IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 26 July 2024, accepted 14 August 2024, date of publication 21 August 2024, date of current version 29 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3446843

RESEARCH ARTICLE

Greenshields Model-Based Fuzzy System for Predicting Traffic Congestion on Highways

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ABSTRACT Highways serve as vital connectors between cities, yet they often suffer from traffic congestion as the population continues to grow. Various intelligent frameworks or models for traffic status prediction have been employed in the Intelligent Transport System (ITS) to provide services for convenient and safe traveling, effective traffic management, and smart signal control. Most of these frameworks typically involve learning processes that utilize learning algorithms and requires training data. For highway traffic, the Greenshields model offers a practical relationship among vehicle speeds, traffic flows, and traffic density, which can serve as fundamental knowledge for developing intelligent traffic management systems. This paper proposes a fuzzy logic system based on the Greenshields model as the knowledge base for quickly predicting highway traffic congestion without extensive preparing data. Our system operates in two modes: jam and non-jam modes. In each model, the two inputs of vehicle speed and traffic flow are processed respectively with specified membership functions for effective fuzzification. The set of rules and conditions guided by the Greenshields theory is governed by the inference mechanism, which makes decisions according to the input field. Subsequently, the defuzzification process converts the fuzzy sets obtained by the inference engine into a congestion level as the output. To validate the accuracy of our system, a polynomial regression model utilizing realistic data from roadside equipment on the Sun Yat-Sen Highway in Taiwan is established for comparison. Comparing the observed data points from the polynomial regression model with the outputs obtained from our system using the same inputs, both predicting outputs are found to be consistent, affirming the practical feasibility of the proposed system. Moreover, our proposed scheme is adaptable to suit diverse road conditions without extensive training data and possesses a short memory to perform tasks. Integrating several systems by cascading them across different segments of the highway enables rapid congestion prediction for long-distance traffic. These advantages make the proposed system much more convenient for performing congestion prediction for traffic management and control in ITS.

INDEX TERMS Fuzzy logic, Greenshields model, ITS, polynomial regression, traffic congestion, traffic flow.

I. INTRODUCTION

Highways serve as the lifeblood of modern urban connectivity, supporting seamless movement between cities and regions. According to statistics from the Freeway Bureau of Taiwan [1], daily vehicle usage on Taiwan highways increased by 1.5% compared to the previous year, reaching over 87 million vehicle kilometers (MVK) in 2023. Generally, the capabilities of roads and transportation systems struggle to cope with the explosive growth of vehicles in countries experiencing rapid economic expansion, particularly during rush hours. The increased traffic flows on highways not only prolong periods of traffic congestion but also elevate the probability of accidents. To improve various traffic situations and provide safe and efficient travel services, having real-time information on traffic and road conditions for further processing is essential. By applying advances in technologies such as electronics, communications, computers, control, sensing, and detection across transportation systems, the Intelligent Transport System (ITS) provides services related to traveling and traffic management, enabling road users to make more convenient, smarter, faster, and

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaojie Su.

safer use of transport networks [2], [3], [4], [5]. ITS can be divided into four subsystems: surveillance and collecting subsystems that monitor and collect traffic-related information for effective traffic management and control, analyzing and decision-making subsystems that employ intelligent algorithms to analyze data and make decisions, control and management subsystems that implement effective control and traffic management strategies, and communication subsystems that transmit data between subsystems for information sharing [6], [7]. Traffic management and control involve traffic congestion prediction, traffic flow control, accident detection, and route guidance for efficient travel between cities, ensuring timely arrival at destinations. An effective traffic status prediction scheme is a key component to achieve efficient performance improvement for traffic management and control models.

