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Adaptive Neuro-Fuzzy Modeling for Traffic Volume Prediction

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Abstract

In the realm of modern urban planning and transportation management, the accurate prediction of traffic volumes has emerged as an indispensable tool for efficient traffic flow and strategic infrastructure development. As cities continue to grow and traffic congestion becomes increasingly complex, the need for precise traffic volume forecasting has become paramount. This research addresses this critical need by leveraging the Adaptive Neuro-Fuzzy Inference System (ANFIS) to model and predict traffic volumes with remarkable accuracy. ANFIS's unique ability to capture intricate patterns within data, particularly in the context of varying vehicle categories and daily fluctuations, makes it an ideal candidate for this task. With a rich dataset spanning 31 working days and encompassing five vehicle categories, including two-wheelers, four-wheelers, heavy vehicles, light vehicles, and other vehicles, this study aims to showcase the potential of ANFIS as a pioneering solution for enhanced traffic prediction accuracy. It is observed that developed model has 89.91% accuracy level. By fusing advanced machine learning techniques with real-world traffic data, this research contributes to the advancement of transportation planning and management, ultimately leading to more optimized traffic systems and sustainable urban development.

Keywords: ANFIS, Traffic volume, Modelling, RMSE.

INTRODUCTION

Accurate traffic volume prediction stands as a linchpin in the realm of transportation planning and management, playing a pivotal role in shaping the efficiency, safety, and sustainability of urban mobility. The ability to anticipate traffic volumes with precision facilitates the development of proactive strategies to mitigate congestion, reduce travel times, and enhance overall traffic flow. Such forecasts empower urban planners to make informed decisions about infrastructure development, road expansions, and traffic signal optimization, leading to optimized road networks that cater to current and future demands. Moreover, by understanding traffic patterns and predicting peak congestion hours, authorities can implement dynamic traffic management systems that alleviate bottlenecks and enhance the commuting experience for citizens. Beyond mere traffic flow, accurate volume prediction assists in environmental conservation by reducing fuel consumption and harmful emissions associated with idling vehicles. As urban populations continue to grow, the strategic insights offered by reliable traffic volume forecasts play a critical role in creating sustainable and livable cities, wherein efficient transportation systems harmonize with economic growth and environmental well-being.

Predicting traffic volume is a crucial aspect of transportation planning, and various methodologies have been developed to address this challenge. Williams and Hoel (2003) employed a seasonal ARIMA process to model and forecast vehicular traffic flow. This statistical approach captured cyclic patterns in traffic data. Chien and Ding (2002) utilized a multilayer feed forward neural network for short-term traffic flow prediction. The model demonstrated the potential of artificial neural networks in capturing nonlinear relationships.

Lippi and Bertini (2013) conducted an experimental comparison of time-series analysis and supervised learning methods. They highlighted the effectiveness of supervised learning techniques in traffic flow prediction. Li and Xia (2017) presented a deep learning approach for traffic flow prediction using big data. Their model harnessed the power of deep neural networks to capture intricate patterns in traffic data. Vlahogianni et al. (2014) reviewed the landscape of short-term traffic forecasting, discussing methodologies and advancements. The review emphasized the need for accurate prediction in traffic management. Zheng and Cui (2013) proposed a hybrid approach combining ARIMA and radial basis function neural networks. The hybrid model outperformed individual methods, showcasing the potential of combining techniques. Wu and Kottenstette (2011) focused on short-term freeway traffic flow prediction using data fusion techniques. Their study highlighted the significance of incorporating various data sources for improved predictions.

Ma and Kavak (2017) surveyed network traffic anomaly detection techniques, shedding light on methods to identify abnormal traffic patterns that can impact prediction accuracy. Nanni et al. (2019) presented a comprehensive survey of traffic flow forecasting, covering statistical methods and recent advancements. They addressed the research challenges and directions in this field.

