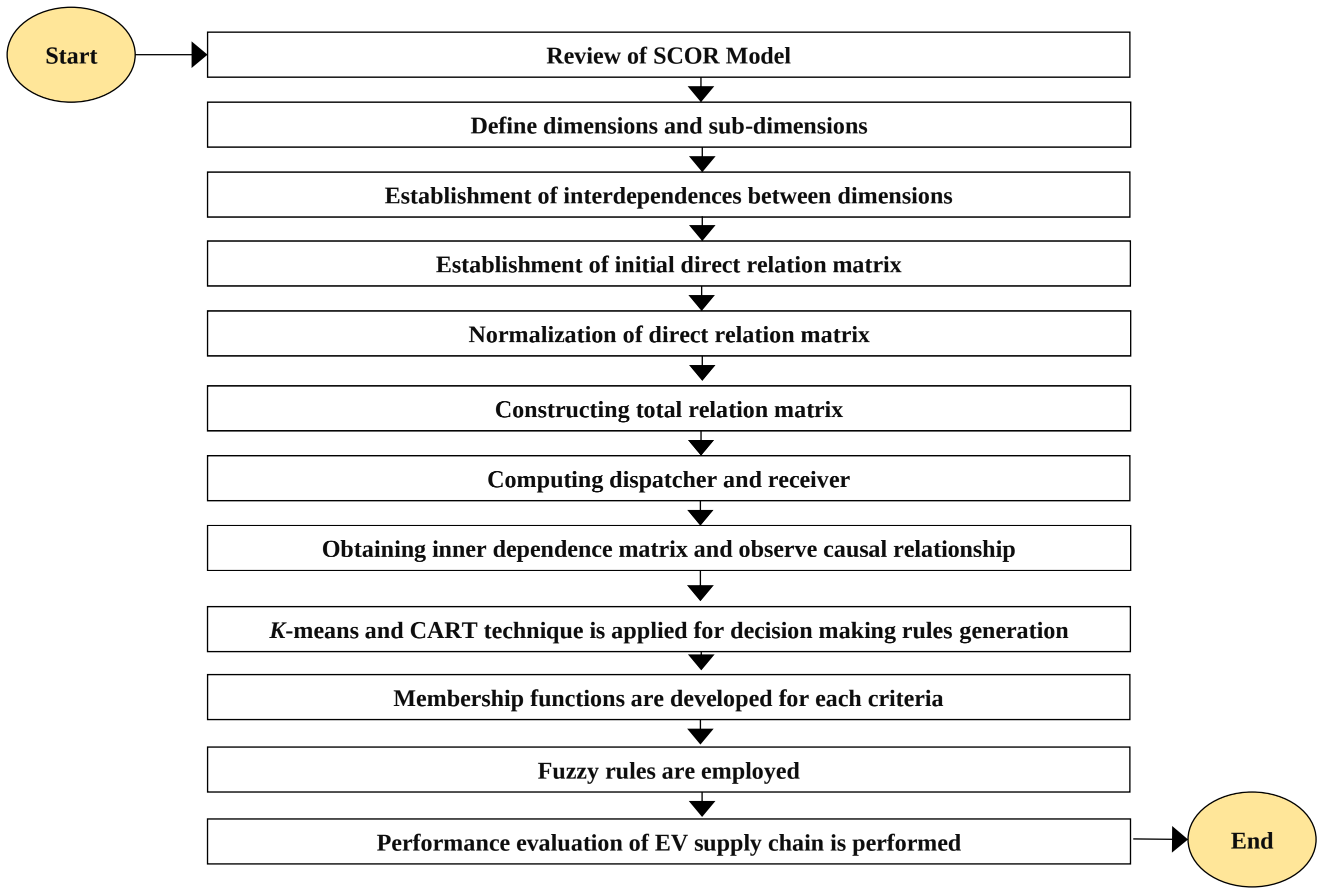



**Figure 2.** The proposed method.

**Table 1.** Performance attributes and level 1 and level 2 indicators.

| Focused group | Attribute | Level 1 Indicators | Level 2 Indicators |
|---|---|---|---|
| Internal | Cost | Total cost to serve | Planning Cost |
| | | | Sourcing Cost |
| | | | Material Landed Cost |
| | | | Production Cost |
| | | | Order Management Cost |
| | | | Fulfillment Cost |
| | | | Returns Cost |
| | | | Cost of Goods Sold |
| | Assets | Cash-to-Cash Cycle Time | Days Sales Outstanding |
| | | | Inventory Days of Supply |
| | | | Days Payable Outstanding |
| | | Return on Supply Chain Fixed Assets | Supply chain fixed assets |
| | | Return on Working Capital | Accounts Receivable (Sales Outstanding) |
| | | | Accounts Payable (Payables Outstanding) |
| | | | Inventory |
| Customer | Reliability | Perfect Order Fulfillment | Delivery Performance to Customer Commit Date |
| | | | Documentation Accuracy |
| | | | Percentage of Orders Delivered In Full |
| | | | Perfect Condition |
| | Responsiveness | Order Fulfillment Cycle Time | Source Cycle Time |
| | | | Make Cycle Time |
| | | | Deliver Cycle Time |
| | Agility | Upside Supply Chain Flexibility | Source: Upside Flexibility |
| | | | Make: Upside Flexibility |
| | | | Deliver: Upside Flexibility |
| | | | Source: Upside Return Flexibility |
| | | | Deliver: Upside Return Flexibility |
| | | Supply Chain Upside Adaptability | Source: Upside Adaptability |
| | | | Deliver: Upside Adaptability |
| | | | Make: Upside Adaptability |
| | | | Deliver: Upside Return Adaptability |
| | | | Source: Upside Return Adaptability |
| | | Supply Chain Downside Adaptability | Make: Downside Adaptability |
| | | | Deliver: Downside Adaptability |
| | | | Source: Downside Adaptability |
| | | Overall value at risk | Risk rating |
| | | | Source: Value at Risk |
| | | | Deliver: Value at Risk |
| | | | Plan: Value at Risk |
| | | | Make: Value at Risk |

### 4.1. Fuzzy logic approach

The fuzzy set theory was suggested in [36] to represent knowledge according to the degrees of membership instead of the crisp membership, which is defined in classical binary logic [37]. The Membership Function (MF) is the major concept in fuzzy logic, which is the numeric representation of the degree according to which an element is assigned to a set. An MF describes the fuzzy set through the assignment of a degree of membership to every element, which can be realized through mapping every point of the input space, named the universe of discourse, to a membership value between 0 and 1. Various kinds of membership functions can be considered [38–42]. Nevertheless, Triangular, Trapezoidal, and Gaussian can be mentioned as the most common cases. Typically, more than one MF is employed for every input variable since a single MF can just describe one fuzzy set. The first stage of the fuzzy logic control process includes identification or looking for the input/output membership functions. Categorization of the information that enters a system is performed by the fuzzy algorithm, after which values indicated the degree of membership in every category is assigned. In rule-based applications of fuzzy logic, membership functions seem to be related to terms observed in the antecedents or results of rules (see Figure 3).