Traffic data and parameters utilized for evaluating and predicting traffic status in the models and frameworks of ITS can be categorized into three main groups: volume and capacity-related factors such as speed, flow, density, and occupancy; time and position-related factors such as position data, map data, travel time, and video monitoring data; and road condition and environment-related factors such as ramping area, road works, and accident events [5]. Traffic data are generally segmented according to time series. Traffic prediction schemes can be divided into three types: frameworks, non-parametric models, and parametric models [4]. Various frameworks or models can be developed on spatial, temporal, or both domains. Recent works for realistic traffic status prediction are based on a framework or action model to perform tasks associated with intelligence beings and representation learning. Frameworks facilitate a collaborative approach of artificial intelligence (AI) and deep learning (DL) technologies, utilizing artificial neural networks or deep neural networks to handle vast amounts of data analysis, conduct efficient learning, and make predictive decisions. Tseng et al. [8] employed the Apache Storm platform to achieve a support vector machine (SVM) based real-time highway traffic congestion prediction (SRHTCP). Li et al. [5] proposed a framework for traffic congestion prediction and visualization based on machine learning and the Fuzzy Comprehensive Evaluation scheme (MF-TCPV). Kessler and Bogenberger [9] investigated detection rate by comparing various freeway congestion patterns to provide recommendations on the optimal application of detection technology. For connected vehicles, frameworks utilizing Internet of Vehicles (IoV) based schemes for traffic status detection are practically feasible for congestion handling. This type of framework typically involves communication techniques through networks or the internet to facilitate collaboration in inputs and decisions. Traffic status estimation (TSE) methods for connected vehicles largely rely on mobile-sensing technologies that require a certain market penetration rate (MPR). Currently, fixed-sensing and mobile-sensing technologies are expected to be used together for traffic surveillance and control. Thakur and Malekian [2] reviewed the utilization of fog computing-based principles in vehicular wireless sensor networks for a vehicular congestion detection system capable of covering a large area and multiple scenarios. Abberley et al. [10] developed a fuzzy system capable of capturing congestion levels on an urban road network based on the Manchester Urban Congestion Dataset. Sun et al. [11] utilized the current surveillance system with a method based on the attention proposal module and a deeply supervised inception network to enhance the accuracy of traffic congestion detection. Ferrara et al. [12] presented a hierarchical multi-level control scheme utilizing a high-level model predictive controller (MPC) to alleviate traffic congestion and reduce vehicle fuel consumption via a platoon of connected and automated electric vehicles (CAVs). Gao et al. [13] developed a rule-based algorithm utilizing full cellular activity (FCA) data to determine the traffic congestion state at on-ramp merging area. Chen et al. [14] presented a roadside sensor data fusion framework that makes use of data from connected vehicles to provide a more accurate traffic flow state estimation. Based on the second order traffic flow model, the macroscopic simulation program for motorway networks (METANET) has been applied for freeway traffic status estimation [15]. Messmer and Papageorgiou [16] introduced a model based on METANET combined with an extended Kalman filter (EKF) to improve traffic status estimation with only fixed sensing. Zhao et al. [17] compared three mixed estimation methods: METANET-EKF, speed-uniformity-EKF, and MPR-KF, providing recommendations on choosing a suitable estimation method with the minimum number of sensors based on the range of MPR for connected vehicles with mixed sensing.

Non-parametric models for traffic prediction typically do not assume a specific form and have the flexibility to adapt to the shape of the data. Artificial neural networks, machine learning methods, and software simulations are often involved in these schemes. Since SVM exhibits greater generalization ability and performs well for limited samples, it can be extended to solve regression problems and excel in time series analysis. Furthermore, instead of adopting a single model, a selected hybrid model is more advantageous in handling traffic prediction problems in certain situations. A combination of the genetic algorithm (GA) and time-delayed neural network for traffic flow prediction was presented by Abdulhai et al. [18]. Xie and Zhang [19] introduced traffic flow prediction using a combination of wavelet transform and neural network models. Chang and Tsai [20] proposed a hybrid model of SVM and the grey prediction (GM) model for traffic flow prediction, aiming to reduce the overshoot effect. Hong et al. [21] presented a hybrid method in the support vector regression (SVR) model for traffic flow prediction. Lopez-Garcia et al. [22] proposed a fuzzy-rule-based scheme by combining the genetic algorithm (GA) and the cross-entropy (CE) method to improve short-term traffic congestion detection. Tang et al. [23], [24] proposed two traffic flows prediction models: one utilizing a combination of artificial neural network and fuzzy C-mean methods, and the other adopting combined denoising schemes and SVM models, respectively.