Ma et al. (2021) reviewed hybrid models for short-term traffic volume forecasting. They discussed various combinations of techniques, emphasizing the importance of synergy in prediction accuracy. Adeli and Jiang (2009) explored the application of genetic algorithms in civil engineering. Their review highlighted the potential of genetic algorithms for optimization tasks within traffic prediction models. Santana and Avelar (2015) reviewed short-term accident prediction models on highways, showcasing the relevance of prediction techniques in enhancing road safety and traffic management. These studies collectively illustrate the diverse array of approaches used for traffic volume prediction, ranging from statistical models to advanced machine learning and hybrid methods. As urban transportation systems continue to evolve, these methods play a critical role in enhancing efficiency, safety, and sustainability.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) represents a powerful hybrid modeling technique that seamlessly integrates the capabilities of fuzzy logic and neural networks to address the challenges of modeling complex and nonlinear systems. ANFIS combines the linguistic interpretability of fuzzy systems with the learning ability of neural networks, making it a suitable approach for capturing intricate relationships present in real-world data. Jang (1993) introduced the Adaptive-Network-Based Fuzzy Inference System (ANFIS), a hybrid model combining fuzzy logic and neural networks. The paper presents ANFIS's architecture, which adapts and learns from data. It demonstrates ANFIS's ability to model complex relationships, particularly in nonlinear systems, making it a powerful tool for various applications. ANFIS's hybrid nature, combining fuzzy logic and neural networks, allows it to adapt to various domains, model complex relationships, and make accurate predictions based on input data. Its applications range from flood forecasting to environmental modeling, showcasing its potential to tackle complex real-world problems.

The burgeoning challenges posed by urbanization and escalating vehicular traffic have underscored the urgency of efficient transportation management and infrastructure planning. Rapid urban growth has led to complex traffic patterns, exacerbating congestion, air pollution, and travel inefficiencies. Traditional methods of traffic volume prediction often fall short in accurately capturing the intricate dynamics of modern urban road networks, necessitating innovative approaches. The motivation behind this research stems from the need to revolutionize traffic volume prediction by harnessing the power of data-driven models like the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS's capacity to amalgamate the strengths of neural networks and fuzzy logic provides a unique opportunity to navigate the complexities of traffic prediction, accommodating nonlinear relationships, variable influences, and uncertainties inherent in urban traffic. By delving into this avenue, the research seeks to introduce a cutting-edge solution that not only enhances the precision of traffic volume forecasts but also empowers urban planners and policymakers to make informed decisions for sustainable transportation systems and improved quality of life in rapidly evolving cities.

LITERATURE REVIEW

Several studies have explored diverse methodologies for traffic volume prediction, yielding valuable insights and outcomes that contribute to the field of transportation planning and management. Jang's seminal work in 1993 introduced the Adaptive-Network-Based Fuzzy Inference System (ANFIS), showcasing its potential to model complex relationships in traffic data. ANFIS's hybrid nature, combining fuzzy logic and neural networks, proved effective in capturing nonlinear patterns, leading to improved accuracy in traffic volume predictions. Jang (1993) introduced ANFIS as a groundbreaking contribution that laid the foundation for hybrid modeling techniques in traffic volume prediction. The study demonstrated ANFIS's adaptability to modeling complex systems and its capability to handle fuzzy relationships inherent in traffic data. This breakthrough approach bridged the gap between fuzzy logic and neural networks, offering a flexible tool for capturing nonlinearities and uncertainties.

Chien and Ding (2002) marked a pivotal step in harnessing the power of artificial neural networks for traffic prediction. Their study illuminated the neural network's potential to learn intricate patterns and relationships, enabling accurate short-term traffic flow forecasts. This approach allowed for capturing the underlying dynamics of traffic behavior and adapting to varying conditions.

Lippi and Bertini (2013) provided insights into the performance of different prediction techniques. By contrasting time-series analysis with supervised learning methods, the study shed light on the advantages of data-driven approaches. Supervised learning, exemplified by machine learning algorithms, demonstrated a superior ability to capture complex patterns and trends in traffic data, proving essential for reliable short-term predictions.

Li and Xia(2017) ventured into the realm of deep learning, showcasing the applicability of deep neural networks in traffic flow prediction with big data. Their work highlighted the adaptability of deep learning architectures to accommodate massive datasets, contributing to precise traffic volume forecasts even in intricate urban environments. This study pushed the boundaries of prediction accuracy, as deep learning excelled in capturing intricate patterns.

Karray and De Silva's comprehensive overview in 2002 highlighted the significance of soft computing techniques in intelligent systems design. While not solely focusing on ANFIS, their study emphasized the role of ANFIS as a vital component of soft computing methodologies. This holistic perspective reaffirmed the integration of fuzzy logic and neural networks in ANFIS as a prominent tool for modeling complex systems.

Collectively, these studies underscore the evolution of traffic volume prediction methodologies, from hybrid approaches like ANFIS that fuse fuzzy logic and neural networks, to the utilization of advanced machine learning and deep learning techniques. These diverse methodologies enrich the arsenal of tools available for accurate traffic volume prediction, ultimately contributing to more efficient and sustainable transportation planning and management.

