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Enhancing Vehicular-to-Everything Communication Efficiency with Fuzzy Machine Learning Techniques and Mathematical Modelling

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Abstract: Vehicular communication networks perform a key role in intelligent transportation systems. Different kinds of communication networks exist to enhance the functioning of smart systems of transportation. The categorization of vehicular networks shall be generalized as vehicle-to-everything (V2X). The vehicular efficiency of V2X depends on diverse factors and this research work employs fuzzy machine learning techniques to determine the core features. This study explores all the possible factors persuading the vehicular efficiency of V2X. This work proposes a mathematical model incorporating fuzzy logic-based supervised machine learning approaches in handling uncertain and imprecise data. The qualitative features are decided based on the integrated approach of fuzzy and machine learning. The mathematical model developed in this research work is based on this integrated framework and the results of the model are more significant in the domain of smart intelligent systems. This model shall be further discussed with different categorizations of machine learning approaches to extend this work. This model presented in this work facilitates the automotive decision-makers and policymakers in identifying the crucial factors contributing to the efficiency of V2X.

Keywords: *Vehicle-to-Everything, Fuzzy logic, Supervised algorithms, Machine learning.*

1. Introduction

The intelligent transportation system is intensely influenced by advancing vehicular networks and rapidly increasing technologies. Several vehicular networks such as Vehicle-to-Vehicle (V2V), Vehicle-to-infrastructure (V2I), Vehicle-to-network (V2N), and Vehicle-to-Pedestrian (V2P) are established. These vehicular networks shall be generalized as these networks shall be characterized as the constituents of the network of Vehicle-to-Everything (V2X). The network of V2X is an inter associated network intended to promote safe and efficient transportation by considering both the intrinsic and extrinsic factors interconnected with this framework. Vehicular efficiency in the case of V2X is determined by several aspects related to network structure, connectivity, vehicle movement, latency, traffic flow, and many others subjected to the environment. These are considered to be the essential inputs and data acquisition on these entities is significant for decision-making. The management of V2X efficiency encounters several challenges of vehicular mobility, congestive traffic, communication chaos, and other environmental conditions. To tackle such difficulties, machine learning algorithms (ML) are applied to deal with large data sets in framing solutions to the problems of vehicular efficacy. The ML approaches are highly efficient in designing suitable vehicular networks by resolving the factors hurdling vehicular efficiency. The different kinds of machine learning algorithms categorized under supervised, unsupervised, and reinforcement shall be employed to make optimal decisions on vehicular efficiency. However, this deterministic kind of ML algorithm are termed as conventional as these approaches are incompetent to deal with uncertain data following various patterns. These shortcomings in data handling have unveiled the instances of integrating fuzzy notions.

The theory of fuzzy logic is applied in decision making circumstances to deal with data types that are imprecise. The practical implications of this fuzzy based logic are reflected in deriving solutions to the intricate problems. A complex decision-making environment demands a versatile and robust framework with the potency to handle uncertainty with logical reasoning and it is possible only with fuzzy logic. The fuzzy integrated phenomena yield

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better results in comparison with the independent existence of that phenomenon. In a similar fashion, the machine learning algorithms shall be integrated with fuzzy logic to treat the uncertainties and inconsistencies present in the data pertinent to determining the vehicular efficiency of V2X. The approaches of Fuzzy Machine learning (FML) are capable of integrating the principles of fuzzy logic to make reasoning and decision-making more flexible and adaptable. These fuzzy-based tools are interpretable and competent in making computations. Another notable merit of FML is the inherent capacity to handle small data sets. In some cases of decision-making, the scales of data availability may not be large always. The variations in the magnitude of data shall be dealt with fuzzy-based machine techniques. The synergy of fuzzy logic with traditional machine-learning approaches results in a robust and adaptable decision tool. Furthermore, the mathematical modeling framework is crucial as it plays a key role in comprehending and enhancing the elements of the V2X system of communication. A mathematical framework accommodating fuzzy machine learning shall be developed by defining the fuzzy expressions and rules based on the opinions of the experts. The fuzzy inference systems with a mathematical background enhance the performance of the model. This framework will facilitate in gaining more insights on enhancing the performance of the communication system as a whole.