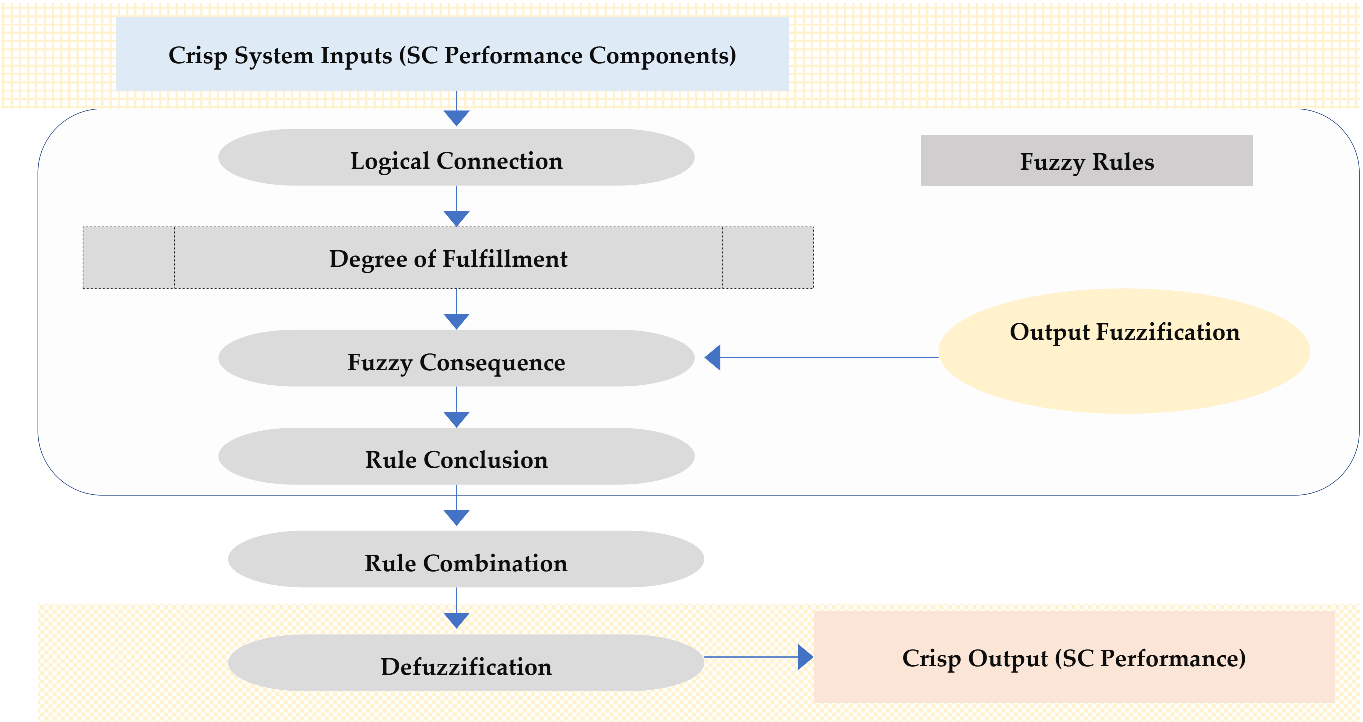



**Figure 3.** Fuzzy logic modeling procedure.

**Table 2.** Customer-focused indicators.

| Attribute | Description | Level 1 Indicators | Description |
|---|---|---|---|
| Reliability (C1) | Reliability is defined as the capacity to fulfill tasks as anticipated, with a primary emphasis on the predictability of process outcomes. | Perfect Order Fulfillment (C1.1) | The percentage of orders for which delivery performance is met, as measured by the presence of delivery damage and the availability of complete and accurate documentation. |
| Responsiveness (C2) | Responsiveness pertains to the swiftness with which tasks are executed, specifically, the pace at which a supply chain delivers products to the consumer. | Order Fulfillment Cycle Time (C2.1) | The typical actual cycle time that is consistently achieved to fulfil orders placed by customers. |
| Agility (C3) | Agility refers to the capacity to react to external influences, specifically, the capability to adapt to market changes with the aim of gaining or retaining a competitive edge. | Upside Supply Chain Flexibility (C3.1) | The number of days needed to achieve a 20 percent increase in delivered quantities that was not planned. |
| | | Supply Chain Upside Adaptability (C3.2) | The highest possible percentage increase in quantity delivered that can be accomplished in a period of 30 days that is still considered sustainable. |
| | | Supply Chain Downside Adaptability (C3.3) | The decrease in ordered quantities can be maintained up to 30 days before the delivery date without resulting in any inventory surplus or additional costs. |
| | | Overall value at risk (C3.4) | The sum of the probabilities of risk events occurring in key supply chain functions, when multiplied by the financial impact of these events. |

### *4.2. Decision trees*

Classification and Regression Tree (CART) is a computational–statistical algorithm for generating predictions in the form of a decision tree [43]. The CART technique is a method used to partition data into final nodes (child nodes) using a series of binary splits which begin at a parent node [44–48]. By binary split, it is meant that every node can split into just two fresh nodes at a split level. The partition is repeated by CART for every child node, going on in a recursive manner until the uniform level in the desired general node can be acquired or a specific ceasing criterion is considered. Normally, the modeling algorithm stops if the maximum tree depth determined by the user is achieved or in the case that it is not possible to make more splits since no considerable predictor variable has remained to split the node. The CART splitting algorithm in every node works according to the notion that every child node needs to have higher ‘‘purity’’ compared to the original parent. ‘‘Purity’’ represents a notion associated with the values of the desired variable leading to zero variance between the splitting stages. The splitting procedure forms a tree structure according to a set of ‘‘if–then’’ rules which provide the decision-makers with the required guidance. The tree structure output of CART supplies information on the major factors and interplay of critical components for SC evaluation in a conveniently interpretable manner.

### *4.3. DEMATEL*

DEMATEL was suggested for the first time by the Battelle Memorial Institute via its Geneva Research Centre [49]. This technique is widely used in solving decision-making problems where the interdependencies among the criteria are considered vital in their evaluation [50–52]. The DEMATEL methodology is defined in the following brief stages [53]:

Stage 1: Calculation of the primary direct-relation matrix is in the first step. Experts provides the pairwise comparisons between the criteria of the system by the scores ranging from 0 to 4, indicating 0 for ‘‘no impacts” to 4 for ‘‘very high impacts”. A primary direct-relation matrix can be established through pairwise comparisons regarding the impacts as well as directions among criteria. An instance of an influence map can be observed in Figure 4 according to which the strength of the impact ranges from 0 to 4. In this stage, for $n$ criteria, an initial matrix $A = [a_{ij}]$ ($a_{ij}$ denotes direct influence of factor $i$ on factor $j$) is obtained using the pairwise comparisons.