Traffic status evaluation and prediction in parametric models typically employ statistical or regression analysis. By capturing the key characteristics of traffic flow within a specified problem, the requisite functions for prediction or control can be derived through simulations or computations utilizing empirical data. Xu et al. [25] proposed a robust and interpretable Bayesian multivariate adaptive-regression splines model, yielding more accurate traffic predictions compared to corresponding temporal models. Dell'Acqua et al. [26] developed a novel nearest neighbor regression method to enhance the efficiency of the data-driven algorithms for traffic flow prediction. In certain traffic scenarios, employing a hybrid model that combines different algorithms or models can yield superior prediction results. Van der Voort et al. [27] devised a self-organizing map combined with the autoregressive integrated moving average (ARIMA) time series model to create a hybrid forecasting model. Zhao et al. [28] introduced a reliable model for short-term traffic forecasting by merging the ARIMA model and a travel distance estimation algorithm. Oh et al. [29] proposed a multifactor pattern recognition model that integrates Gaussian mixture model clustering with an artificial neural network for traffic flow prediction.

Among traffic status predictions, travel time stands out as a more intuitive and practical metric for road users to comprehend. It holds a pivotal role in ITS and serves as a convenient index for traffic managements. Several frameworks for travel-time prediction have been proposed, including neural network models, SVM methods, regression model analysis, and K nearest neighbors (K-NN) models. However, these prediction models often entail longer training times due to the vast amount of data utilized. Innamaa [30] utilized neural networks for short-term travel time prediction on interurban highways. Tang et al. [31] developed an evolving fuzzy neural network model for travel speed prediction. Derrow-Pinion et al. [32] introduced a graph neural network estimator with Google Maps for travel-time prediction based on Meta-Gradients for training schedules. Wu et al. [33] applied support vector regression (SVR) for travel time prediction. Yang et al. [34] proposed a GA-SVM model for bus arrival time prediction, showing improved accuracy. Zhang and Rice [35] focused on enhancing travel time prediction using a linear regression method. Khosravi et al. [36] introduced a GA-based scheme to improve travel time prediction intervals. Cho et al. [37] leveraged Gated Recurrent Units (GRU) to enhance the efficiency of recurrent neural network (RNN) training for travel time prediction. Zhao et al. [38] jointly utilized optimized GRU and weight stochastic gradient descent (WSGD) algorithms with GPS data for truck travel speed prediction. Ting et al. [4] established a vehicle travel time prediction method with high performance in prediction accuracy and execution time, based on GRU neural network and eXtreme Gradient Boosting (XGBoost) models through time series linear regression. Yu et al. [39] proposed a framework based on the K-NN method to integrate cluster analysis and principal component analysis for bus arrival time prediction. Liu [40] suggested a dynamic K-NN method based on a large database to enhance the accuracy of the travel time model.

For analyzing the statistical properties of large traffic flows, Greenshields, Greenberg, and nonlinear models are often essential. Liu et al. [41] proposed an improved general-logistic-based speed-density model incorporating heavy vehicle effects for highway traffic status prediction. Karchroo and Sastry [42] presented a method to predict highway travel time based on density-based functions. Rice and Van Zwet [43] introduced a linear time-varying model with time-varying coefficients for travel time prediction, utilizing available freeway sensor data. Direct travel time measurements are increasing popular due to on-board positioning and communication technologies. Additionally, as parametric models, ARIMA and their extended versions are widely employed travel time prediction [44], [45]. Raiyn and Toledo [46] proposed an exponential moving average (EMA) forecast scheme as an extended ARIMA model for short-term freeway travel time prediction. Soriguera and Martínez-Díaz [47] presented a data fusion scheme to correct drift in cumulative count curves, improving travel time prediction. The standard Bureau of Public Road (BPR) model is frequently employed for highway travel time evaluation, with parameters calibrated based on real-time traffic data [48]. Skabardonis and Dowling [49] enhanced the BPR model for travel time prediction by comparing field data and conducting simulations to identify the best parameters. Liu et al. [50] developed a traffic simulation procedure to estimate travel time functions for heterogeneous traffic flows on freeways. Specifically, for the travel time prediction after incidents on freeways, Ru et al. [51] proposed a model based on the BPR model for both regular and accident conditions. Generally, direct travel time prediction necessitates a framework considering various factors, particularly accident conditions, for complex computations and simulations.