The objective of this research work is to develop a mathematical framework considering the implication of fuzzy-based machine learning in determining the vehicular efficacy of V2X communication. As the decision scenario involves many qualitative input features the FML-based approach of modelling is chosen for this study. The other contents of this work are organized into the following sections. The state of the art of related works is presented in section 2. The framework of fuzzy-based machine learning with mathematical modeling is sketched out in section 3. Section 4 applies the discussed approach to resolve the decision-making problem of determining vehicular efficacy. Section 5 discusses the results in brief and the last section concludes the work with future research directions.

2. State of Art of Research

This section presents a detailed description of the literature review related to the applications of fuzzy-based machine learning in the context of vehicular networks subjected to intelligent transportation systems. The existence of research gaps and the novel contributions made in this work are also discussed in this section.

The onset of research in the areas of building smart transportation systems is gaining more momentum in recent times with the integration of machine learning and fuzzy machine learning approaches. The recent contributions made are discussed as follows with a special focus on the key research contributions. Naga et al [1] discoursed a comprehensive survey of vehicular networks in intelligent transportation systems. Lu et al [2] in the systematic review, described the robust tendency of fuzzy-based machine learning. Bressane et al [3] presented their findings on the potency of these machine-learning approaches in handling uncertainty. Gheisarnejad et al [4] introduced type-3 fuzzy-based controlling systems in telecom converters to enrich the functioning and consistency of operations. Castillo and Melin [5] discussed the implications of type-3 fuzzy logic in an intelligent control system. The fuzzy logic integrated telecom control systems are more viable than the conventional control settings. Roy et al [6] applied the linguistic interval type of fuzzy logic in vehicle routing.

Gollapalli et al [7] applied a neuro-fuzzy kind of approach to make predictions on road traffic congestion. This fuzzy approach associates fuzzy logic with the learning framework of neuro systems to develop more efficient transportation systems. Khan et al [8] employed clustering techniques to deal with unsupervised data sets in devising optimal planning for 5G networks. Almazroi et al [9], Archana, and Shahabadkar [10] developed a predictive model with advanced algorithms on transmissions in progressive networks. Erdebilli and Aslan [11] designed an autonomous approach to uncertainty management in deciding on facility locations. Ezhilarasi et al [12] leveraged the technique of fuzzy-based neural networks with feed-forward propagation to make detections on routing attacks in vehicular networks. Yazdinejad et al [13] proposed a decision framework with fuzzy blockchain to make detections on threats in IoT integrated networks and to ensure network security. Bowlin et al [14] discussed the challenges of vehicular networks based on blockchains from the perspectives of data security, privacy, and scalability. Martinelli et al [15] formulated a machine learning-based decision model with fuzzy parameters to evaluate the stability of the grids.

Li et al [16] employed fuzzy-based learning methods in diagnosing the faults in the vehicle systems. A comparative analysis of the conventional over the modern diagnosis methods is also made to determine the ways of enhancing the system's reliability. Marappan [17] framed an anomaly identification model for building an effective transmission system with a fuzzy-based deep learning approach. Chen et al [18] discussed the characteristics of road networks in a vehicular network system. Lenard et al [19] explored the modeling of vehicular networks to deal with the challenges in quality sustenance. Tarafdar et al [20] applied a fuzzy-based decision approach to enrich the predictions of the intrusions. Aljohani and Almutairi [21] discussed the competency of these techniques in detecting security threats. Chen and Liu [22] used soft computing to detect faults in grids. Yang [23] contributed to security management via mathematical models and fuzzy logic and the various types of fuzzy parameters were discussed [25-

52]. The aforementioned survey of works reflects the implications of fuzzy-based machine learning in making decisions related to vehicular networks with special reference to predictions of threats and security issues. The mathematical modeling approach with fuzzy logic and machine learning techniques provides a more comprehensive framework to accommodate various inputs and output variables. This broad architecture is capable of handling uncertain data types. However, there are a few shortcomings which are identified as follows. These fuzzy-based machine learning algorithms are widely applied in making predictions subjected to the traffic flow but not much on the vehicular efficiency as a whole. Hence this research work intends to develop a hybrid model considering the objective of maximizing the efficacy of V2X with feature reduction using fuzzy-c-means clustering and fuzzy logic-based neural networks.