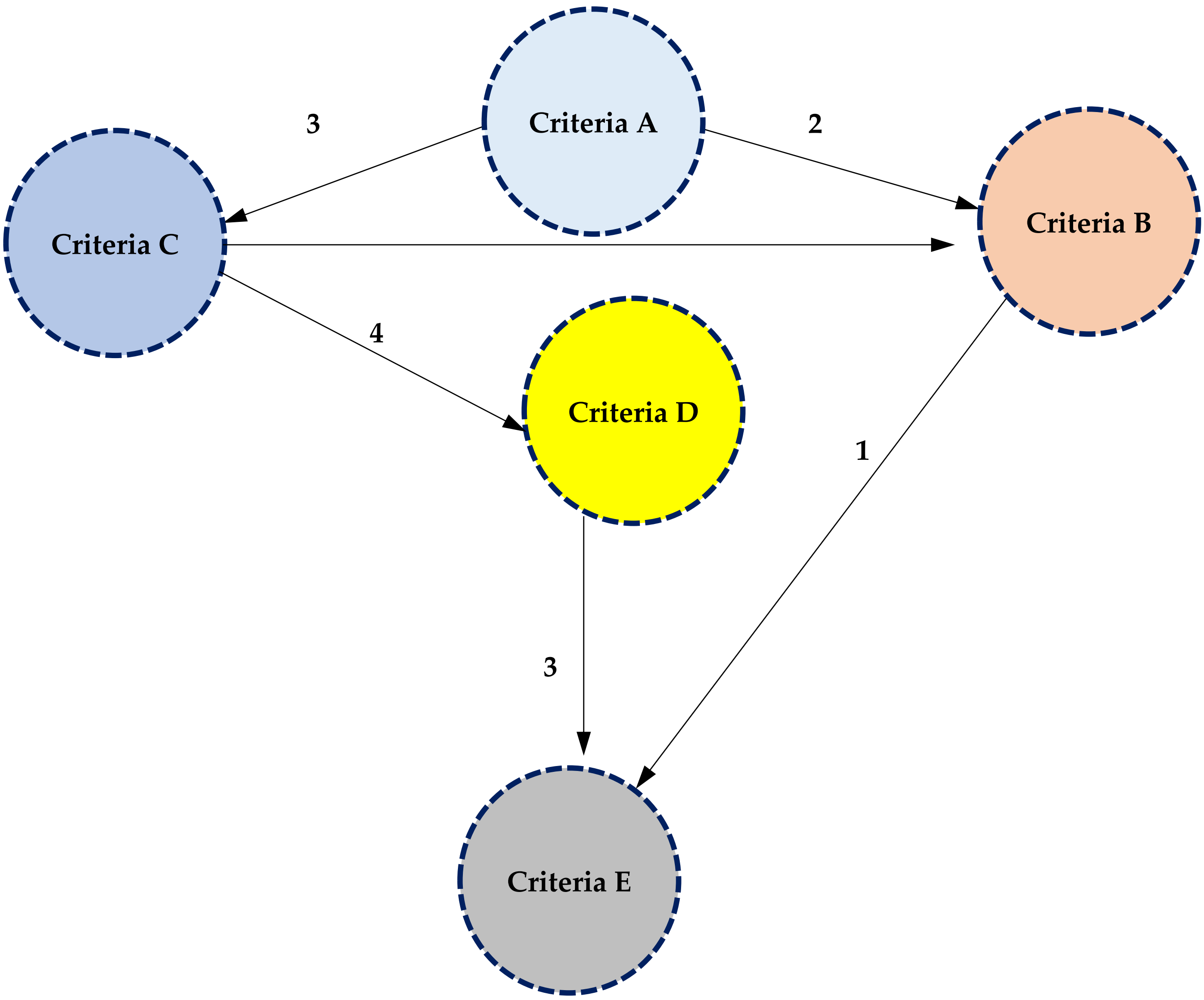



**Figure 4.** Example of an influence map.

Stage 2: In this step, normalization is done for the direct-relation matrix. The normalized direct-relation matrix $X$ can be acquired using Eqs 1 and 2, according to which all major diagonal elements will be zero.

$$X = y.A \tag{1}$$

$$y = \underbrace{\min}_{i,j}\left[\frac{1}{\max_{1\le i\le n}\sum_{j}^{n} a_{ij}}, \frac{1}{\max_{1\le i\le n}\sum_{i}^{n} a_{ij}}\right] \tag{2}$$

Stage 3: In this step, DEMATEL obtains the total-relation matrix. After obtaining the normalized direct-relation matrix, $T$ which is the total-relation matrix is achieved through the following equation:

$$T = X(I - X)^{-1} \tag{3}$$

Where identity matrix is indicated by $I$.

Stage 4: In this step, the row and column overall values of $T$ can be obtained as column vectors $r$ and $s$ correspondingly:

$$T = [t_{ij}]_{n\times n} \qquad i, j = 1,2, \dots, n \tag{4}$$

$$r_i = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \qquad i = 1,2, \dots, n \tag{5}$$

$$s_j = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} \qquad j = 1,2, \dots, n \tag{6}$$

Where the superscript $'$ represents transpose. $(r_i + s_i)$ forms an indicator of the influence strength given and taken, which means that $(r_i + s_i)$ represents the level of the overall impacts that factor $i$ may have in the system. Thus, if $(r_i - s_i)$ has a positive value, subsequently, factor $i$ will have a net impact on the other factors, and if $(r_i - s_i)$ has a negative value, then factor $i$ will be totally under the influence of the other factors.

## 5. Method Evaluation

### *5.1. DEMATEL*

A questionnaire survey was utilized in the present study for data collection. Data were gathered from 180 respondents in the universities who have had experience in the area of the supply chain in industries. They have worked in the private and public universities in the centers and departments of transportation and logistics, and sustainability and environment. Table 3 provides a breakdown of demographic information about the survey respondents. The majority of the respondents were male (57.22%) and held a PhD degree (80.56%). In terms of employment status, a significant portion were full-time employees (91.67%). Regarding age distribution, the largest group fell within the 30–40 age range (43.89%), followed by 41–50 (22.78%), and over 50 (27.22%). The respondents belonged to various faculties, with transportation and logistics (43.33%) and environmental sustainability (37.22%) being the most represented. Faculty ranks varied, with associate professors (46.67%) making up the largest group. Work experience in the industry was diverse, with the majority having 1–3 years of experience (49.44%). Furthermore, the majority of the respondents have worked in the industry for 1–3 years. Reliability (C1), Responsiveness (C2), and Agility (C3) were chosen as the primary performance features, while Perfect Order Fulfillment (C1.1), Order Fulfillment Cycle Time (C2.1), Upside Supply Chain Flexibility (C3.1), Supply Chain Upside Adaptability (C3.2), Supply Chain Downside Adaptability (C3.3), as well as Overall value at risk (C3.4) have been chosen as the first level indicators for measurement of EV supply chain performance. DEMATEL aimed at determining the network associations of the criteria affecting each other. Influencing associations were found through questionnaires provided for every expert to rank each criterion regarding the suitable vendor on a 4-point scale at a range of 0–4, in which zero indicated “no influence” and four indicated “very high influence” correspondingly. Development of the questionnaire took place according to the pairwise comparison, based on which every question includes a pairwise comparison of two criteria. The experts had to score the intensity of the corresponding significance of the two criteria in every pairwise comparison.As shown in Table 4, the average initial direct matrix $A$ is determined. We then calculated the normalized initial direct-relation matrix D. Then, Eq 4 was used to derive the overall relation matrix T as indicated in Table 5. The overall sum of the effects given to and taken from every criterion can be observed in Table 6 with the use of Eqs 5 and 6.

**Table 3.** Demographic information of the respondents.

| Item | Value | Frequency | % |
|---|---|---|---|
| Gender | Male | 103 | 57.22 |
| | Female | 77 | 42.78 |
| Education | PhD | 145 | 80.56 |
| | Master | 35 | 19.44 |
| Employment Status | Full Time | 165 | 91.67 |
| | Part Time | 15 | 8.33 |
| Age | <30 | 11 | 6.11 |
| | 30–40 | 79 | 43.89 |
| | 41–50 | 41 | 22.78 |
| | >50 | 49 | 27.22 |
| Faculty | Transportation and logistics | 78 | 43.33 |
| | Environmental Sustainability | 67 | 37.22 |
| | Business School | 14 | 7.78 |
| | Industrial Engineering | 21 | 11.67 |
| Faculty Rank | Lecturer | 23 | 12.78 |
| | Assistant Professor | 37 | 20.56 |
| | Associate Professor | 84 | 46.67 |
| | Professor | 36 | 20.00 |
| Work Experience in Industry | <1 year | 67 | 37.22 |
| | 1–3 years | 89 | 49.44 |
| | 4–6 years | 14 | 7.78 |
| | 7–9 years | 7 | 3.89 |
| | >9 years | 3 | 1.67 |

**Table 4**. Initial direct matrix A.

| Criteria | Reliability | Responsiveness | Agility |
|---|---|---|---|
| Reliability | 0.00 | 3.30 | 3.80 |
| Responsiveness | 3.70 | 0.00 | 3.60 |
| Agility | 1.80 | 1.80 | 0.00 |

**Table 5.** Total influential relation matrix T.

| Criteria | Reliability | Responsiveness | Agility |
|---|---|---|---|
| Reliability | 1.11 | 1.36 | 1.75 |
| Responsiveness | 1.48 | 1.09 | 1.78 |
| Agility | 0.87 | 0.84 | 0.86 |

**Table 6.** Sum of influences given and received on each criterion.

| Criteria | $r_i$ | $s_i$ | $r_i + s_i$ | $r_i - s_i$ |
|---|---|---|---|---|
| Reliability | 4.22 | 3.46 | 7.67 | 0.76 |
| Responsiveness | 4.34 | 3.29 | 7.64 | 1.05 |
| Agility | 2.57 | 4.38 | 6.95 | -1.81 |

A limit of 1.24 has been selected by the participating experts to establish a suitable Network Relationship Map (NRM). The results of the NRM of the DEMATEL method are presented in Figure 5. In Figure 5, we also present the impact-direction map which provides valuable cues for accurate SC assessment. From the network relationship map of SC performance indicators, it is found that reliability is more important compared with responsiveness and agility. In addition, it is found that agility always receives impacts of responsiveness (T=0.1.36) and reliability (T=1.75).