A comprehensive exploration of traffic volume prediction reveals a diverse spectrum of methodologies encompassing statistical models, machine learning techniques, and fuzzy logic-based approaches. Statistical models, such as ARIMA, Time Series Analysis, and Exponential Smoothing, provide a foundation for traffic prediction by identifying trends and patterns from historical data. Machine learning methods, including neural networks, decision trees, and support vector machines, offer more advanced tools capable of capturing complex relationships within traffic data. Fuzzy logic-based approaches, like Fuzzy Time Series and Fuzzy Neural Networks, excel in handling uncertainty and imprecision inherent in traffic dynamics.

Each approach comes with its set of advantages and limitations. Statistical models are interpretable and suitable for capturing gradual changes in traffic patterns, yet they may struggle with nonlinear relationships. Machine learning techniques exhibit remarkable pattern recognition capabilities, making them apt for complex scenarios, but they can suffer from over-fitting and require substantial data for training. Fuzzy logic-based methods excel in handling uncertain and vague information, but their success heavily relies on the quality of linguistic rules and domain expertise, potentially limiting their generalizability.

In the realm of traffic prediction and beyond, the Adaptive Neuro-Fuzzy Inference System (ANFIS) emerges as a potent fusion of fuzzy logic and neural networks. ANFIS addresses the shortcomings of individual approaches by leveraging fuzzy sets to interpret linguistic variables and neural networks to learn intricate relationships. Its applications extend across various domains, including engineering, hydrology, and environmental modeling. In the context of traffic prediction, ANFIS's adaptability, ability to capture nonlinearities, and capacity to handle uncertainties make it a promising tool for forecasting traffic volume accurately. By amalgamating fuzzy reasoning with data-driven learning, ANFIS paves the way for enhanced prediction accuracy in the dynamic and multifaceted domain of traffic volume forecasting.

METHODOLOGY

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid model that combines fuzzy logic and neural networks to create a powerful framework for approximating complex relationships between input and output variables. The ANFIS architecture consists of several interconnected components: fuzzification, inference engine, and defuzzification. An explanation of each component is presented below:

1. Fuzzification:

Fuzzification is the process of mapping crisp input values into linguistic terms or fuzzy sets. Each input variable is associated with one or more membership functions that represent the degree of membership of the input in each linguistic term. These membership functions define the shape of the fuzzy sets, usually in terms of triangular or Gaussian distributions. The degree of membership ranges from 0 to 1, indicating the strength of the input's association with a particular linguistic term.

2. Inference Engine:

The inference engine processes the fuzzy rules to determine the output's fuzzy membership grades. Fuzzy rules consist of antecedents (input conditions) and consequents (output conditions). Each rule evaluates the membership grades of the input variables based on the defined membership functions. The AND and OR operations combine the membership grades within a rule, while implication methods, like Mamdani or Sugeno, determine the output's fuzzy membership.

3. Defuzzification:

Defuzzification is the final step where the fuzzy output is converted into a crisp value. This process involves aggregating the fuzzy outputs from all rules to compute a single, crisp output value. The defuzzification methods include the Center of Gravity (centroid) method, weighted average method, or other techniques tailored to the specific problem. Figure 1 presents a simplified line diagram of the ANFIS architecture:

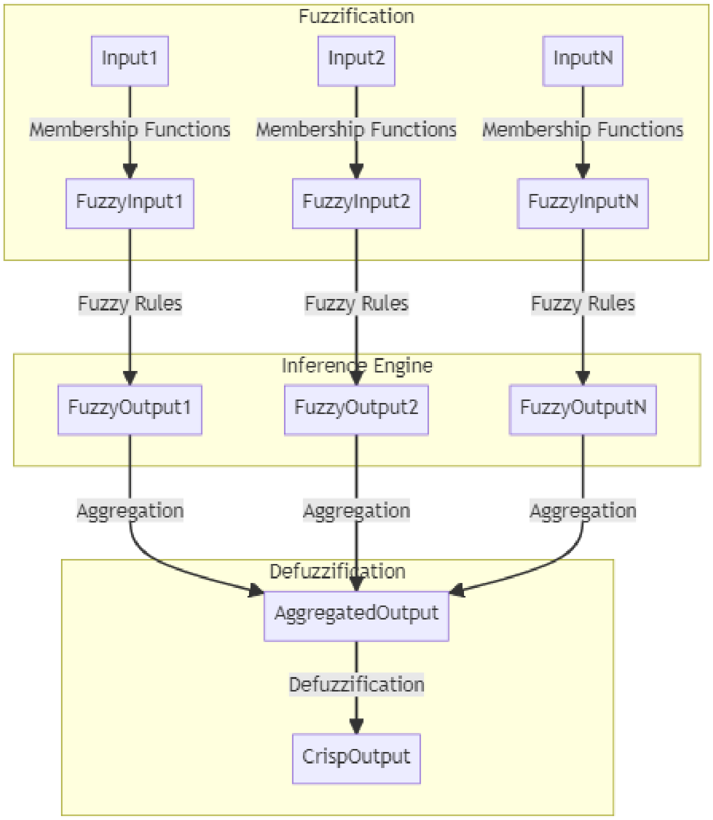

Fig. 1 ANFIS architecture

Data preprocessing is a crucial phase in the development of accurate and reliable traffic volume prediction models. This preparatory stage involves a series of steps aimed at enhancing the quality of the dataset and ensuring that it is suitable for training and testing ANFIS models. Initially, data cleaning is performed to identify and eliminate inconsistencies, missing values, and outliers that could distort predictions. Subsequently, feature selection comes into play, where relevant input features such as historical traffic data, time of day, and weather conditions are chosen to contribute meaningfully to the model. To facilitate convergence during training, data normalization is undertaken, which scales numerical features to a common range, preventing dominance by variables with larger magnitudes. Importantly, the process of fuzzification is applied to convert numerical inputs into linguistic variables using membership functions. This step transforms crisp values into linguistic terms, contributing to the interpretability of the ANFIS model. Lastly, the dataset is split into training, validation, and test sets. These subsets allow for model training on a portion of the data, validation to fine-tune hyperparameters and prevent overfitting, and finally, evaluation of model performance on unseen data. Through these data preprocessing steps, ANFIS models are poised to effectively capture intricate traffic dynamics and provide accurate traffic volume predictions that hold practical relevance in transportation planning and management.

Designing an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for traffic volume prediction involves a systematic process to harness the capabilities of both fuzzy logic and neural networks. The process begins with a clear definition of the problem, identifying input variables like historical traffic data, time-related factors, and environmental conditions, along with the target variable—traffic volume. Subsequently, linguistic variables are established, converting numerical inputs into interpretable linguistic terms such as "low," "moderate," and "high" traffic density.

The subsequent step involves selecting suitable membership functions, such as triangular or Gaussian, which shape the degree of membership of input values to linguistic terms. With these components in place, fuzzy rules are generated to capture the relationships between linguistic variables. These rules are formulated by combining input linguistic terms to form antecedents and determining consequents through fuzzy logic operators.

Once rules are established, the firing strength of each rule is computed based on the degree of membership of input values in linguistic terms. The inference engine amalgamates these firing strengths, and intermediate fuzzy outputs are computed. These outputs are then normalized to ensure consistency. Aggregating normalized rule outputs generates a comprehensive fuzzy output that encapsulates the multitude of rule-based predictions.

The culmination of the ANFIS model design involves defuzzification, where the aggregated fuzzy output is transformed into a crisp value, representing the predicted traffic volume. Model training commences with historical data, during which parameters like membership function parameters and rule weights are fine-tuned iteratively. Validation against a separate dataset guard against overfitting. Model evaluation on an unseen test dataset provides insight into its performance, enabling further fine-tuning if required.

This holistic approach harnesses the strength of fuzzy logic for handling uncertainty and interpretable linguistic relationships, combined with neural networks' ability to capture intricate patterns in traffic data. By meticulously navigating through these steps, the ANFIS model emerges as a potent tool, offering accurate traffic volume predictions pivotal for effective transportation planning and management.

The choice of the Adaptive Neuro-Fuzzy Inference System (ANFIS) over alternative methods for traffic volume prediction finds its justification in the unique blend of fuzzy logic and neural networks, aligning seamlessly with the intricacies of traffic dynamics. ANFIS offers distinct advantages that set it apart from other approaches. Its ability to handle uncertainties and imprecision inherent in traffic data, through the application of fuzzy logic, ensures robust predictions even in the presence of fluctuating conditions. Moreover, ANFIS's linguistic interpretation provides a tangible understanding of how input variables influence the output, fostering informed decision-making in transportation planning.