3. Methodology

This section presents the detailed procedure of fuzzy-based machine learning in a general perspective and also sketches the procedural framework of fuzzy neural networks. Fig.1 is the pictorial representation of the general framework.

3.1. Steps Involved in General Fuzzy-based Machine Learning Framework

Step 1: Problem Definition

In this first step, the decision problem is well-defined. The input and output variables are well identified.

Step 2: Fuzzification

In this stage, the fuzzy sets are defined for each of the variables. The suitable membership functions and the fuzzy IF -THEN rules are defined. In general, the trapezoidal fuzzy numbers are used to make suitable representations as in (1).

$$\mu_A(x) = \begin{cases} 0 & if\ x \le a \\ \frac{x-a}{b-a} & if\ a < x \\ 1 & if\ b < x\ \le c \\ \frac{d-x}{d-c} & if\ c < x\ \le d \\ 0 & if\ x > d \end{cases} \quad \text{-----------------}$$

(1)

Step 3: Fuzzy Inference System

The fuzzy inference engine system is employed to apply the fuzzy rules to the fuzzy input forms. The most commonly applied methods are Mamdani and Sugeno. The aggregate of all the fuzzy output values is determined using eq.2

$$\mu_{output}(z) = \max(\mu_1(z), \mu_2(z), \ldots., \mu_n(z)) \quad \text{-----------------}$$

(2)

Step 4: Defuzzification

The final fuzzy output values are determined using the methods of defuzzification especially the centroid method, bisector method, and many other methods.

$$z^* = \frac{\int z * \mu_{output}(z)dz}{\int \mu_{output}(z)dz}$$

Step 5: Conjoining with Machine Learning

The required data is collected with input and output variables. The machine learning algorithms applied generally are integrated with fuzzy logic to derive optimal results.

Step 6: Model Validation

The formulated model is validated by subjecting to training and testing of the data. Also, necessary changes are made to modify the model based on the requirements.

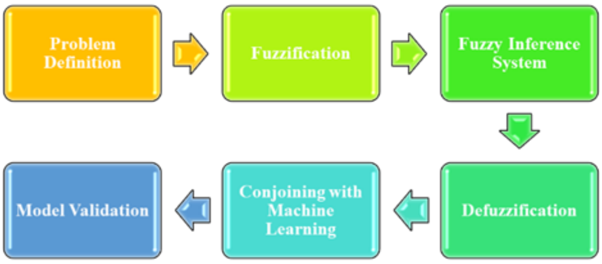

Fig 1. General Algorithmic Framework of Fuzzy Machine Learning

3.2. Fuzzy Neural Network Framework

The algorithmic framework of fuzzy neural network follows the procedure of the general architecture of fuzzy machine learning modality, however in few aspects it differs in terms of representations and assumptions. The overall framework of fuzzy neural network is presented in Fig. 2.

Step 1: Fuzzification

The crisp inputs and the outputs are represented using fuzzy expressions. For each input variable xi and the output variable yj, the respective fuzzy sets with membership functions are framed.

Step 2: Framing of Fuzzy Rules

The rules Rh connecting both the inputs and the outputs are framed using fuzzy representations.

Step 3: Fuzzy Inferences

The extent of activating each of the rules Rh is determined and it is performed by using the min and max operators. The activating function ah for each of the rule is defined by

$$\alpha_j = \min\left(\mu_{A_1^j}(x_1), \mu_{A_1^j}(x_2), \ldots, \mu_{A_1^j}(x_n)\right)$$

Step 4: Defuzzification

The centroid method is applied to defuzzy the fuzzy representations to crisp values for making further result analysis.

$$y = \frac{\sum_{j=1}^{m} \alpha_j * y_j}{\sum_{j=1}^{m} \alpha_j}$$

Step 5: Conjoining with Neural Network

The above-mentioned steps are associated primarily with the fuzzifying process and this step deals with the integration of the same with the neural network. The process of integration comprises initialization of the parameters, forward pass, error calculation (L) and backpropagation (θ) to update the parameters.