### *5.2. CART and fuzzy logic results*

DEMATEL was employed to identify the weights of SC performance indicators. In the next step, CART has been employed to identify the associations of the factors and performance of the supply chain. This way, we would be capable of generating linguistic decision rules that are conveniently understandable to be used in making decisions. CART was capable of solving the problem of finding rules in fuzzy rule-based techniques with no human intervention in the present study. This technique is beneficial because of its potential to generate decision rules automatically in the form of "IF-THEN". Given the primary objective of the present study to identify the significance level of performance indicators in SCORE influencing the SC performance, the application of CART was beneficial due to difficulties in the manual generation of the decision rules from the gathered data. Later, the development of the system based on fuzzy rules was carried out using the discovered decision rules. It should be noted that this system worked according to the rules found through the CART technique because learning from the data was impossible. Then, the 5-Likert numerical data were changed into linguistic variables of "Very Low", "Low", "Moderate", "High", and "Very High" to assist CART in finding the decision rules. The obtained decision rules were subsequently employed in systems working based on fuzzy rules. Triangular membership functions were used for the implementation of the fuzzy rule-based system. This kind of membership function with "Very Low", "Low", "Moderate", "High", and "Very High" linguistic variables were taken into account for every variable.

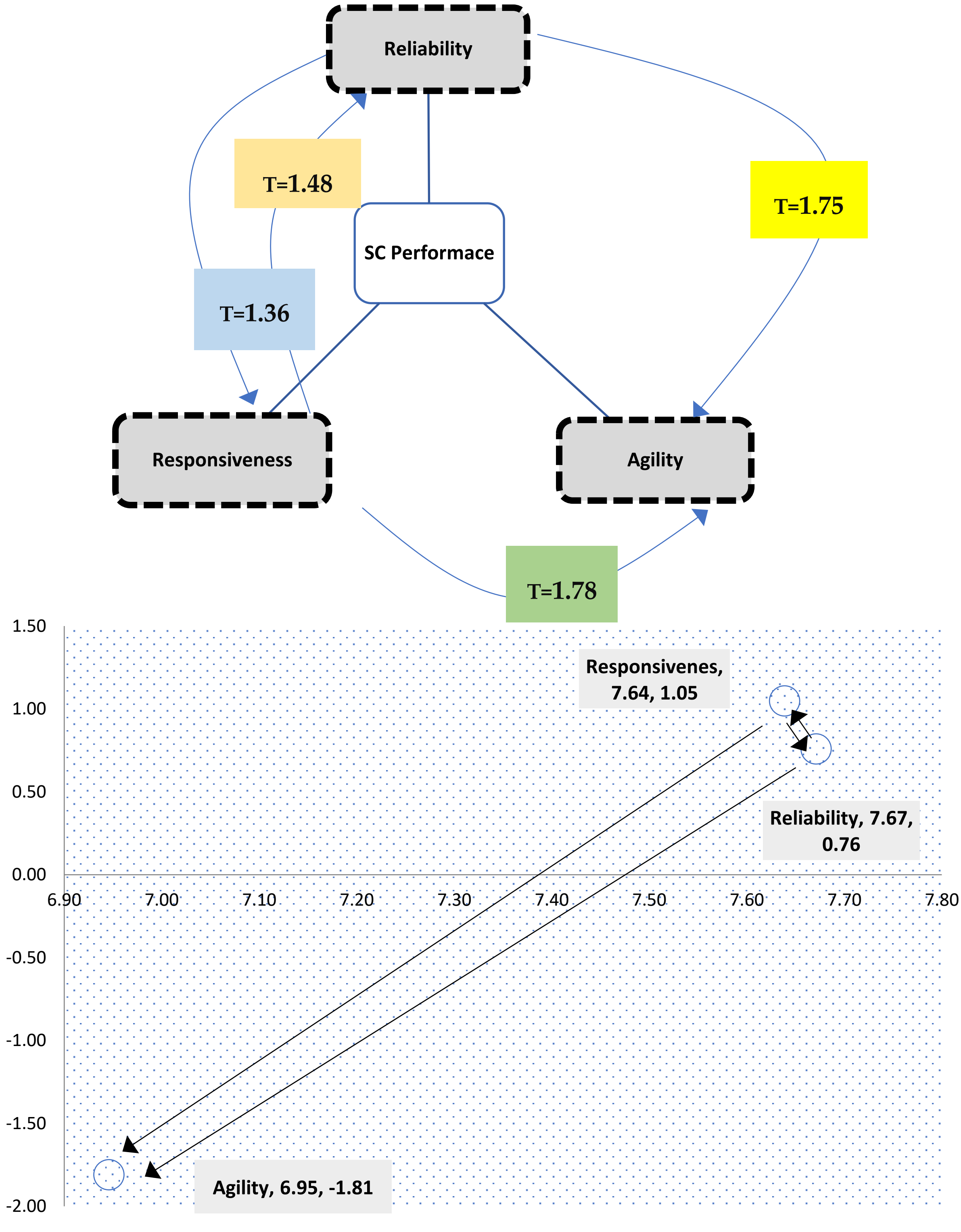



**Figure 5.** Network relationship map of SC performance indicators.

To better discover the decision trees, a clustering method was applied to the collected data. We used k-means for this task. We set $k$=3 to generate three clusters from the data. In Figure 6, the clusters are visualized versus the indicators and SC performance. In addition, the correlation of each performance indicator and SC performance is shown in Figure 7. Table 1 in Appendix A presents several decision rules which represent the exact associations of the SC performance and SCOR mode indicators in three generated clusters. As an instance, it is understood from the first rule that with [moderate] Reliability, [high] Responsiveness, and [high] Agility, a high-performance level would result. Moreover, the significance of every factor in every rule can be found from these rules. As an instance in the rule mentioned above, according to the experts' opinions, if Reliability, Responsiveness, and Agility in the EV supply chain are at a high level, it is possible to achieve a higher level of performance. These rules have the capability of being conveniently understood because they have been provided in linguistic forms. As a result, they are employed in fuzzy systems to design a system based on knowledge and indicate the role of every indicator in the performance of the supply chain in EVs industries. It is worth noting that timely improvement of systems that are based on knowledge is possible when novel data from new participants can be accessible since the rules produced by CART will be updated using the fresh data.