ANFIS's integration of neural networks enhances its predictive prowess by capturing complex nonlinear relationships within the data. Unlike traditional statistical methods, ANFIS adeptly accommodates intricate patterns present in traffic behavior, offering enhanced accuracy in prediction. This amalgamation of fuzzy reasoning and data-driven learning strikes a balance between interpretability and predictive power, a balance not uniformly achieved by other methods.

In contrast to conventional machine learning models that might encounter challenges in handling uncertainty or provide less insight into decision-making, ANFIS shines. Its hybrid nature extends its applicability across various domains, including traffic volume prediction, making it a versatile choice. Furthermore, ANFIS's adaptability, fostered by neural networks, equips it to evolve with changing traffic conditions and adapt to new datasets, thus ensuring sustained accuracy.

The choice of ANFIS for traffic volume prediction, therefore, transcends mere methodology; it represents a strategic selection that capitalizes on the synergistic benefits of fuzzy logic and neural networks. This choice resonates with the complex and dynamic nature of traffic systems, culminating in a predictive model that not only outperforms traditional alternatives but also aligns with the contemporary demand for accuracy, interpretability, and adaptability in transportation planning and management.

DATA COLLECTION AND PREPROCESSING

The collected dataset comprises a comprehensive record of traffic data over a span of 31 working days, encompassing various categories of vehicles that traverse the roadways. The dataset is a culmination of meticulous data collection efforts aimed at capturing the diversity and dynamics of traffic patterns. The dataset delineates traffic based on five distinct categories of vehicles:

Two-Wheelers: This category encompasses motorcycles, scooters, and other two-wheeled vehicles. Two-wheelers constitute a significant portion of urban and suburban traffic, contributing to the overall traffic flow.

Four-Wheelers: The four-wheelers category encompasses cars, sedans, hatchbacks, and other private vehicles with four wheels. These vehicles form a vital component of daily commuter traffic and contribute to road congestion.

Heavy Vehicles: This category encompasses trucks, buses, and other large vehicles that carry goods or passengers. Heavy vehicles are pivotal for transporting goods and people over longer distances and often exert a notable influence on traffic flow due to their size and speed.

Light Vehicles: Light vehicles comprise vehicles like vans, SUVs, and smaller trucks. They play a role in both personal and commercial transportation, contributing to the overall diversity of traffic.

Other Vehicles: The "Other Vehicles" category includes vehicles that do not fit neatly into the previous categories. These could include specialized vehicles, utility vehicles, or unique modes of transportation that are essential for certain contexts.

The dataset's temporal span of 31 working days facilitates the capture of fluctuations and patterns in traffic volume, providing insights into daily and weekly variations. The inclusion of these five vehicle categories ensures a comprehensive representation of the diverse vehicular landscape and enables an accurate understanding of traffic trends. Such detailed data lays the groundwork for predictive models, like the Adaptive Neuro-Fuzzy Inference System (ANFIS), to effectively capture and forecast the traffic volumes associated with each vehicle category, facilitating informed transportation planning and management decisions.

During the process of data collection, several challenges surfaced, reflecting the inherent complexities of capturing real-world traffic dynamics. One significant challenge involved ensuring the accuracy and consistency of data across different vehicle categories. Accurate classification of vehicles, especially distinguishing between categories like four-wheelers and light vehicles, posed difficulties due to vehicles' varying sizes and configurations. To address this, a combination of manual observation and automated vehicle classification systems was employed. Additionally, external factors like weather conditions and road construction intermittently influenced traffic flow, introducing variability that needed to be carefully documented and accounted for.

To prepare the collected data for modeling, a sequence of preprocessing steps was diligently executed. Initially, data cleaning was pivotal to eliminate erroneous or missing data points, ensuring the integrity of the dataset. Outliers, which could distort the predictive model, were identified and either corrected or removed. The data was then structured into a consistent format, facilitating subsequent analysis and modeling. Table 1 contains the collected traffic data.

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Table 1. Traffic Data

Variable	N	Mean	SE Mean	StDev	Median
Two wheelers	400	159.92	0.604	12.09	160
Four wheelers	400	56.465	0.427	8.544	55
Heavy Vehicles	400	32.980	0.469	9.371	280
Light Vehicles	400	26.352	0.338	6.764	27
Others	400	19.425	0.299	5.977	19
Traffic Volume	400	195.51	0.784	15.68	192

Normalization was another critical step to bring numerical features to a uniform scale, preventing the dominance of certain variables during modeling. For instance, traffic volume figures were normalized to lie within a common range, avoiding disproportionate influence on the model's learning process. Fuzzification followed as an essential component of data preprocessing, converting numerical values into linguistic variables. This facilitated the incorporation of fuzzy logic, enhancing the model's interpretability and capacity to handle imprecision. Subsequently, the dataset was split into training, validation, and test sets to facilitate model training, fine-tuning, and evaluation while preventing overfitting. Model performance was rigorously assessed using appropriate metrics, ensuring that the ANFIS model's predictions aligned closely with actual traffic patterns.