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \text{ and } \theta \leftarrow \theta - \eta\frac{\partial L}{\partial \theta}$$

Step 6: Model Training

The developed hybris model is subjected to training and later modified based on the requirements.

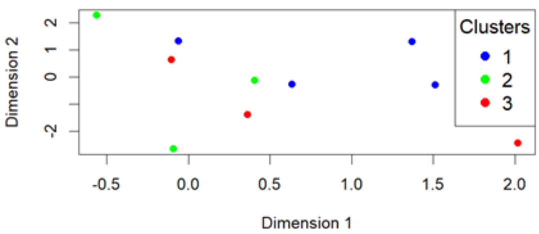

Fig 2. Framework of Fuzzy Neural Network

4. Application of Mathematical modeling with FML in decision-making on vehicular efficiency of V2X

This section applies the mathematical framework of the fuzzy-based machine learning approach in computing the vehicular efficiency of V2X. The factors or the criteria that are generally considered for this study are presented in the following Fig 3.

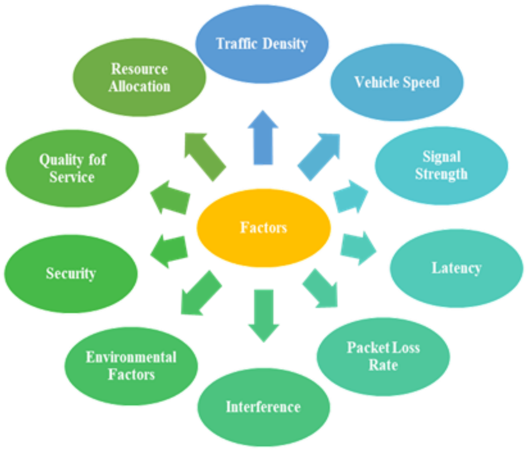

Fig 3. Overall Factors of Vehicular Efficiency

The criterion reduction is applied to determine the core factors and they are considered to be the input features of this model. The fuzzy -c-means of

clustering is employed to reduce the number of features. The criteria are reduced based on their significance into three clusters namely “High”, “Moderate”, and “Low”. The pictorial representation of the clustering is presented in Fig. 4.

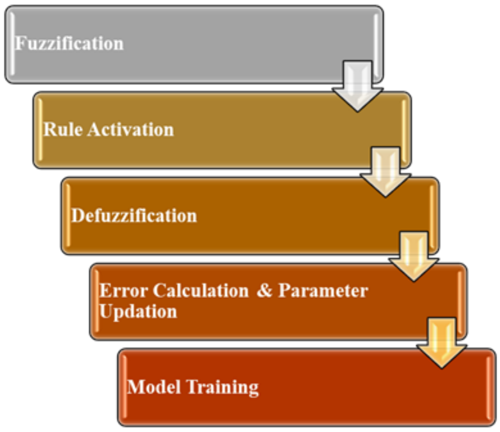

Fig 4. Fuzzy -c-means of clustering of criteria by significance

As a result of this fuzzy-based clustering, the significant criteria are identified and are presented in fig 5.

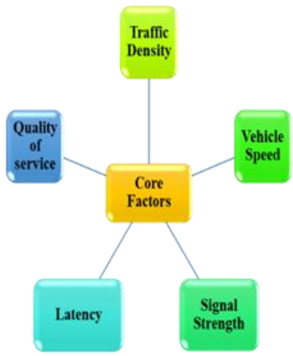

Fig 5. Core Factors after Reduction

The attributes of traffic density, vehicle speed, signal strength, latency and quality of service are identified as the core factors in making decisions on the communication efficiency of V2X. The description of these factors and their association with communication efficiency is presented in Table 1.