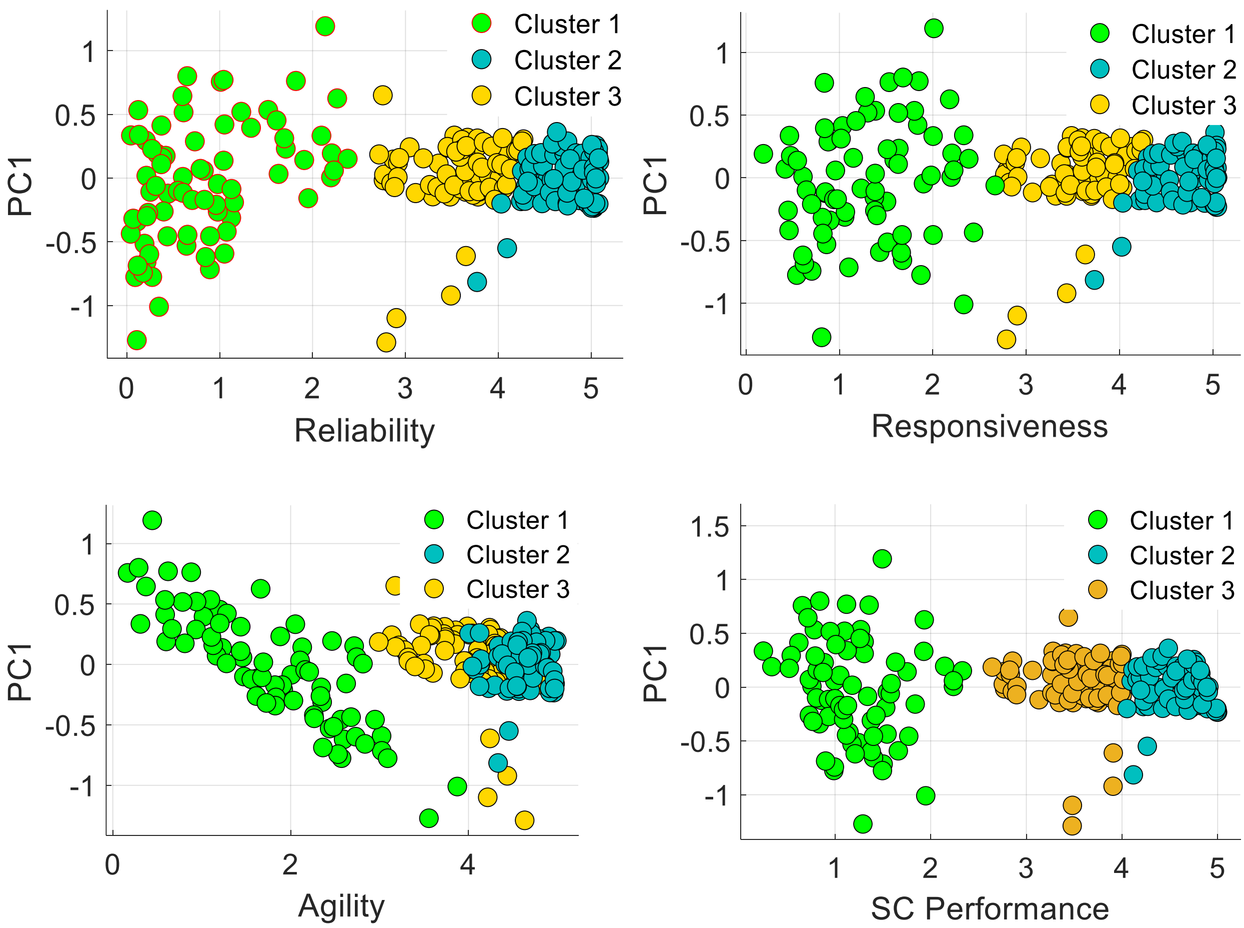



**Figure 6.** Clusters generated by *k*-means for supply chain evaluation.

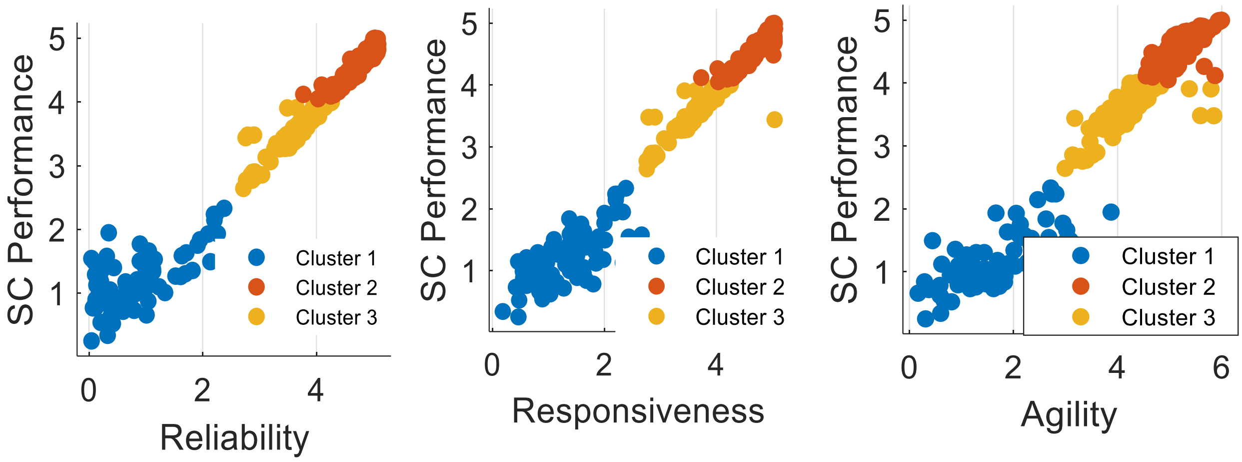
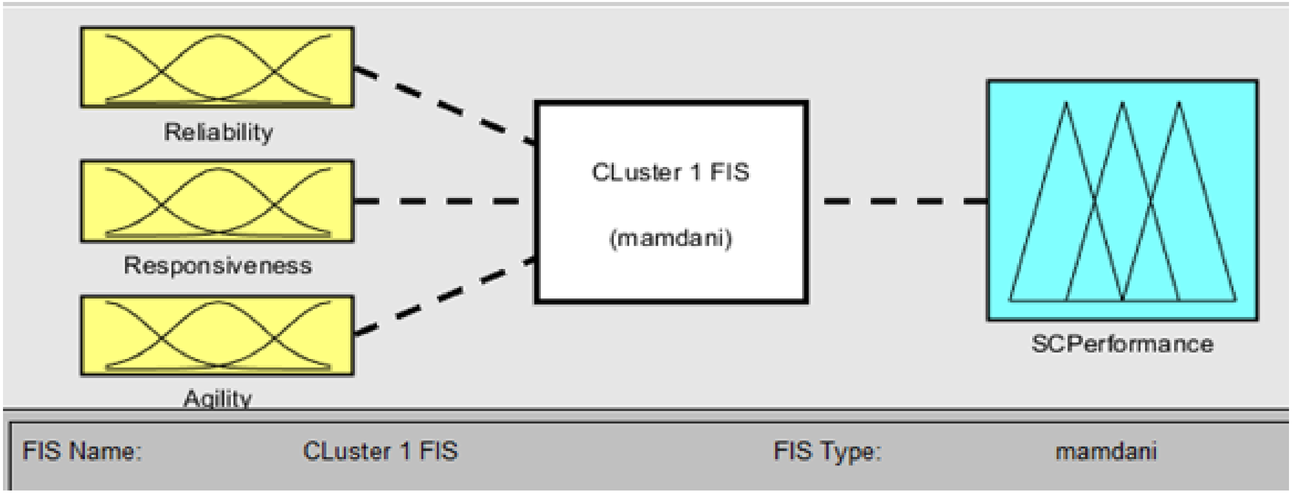
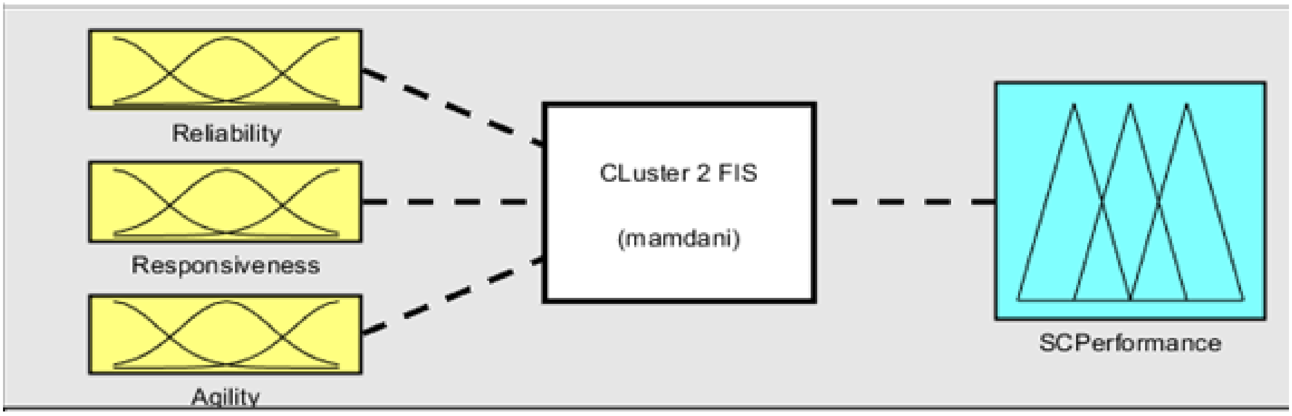



**Figure 7.** Correlation between the performance indicators and SC performance.

The fuzzy system was implemented in the fuzzy logic toolbox of Matlab software (see Figure 8). According to the discovered rules by CART, a fuzzy system based on rules was designed to identify the effect of different indicators on the performance of the EV supply chain. The FIS models are used to predict the impacts of SCOR indicators on the performance of the supply chain. Prediction of Reliability (C1), Responsiveness (C2) as well as Agility (C3) by the first level indicators of Perfect Order Fulfillment (C1.1), Order Fulfillment Cycle Time (C2.1), Upside Supply Chain Flexibility (C3.1), Supply Chain Upside Adaptability (C3.2), Supply Chain Downside Adaptability (C3.3), and Overall value at risk (C3.4) is performed in the FIS 1-3. Then, the last FIS aims at predicting the performance of the supply chain by Reliability (C1), Responsiveness (C2) as well as Agility (C3) (see Figure 8).