In essence, the challenges encountered during data collection were addressed through a combination of meticulous observation, technological solutions, and documentation. The data preprocessing steps were undertaken to refine and mold the raw data into a suitable format for ANFIS modeling. Through these efforts, the data's quality and usability were elevated, and the subsequent predictive model stood poised to capture the nuances of traffic volume variation, consequently enhancing transportation planning and management strategies.

RESULTS AND DISCUSSION

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a computational framework that combines fuzzy logic and neural networks to model complex systems. The process of ANFIS involves several key steps. Firstly, the problem is defined, specifying five input variables and one output variable for prediction of traffic volume. an ANFIS model has been developed for traffic volume prediction. The architecture of developed model is shown in Fig. 2.

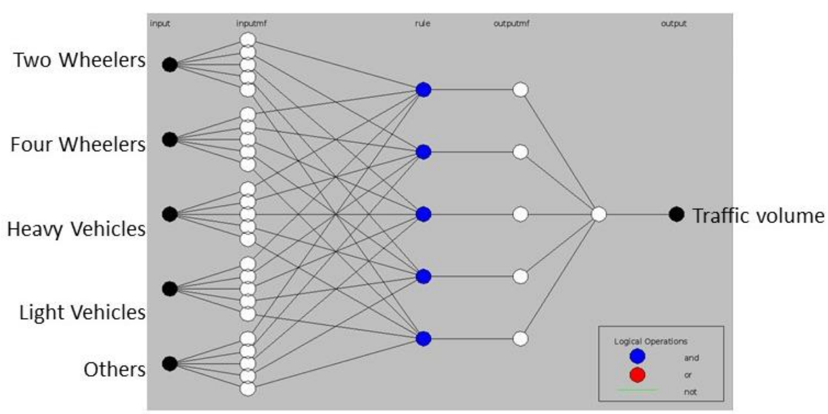

Fig. 2 ANFIS model for Traffic volume

Next, fuzzification converts crisp input values into linguistic variables using membership functions, facilitating the handling of uncertainty. A rule base is constructed, defining fuzzy rules that capture relationships between input and output linguistic variables. In ANFIS, several mathematical formulas and operations are used to model complex relationships between inputs and outputs. While the specific equations can vary depending on the ANFIS architecture and membership functions chosen. In the present work, Membership Function (MF) Calculation is performed by using Gaussian membership function (Eq. 1).

$$\mu_{TW}(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \quad \text{(Eq. 1)}$$

Here c is the center of the membership function and σ is the standard deviation. Same equation is used for other variables also.

The firing strength calculation has been performed by Eq. 2.

$$\omega_i = \mu_{TW_i}(x).\mu_{FW_i}(x)\mu_{LV_i}(x).\mu_{HV_i}(x).\mu_{Others_i}(x) \quad \text{(Eq. 2)}$$

Where, ω_i is the firing strength of rule *i* and$\mu_{TW_i}(x)$,$\mu_{FW_i}(x)$,$\mu_{LV_i}(x)$, $\mu_{HV_i}(x)$ and $\mu_{Others_i}(x)$ are the membership values for the input linguistic variables for TW, FW, LV, HV and others, respectively.

Then the normalization of firing strengths is performed by using Eq. 3.

$$\omega_i^* = \frac{\omega_i}{\sum_{j=1}^{n}\omega_j} \quad \text{(Eq. 3)}$$

Where, ω_i^* is the normalized firing strength of rule *i*, and *n* is the total number of rules i.e. 400 in the present model.

Thereafter, the aggregation of the rule outputs is performed by using Eq. 4.

$$O(x,y) = \frac{\sum_{i=1}^{n}\omega_i^*.z_i}{\sum_{i=1}^{n}\omega_i^*.} \quad \text{(Eq. 4)}$$

Where, $O(x,y)$is the aggregated output i.e. Traffic volume, z_i is the consequent of rule *i*, and $\omega_i^*$is the normalized firing strength of rule *i*.