The sample data in terms of Linguistic variables is presented in Table 2

Table 2. Sample Data

S.No	*TD*	*VS*	*SS*	*LT*	*QS*	*CE*
1	Low	Fast	Moderate	Low	High	High
2	High	Fast	Weak	High	Low	Low
3	Medium	Moderate	Strong	Medium	Low	Medium
4	Low	Slow	Moderate	Low	High	High
:						
:						
20	Medium	Slow	Weak	Medium	Medium	Medium

The trapezoidal fuzzy number for each of the linguistic representations of the input features and the output variable are presented in the following Tables

Table 3. Quantification of Linguistic Variables of Traffic Density

Linguistic Variable	*Trapezoidal Representation*
Low	[0,0,10,20]
Medium	[10,20,30,40]
High	[30,40,50,60]

Table 4. Quantification of Linguistic Variables of Vehicle Speed

Linguistic Variable	*Trapezoidal Representation*
Slow	[0,0,20,40]
Moderate	[20,40,60,80]
Fast	[60,80,100,100]

Table 5. Quantification of Linguistic Variables of Signal Strength

Linguistic Variable	*Trapezoidal Representation*
Weak	[-100, -100,70, -50]
Moderate	[-70, -50, -30, -10]
Strong	[-30, -10,0,0]

Table 6. Quantification of Linguistic Variables of Latency

Linguistic Variable	*Trapezoidal Representation*
Weak	[0,0,50,100]
Moderate	[50,100,150,200]
Strong	[150,200,250,300]

Table 7. Quantification of Linguistic Variables of Quality of Service

Linguistic Variable	*Trapezoidal Representation*
Low	[0,0,20,40]
Medium	[20,40,60,80]
High	[60,80,100,100]

Table 8. Quantification of Linguistic Variables of Communication Efficiency

Linguistic Variable	*Trapezoidal Representation*
Low	[0,0,20,40]
Medium	[40,60,60,80]
High	[60,80,100,100]

The fuzzy rules relating the input five features and the output are presented in Table 9

Table 9. Fuzzy Rules

Fuzzy Rule	IF- Inputs					THEN- Output CE
	TD	VS	SS	LT	QS	
1	High	Fast	Weak	High	Low	Low
2	Low	Moderate	Strong	Low	High	High
3	Medium	Slow	Moderate	Medium	Medium	Medium

By using the packages of "FuzzyR", "neuralnet" in R programming the following fuzzy neural network architecture is obtained and presented in Fig. 6