(a)




(b)

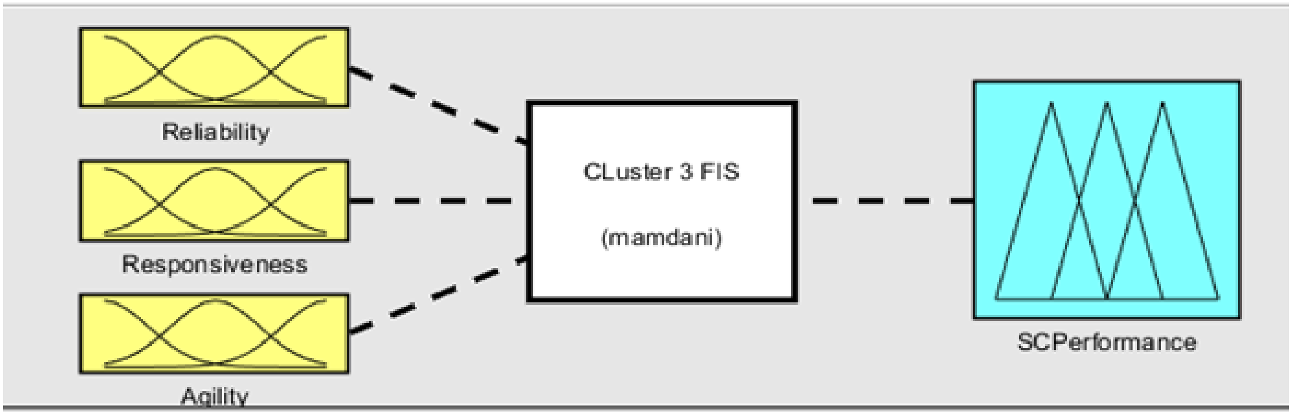



**Figure 8.** Fuzzy inference systems in (a) Cluster 1, (b) Cluster 2 and (c) Cluster 3.

We used Triangular membership functions in every FIS (see Figure 9). The mentioned kind of membership function is broadly utilized to design decision-making models through fuzzy logic techniques. Five linguistic variables have been considered for every factor in the FIS membership functions, including Very Low, Low, Moderate High, and Very High.

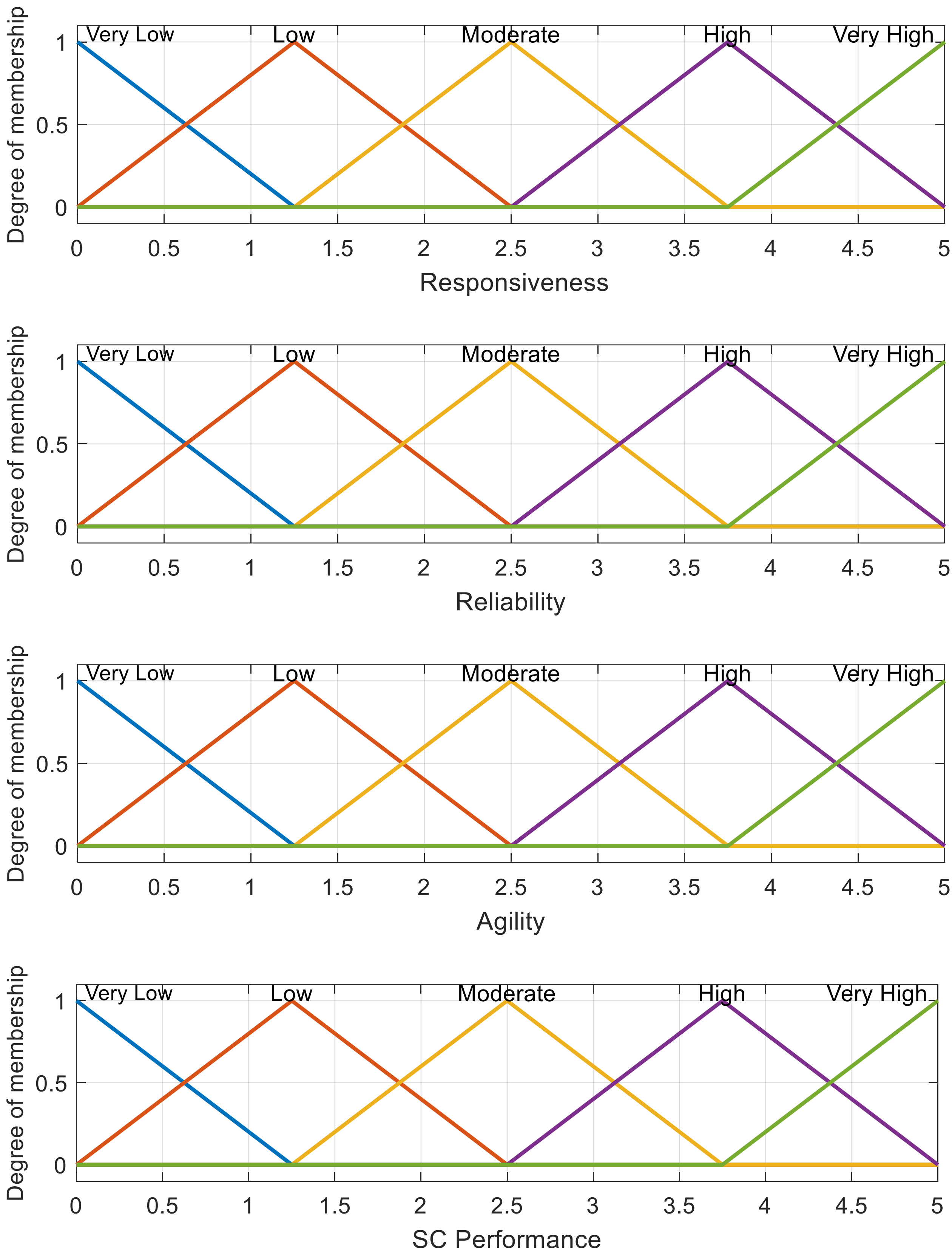



**Figure 9.** Membership functions in fuzzy inference systems.

Figure 10 indicates what was obtained from the FRB method in plots that can illustrate the contribution of individual indicators in the performance of the supply chain. Moreover, the corresponding significance of each indicator is better identified using these plots. This is possible through the incorporation of the identified fuzzy rules into the systems working based on fuzzy rules. Besides, the associations of the indicators and the system's behavior can be found according to the role of every two performance indicators of the model. It should be noted that the behavior of the fuzzy inferences system according to the produced fuzzy rules by CART and the input as well as output parameters can be observed through colors in the surface plots. The factors' significance level is represented in the surface plots (see Figure 10). The rule editor has been presented in Figure 11 for the systems implemented based on the rules. In addition, Figure 11 presents the prediction of SC performance in a fuzzy inference system through discovered rules.