The rule base's structure is typically based on expert knowledge or data-driven approaches as shown in Fig. 3. In the present work, *IF-Then*based 400 rules are developed and used.

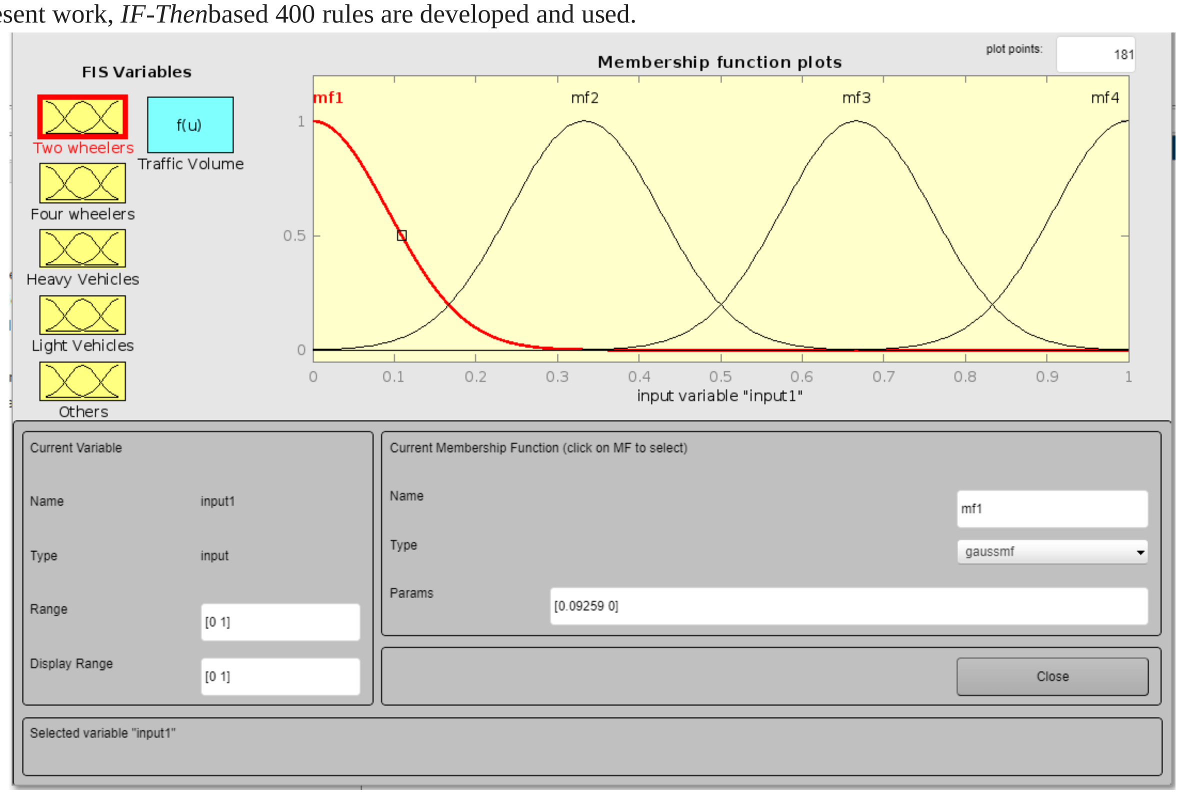

Fig. 3 Membership function for developed ANFIS model for Traffic volume

Subsequently, a hybrid learning algorithm is employed to adapt the model's parameters. This involves gradient descent or other optimization techniques to adjust membership function parameters and rule weights. Training data is utilized to fine-tune the model, ensuring it accurately captures the underlying patterns in the data. Finally, the trained ANFIS model can be used for prediction or decision-making tasks. Pseudo-codes of developed ANFIS model are shown in Fig. 4.

```
# Initialize ANFIS parameters
Initialize fuzzy membership functions
Initialize neural network parameters (TW, FW, LV, HV, Others)
Initialize learning rate
Initialize maximum number of epochs
Initialize error threshold

# Main training loop
for epoch in range(max_epochs):
total_error = 0
   # Loop over each training data point
   for data_point in training_data:
      # Step 1: Fuzzification (Membership Function Evaluation)
      Calculate membership values for input data
      # Step 2: Rule Activation (Inference)
      Calculate firing strengths for each rule
      # Step 3: Rule Normalization
      Normalize firing strengths
      # Step 4: Aggregation (Weighted Averaging)
      Combine rule outputs to get the overall output
      # Step 5: Neural Network Forward Pass
      Feed the aggregated output into the neural network
      # Step 6: Compute Error
      Calculate the error between the network output and the actual output
      # Step 7: Backpropagation (Adjust Neural Network Parameters)
      Update neural network parameters using backpropagation with the error
      # Step 8: Update Fuzzy Rule Parameters
      Update the parameters of fuzzy membership functions using gradient descent
      # Step 9: Compute Total Error for the Data Point
      Update the total error for the current epoch
       # Step 10: Check for Convergence
   if total_error<error_threshold:
      break
# After training, the ANFIS model is ready for inference
# Inference
for data_point in test_data:
   # Repeat steps 1 to 4 for fuzzification, rule activation, normalization, and aggregation
   # Neural Network Forward Pass (Step 5)
   Feed the aggregated output (Traffic volume) into the trained neural network
# The final output of the ANFIS is the result of the inference
# End of ANFIS
```