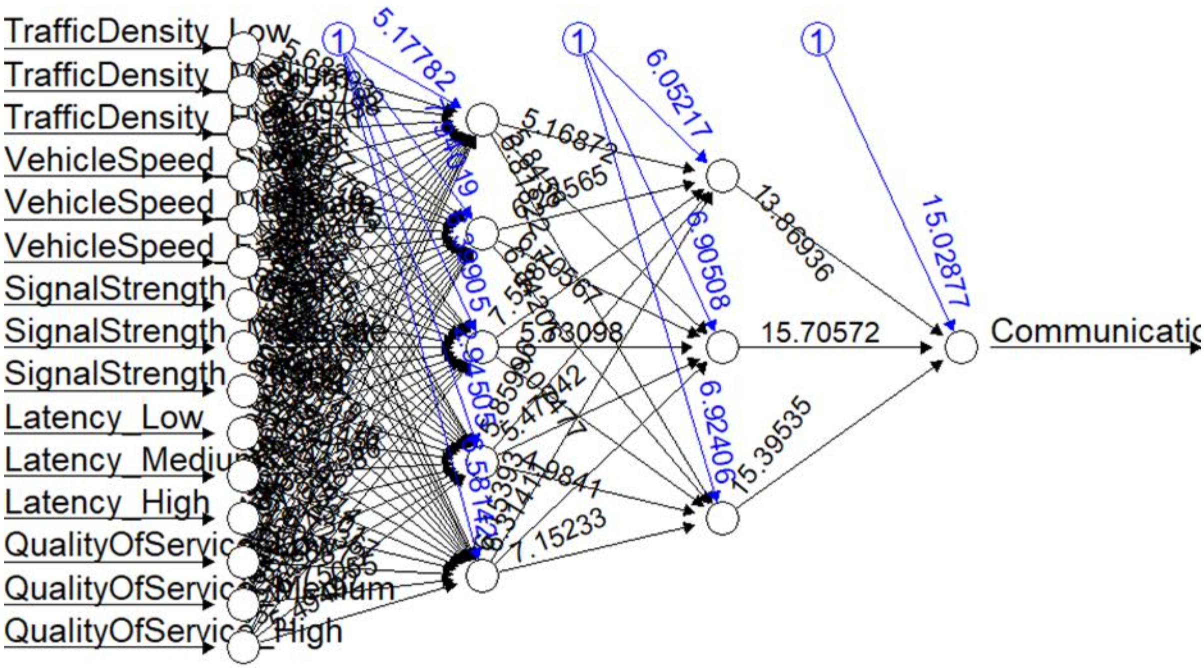

Fig 6. Architecture of Fuzzy Neural Network

The performance measures of this model are presented in Table 10.

Table 10. Performance Measures of the Proposed Model

Accuracy	***Precision***	***Recall***	***F1 Score***
0.92	0.95	0.89	0.92

5. Discussions

The fuzzy based neural network model applied in determining the communication efficiency is more robust and the performance measures reflect the same. However, the consistencies and actual competency of the fuzzy based machine learning algorithms are analyzed by subjecting to other fuzzy based algorithms. The comparative analysis of the performance measures using other FML are presented in Fig. 7 and the respective values are presented in Table 11.

Table 11. Performance Measure Values of the Fuzzy ML methods

Methods	***Accuracy***	***Precision***	***Recall***	***F1 Score***
Fuzzy Support Vector Machines (FSM)	0.89	0.91	0.82	0.9
Fuzzy Decision Trees (FDT)	0.88	0.93	0.85	0.89
Fuzzy Random Forest (FRF)	0.87	0.91	0.83	0.89

The performance values presented in Table 11 are presented graphically to make comparative analysis.

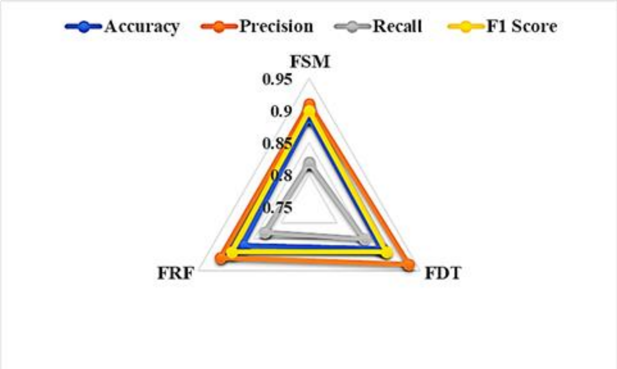

Fig 7. Comparison of Performance Measures

From this graphical representation, the following inferences are made, the fuzzy-based machine learning models are more robust and potent. The degree of accuracy obtained using FML is high in comparison with conventional machine learning and it is evident from the values furnished in Table 12.

Table 12. Performance Measure Values of ML Methods

Methods	*Accuracy*	*Precision*	*Recall*	*F1 Score*
Neural Networks	0.75	0.77	0.69	0.74
Support Vector Machines	0.71	0.73	0.64	0.67
Decision Trees	0.69	0.71	0.62	0.63
Random Forest	0.64	0.64	0.64	0.64

On comparing the performance measures presented it is vivid that the fuzzy-associated machine learning algorithms yield better results in terms of preciseness and accuracy. This shows the efficacy of the contemporary machine-learning approaches in decision-making.

6. Conclusion

This research work presents the modality of integrated fuzzy-based machine learning in making decisions on the communication efficiency of the V2X communication network. The method of fuzzy-c-means clustering is applied in reducing the criterion number from the generally considered set of criteria. Different fuzzy-based machine learning algorithms are applied in making decisions on V2X and the efficacy is tested by making comparisons This hybrid approach finds utility in designing solutions to different decision scenarios. The combination of fuzzy with traditional machine learning methods shall be leveraged in resolving industrial-related problems. The proposed combined approach shall be extended by discussing it with other learning approaches.

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