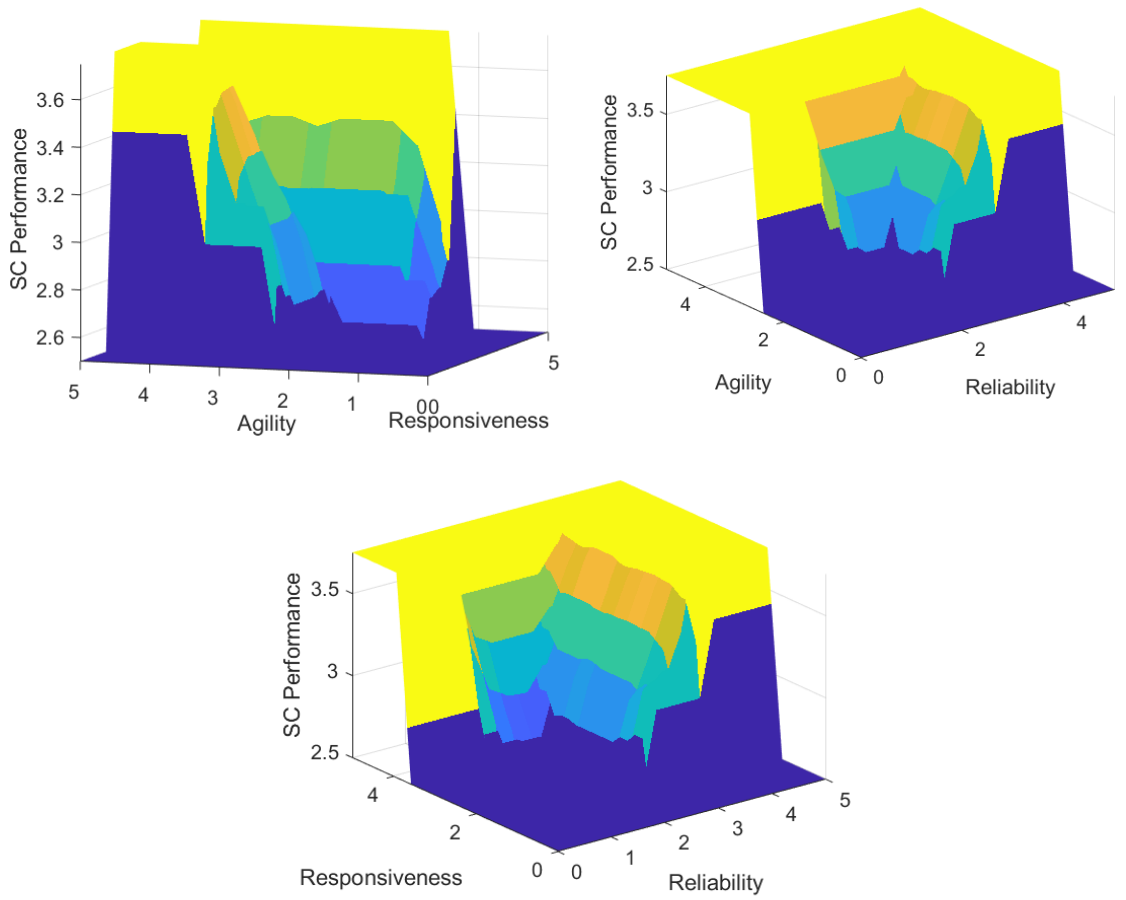



**Figure 10.** SC performance as a function of reliability, responsiveness and agility in fuzzy inference system.

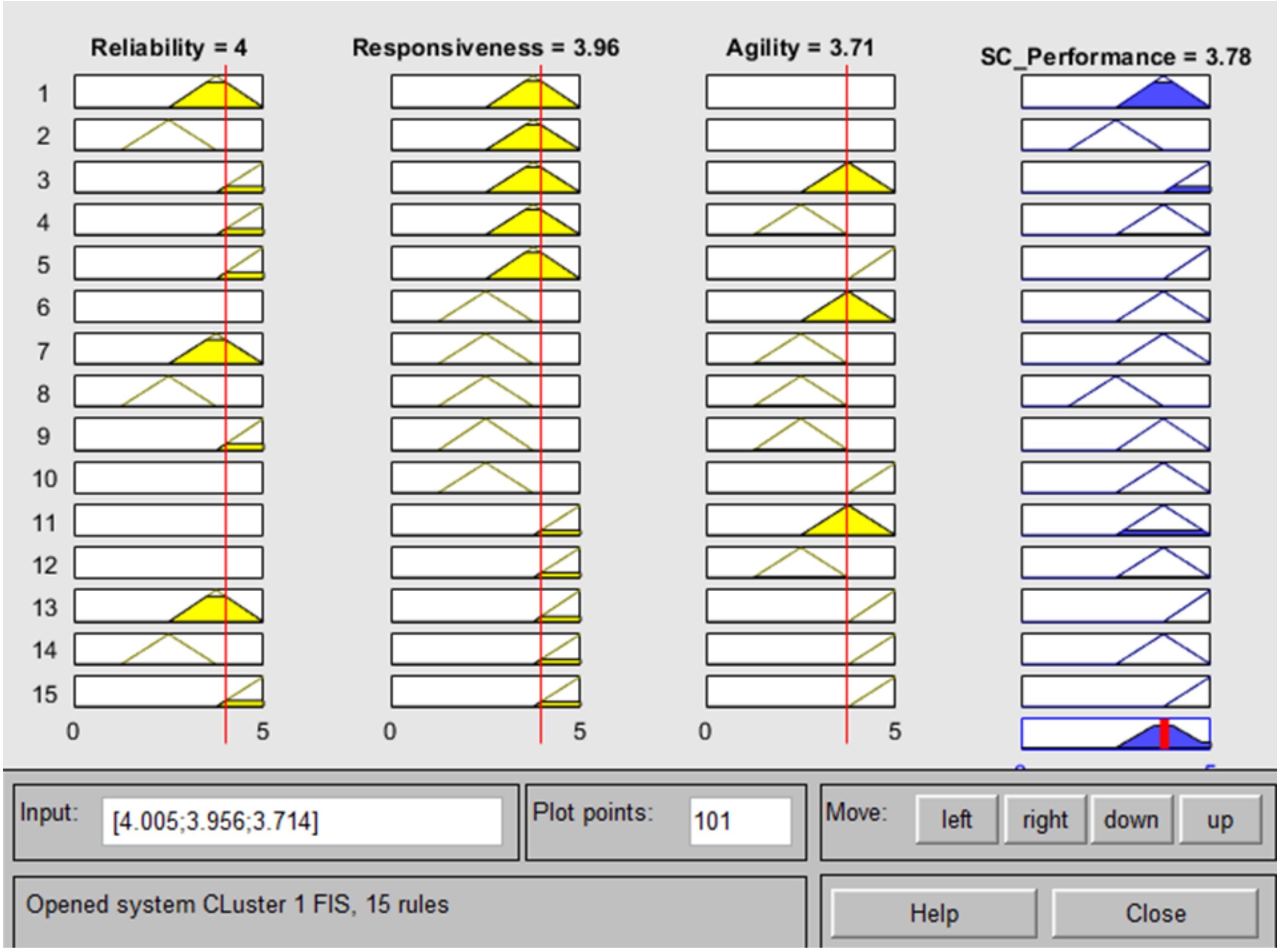



**Figure 11.** Prediction of SC performance in fuzzy inference system.

*5.3. Method evaluation*

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to evaluate the proposed method [54]. MAE is defined as:

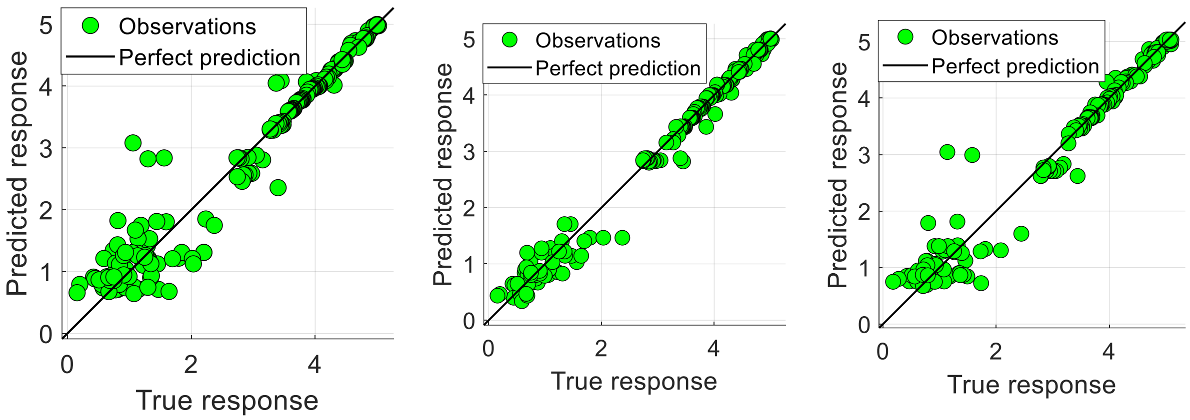
$$\mathrm{MAE} = \frac{\sum |a_i - \hat{p}_i|}{n} \tag{7}$$

Where $a_i$ is the actual value of SC performance, $\hat{p}_i$ is the predicted value of SC performance, and $n$ is the number of samples in each cluster. RMSE is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum |a_i - \hat{p}_i|^2}{n}} \tag{8}$$

To assess the accuracy of fuzzy rule-based models, we used the coefficient of determination ($R^2$). The higher $R^2$ and smaller MAE and RMSE are, the better performance is. The results of $R^2$ and MAE and RMSE are presented in Figure 12. It found that the proposed method has predicted accurately the SC performance in three clusters (Cluster 1: R2=0.952, RMSE=0.333, MAE=0.178; Cluster 2:

R2=0.971, RMSE=0.168, MAE=0.103; Cluster 3: R2=0.964, RMSE=0.268, MAE=0.163) through the fuzzy rules in the fuzzy inference system.




| | | |
|---|---|---|
| $R^2$=0.952 | $R^2$=0.971 | $R^2$=0.964 |
| RMSE=0.333 | RMSE=0.168 | RMSE=0.268 |
| MAE=0.178 | MAE=0.103 | MAE=0.163 |

**Figure 12.** The evaluation results of SC performance in the fuzzy inference system.

We also compared the proposed method with other prediction learning techniques. The results of our comparisons with Support Vector Regression (SVR) [55], Multiple Linear Regression (MLR), Neural Network (NN) [41], and Adaptive Neuro-Fuzzy Inference System (ANFIS) [56–59] are presented in Table 7. Overall, the results reveal that the proposed method which combines clustering, decision trees, and fuzzy rule-based techniques outperform the other techniques in terms of RMSE, MAE and $R^2$.

**Table 7.** Methods comparisons.

| Method | RMSE | MAE | $R^2$ |
|---|---|---|---|
| Proposed Method | 0.245 | 0.127 | 0.965 |
| ANFIS | 0.382 | 0.158 | 0.942 |
| NN | 0.475 | 0.357 | 0.895 |
| MLR | 0.492 | 0.368 | 0.876 |
| SVR | 0.371 | 0.149 | 0.953 |

## 6. Research implications

Electric vehicles are crucial for addressing environmental issues like air pollution and climate change [60,61]. They produce fewer emissions than traditional internal combustion engine vehicles, leading to cleaner air and more sustainable development. Electric vehicles help the country become less dependent on foreign oil by reducing the demand for gasoline. Manufacturing, charging infrastructure, and renewable energy are just a few of the industries that benefit from the booming EV market. Electric vehicles benefit public health because they reduce exposure to noise and air pollution. They provide low-cost, dependable transportation options, which are especially useful in crowded, polluted cities.

In supply chain context, numerous performance measurement models have been developed; however, a performance measurement model based on indicators of customer perceived value (Reliability, Responsiveness, and Agility) in the SCOR model has not been created specifically for the EV supply chain. Customer perceived value, which represents the customer's perception of the benefits and costs associated with a transportation service, holds significant importance in the field of transportation. It plays a crucial role in determining customer satisfaction and loyalty. Moreover, customer feedback should be continuously monitored and analyzed by transportation providers to identify areas for improvement and make necessary adjustments to their services. This approach helps in maintaining high levels of customer perceived value, which is crucial for long-term success in the transportation industry. Additionally, a high level of customer perceived value can foster improved collaboration and communication within the supply chain. When customers perceive that the supply chain delivers high-quality products or services, they are more inclined to engage with the supply chain, provide feedback, and thereby assist the supply chain in identifying areas for improvement and optimizing its operations accordingly. In summary, we found that reliability, responsiveness, and agility are critical characteristics of a successful supply chain in EV. A reliable supply chain ensures consistent delivery of products or services, a responsive supply chain quickly adapts to changing customer needs and market conditions, and an agile supply chain quickly and efficiently responds to supply chain disruptions. By focusing on these characteristics, companies can build more effective and efficient supply chains that meet customer needs and drive business success.

In case of methodology used in this work, a new method was developed in the context of supply chain assessment. The fuzzy logic approach was implemented in this study using decision trees. In transportation studies, the technique of decision trees had been widely employed for prediction tasks. The CART approach was used to automatically discover the decision rules for SC performance evaluation from the data. These rules were then employed in the fuzzy logic approach to identify the associations between the input and output variables, eliminating the need for manual parameterization of variables and decision rules. This characteristic of the suggested method could be considered a positive aspect compared to approaches that relied solely on fuzzy inference, as the definition of appropriate linguistic terms and relative fuzzy numbers could present a significant weakness in such systems. Moreover, the number of indicators and linguistic terms could result in the exponential growth of decision rules, making the design of the rule base system more complicated. Therefore, the adjustment of the inference system was perceived as a learning process involving a team of experts in the area of SC performance and fuzzy inference in real-world applications.

## 7. Conclusions

We strived to introduce a new model based on the SCOR model to measure the performance of the EV supply chain by employing multi-criteria decision-making as well as machine learning techniques. The proposed assessment method was based on DEMATEL, CART and FIS for revealing the significance level of SCOR indicators in EV supply chain. Despite prior method that was merely dependent on FIS, the present work combined multi-criteria decision-making and machine learning to evaluate the performance of the supply chain in the EV supply chain using the SCOR model. The use of CART with the aid of the clustering technique was effective in discovering decision rules from the collected data. According to the discovered fuzzy rules, several fuzzy inference systems were developed and evaluated for the assessment of SC performance. The results confirmed, the reliability performance criteria in the SCOR model have the highest level of importance for SC performance in the EV supply chain compared with the other criteria, responsiveness, and agility. Overall, we found that the employment of a predictive model according to fuzzy logic and the SCOR model is practical in the prediction of SC performance in the EV context. Although the proposed method has effectively predicted the SC performance, there are several limitations that must be considered in future works. First, the proposed method used the CART approach to discover the decision rules from the data. This technique can be optimized using optimization machine learning techniques to better discover the decision rules. In addition, the incorporation of other learning strategies such as ANFIS with the aid of incremental approaches can be effective in the training of the system for large datasets for the evaluation of SC performance. Furthermore, this study can be further developed for the fuzzy MCDM techniques which have been more effective compared with the crisp-based MCDM techniques in the evaluation of criteria of decision-making systems. Moreover, statistical methods, such as Partial Least Squares Structural Equation Modeling (PLS-SEM), are suggested for the development of hypothetical models in combination with the proposed method for assessing factors in the improvement of the EV supply chain.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Author Contributions: Conceptualization, M.N.; methodology, M.N.; software, M.N., R.A.A., H.A., H.A., M.F., S.S.M., A.A., and M.A.; validation, M.N.; formal analysis, M.N.; investigation, M.N.; resources, M.N.; data curation, M.N.; writing—original draft preparation, M.N.; writing—review and editing, M.N., R.A.A., H.A., H.A., M.F., S.S.M., A.A., and M.A.; visualization, M.N., R.A.A., H.A., H.A., M.F., S.S.M., A.A., and M.A. All authors have read and agreed to the published version of the manuscript.

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Data collected or analyzed during the study are available from the corresponding author upon reasonable request.

## Conflicts of interest

The authors declare no conflicts of interest.

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