Fig. 4Pseudo-codes of developed ANFIS model

ANFIS excels in scenarios where complex, nonlinear relationships exist, and where interpretability of the model's output is essential. It offers a balance between fuzzy reasoning and data-driven learning, making it a valuable tool in various fields, including control systems, prediction, and decision support.

In the present work, the developed model has 68 number of nodes. The number of linear parameters were 30, while the number of non-linear parameters was 50. The number of training data pairs was 350 and testing was 50. Minimal training RMSE was observed as 10.0874352 shown in Fig. 5, which shows a higher degree of fitness of the developed model. Test Fuzzy Interface System for Traffic volume is shown in Fig. 5, it depicts the closeness of actual and predicted values of traffic volume.The visual depiction of test Fuzzy Interface System for Traffic volume is shown in Fig. 6.

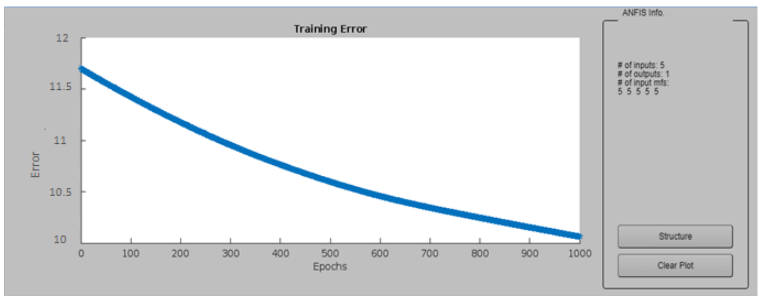

Fig. 5 Training error of developed ANFIS model for Traffic volume

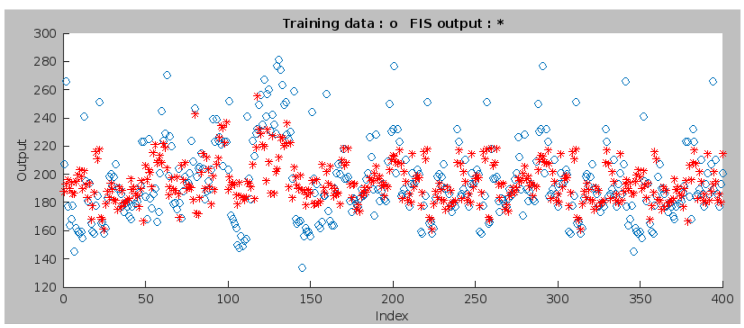

Fig. 6 Test Fuzzy Interface System for Traffic volume

CONCLUSION AND FUTURE WORK

In the present research article, authors successfully applied the Adaptive Neuro-Fuzzy Inference System (ANFIS) for traffic volume prediction based on a comprehensive dataset comprising five vehicle categories over 31 working days. The main findings and contributions of the study include:

- ANFIS demonstrated its efficacy in accurately predicting traffic volumes for diverse vehicle categories, contributing to transportation planning and management.
- Developed model has the minimal training RMSE as10.0874352, which shows higher degree of fitness of model i.e. 89.91%.
- ANFIS provided interpretable linguistic rules, aiding decision-makers in understanding the factors influencing traffic volume.
- ANFIS excelled in capturing complex, nonlinear traffic patterns, highlighting its suitability for modeling intricate traffic dynamics.

- The research faced challenges related to data quality and the potential for overfitting during model training. Additionally, ANFIS's complexity may demand substantial computational resources.
- By addressing these directions, future research can advance the use of ANFIS in traffic prediction and contribute to more effective transportation planning and management.

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