When considering wide-range traffic congestion detection on highways, cellular probe methods are often employed, utilizing transition data from wireless location technologies (WLT) to predict highway road traffic information. Ran et al. [52] presented and compared cellular probe methods, respectively, in handset-based and network-based schemes. Existing network-based cellular probe methods on freeways primarily rely on cellphone handover (HO) data. Guido et al. [53] utilized the handset-based cellular probe scheme to estimate traffic speed based on HO data. While recently available HO data are decreasing, full cellular activity (FCA) data, comprising cellphone activities both on and off calls, are becoming tremendous and accessible. Li et al. [54] proposed a feature-based approach that utilizes FCA data for traffic congestion detection on freeways. The accuracy of congestion detection without road tests improves compared to methods relying solely on cellphone handover data. Compared with cellular probe-based methods relying on on-call WL signal data, Gao et al. [13] utilized FCA data to develop a rule-based algorithm for achieving more accurate freeway traffic congestion detection at on-ramp merging area for connected vehicles. Additionally, Derrow-Pinion et al. [32] proposed a graph neural network (GNN) model for predicting the time of arrival based on user-provided data in web mapping services.

Fuzzy logic constitutes a mathematical framework addressing ambiguous information by integrating degrees of truth through fuzzy sets. It has been a successful and practical alternative for a variety of challenging control applications, providing a convenient method for handling nonlinear dynamics using heuristic information [55], [56]. Fuzzy schemes also have fundamental applications in numerous intelligent algorithms or models within ITS for diverse purposes. Lopez-Garcia et al. [22] employed a fuzzy-rule-based system to enhance short-term traffic congestion detection by optimizing system elements. Based on the Takagi-Sugeno fuzzy inference system, Tang et al. [32] developed an evolving fuzzy neural network model. This model incorporated the K-means method in the training process and utilized the weighted recursive least squares error scheme to optimize model parameters, particularly for travel speed prediction. In the SVM-based real-time highway traffic congestion prediction (SRHTCP) model proposed by Tseng et al. [8], a fuzzy scheme to assess the real time traffic level of road segment under actual conditions. Abberley et al. [10], developed a fuzzy system capable of capturing congestion levels. For emergency vehicle management, Shelke et al. [6] proposed a fuzzy expert system to determine the priority of road segments and the timing for activating traffic signals. Li et al. [5] introduced the machine learning and Fuzzy Comprehensive Evaluation scheme (MF-TCPV) for rating traffic congestion levels, establishing a framework for predicting and visualizing traffic congestion. In the Dynamic and Intelligent Traffic Light Control System (DITLCS) proposed by Kumar et al. [57], a fuzzy inference system was developed to select an appropriate mode based on traffic information. Akopov et al. [58] devised a multiagent fuzzy transportation system (FTS) utilizing a parallel biobjective real-coded genetic algorithm to enhance the maneuverability of manned ground vehicles (MGVs) and unmanned ground vehicles (UGVs). It is evident that fuzzy inference systems are widely employed in various aspects of ITS.

Alsrehin et al. [3] conducted a comprehensive review of approximately 165 studies on traffic management approaches employing data mining and machine learning techniques. Their study revealed that there is no universally accepted standardized traffic management approach within the traffic management community. Nevertheless, vehicle speed, traffic flow, and vehicle density remain the primary influencing parameters of highway traffic. The Greenshields model, Greenberg model, and other nonlinear models are frequently utilized for predicting, managing, and controlling traffic conditions on highways through effective parameter measurements and evaluations [35], [41], [42], [47]. In practice, the Greenshields model provides a simple yet practical relationship among vehicle speeds, traffic flows, and traffic density for freeway traffic [41], [42], [59]. In comparison with other traffic parameters, traffic density is a crucial factor for predicting traffic congestion and evaluating travel time.

Regression models for predicting traffic status can be established using traffic data and by analyzing the relationship between vehicle speed, traffic flow, and density. However, fittings various parameters of static models to practical scenarios can be intricate and time-consuming, as variable factors such as lane numbers, speed limits, and entry/exit conditions differ on each segment of the highway. Additionally, achieving excellent results often requires a vast amount of traffic data to be established regression models, but large datasets may lead to overfitting. Applying an intelligent scheme such as fuzzy logic or artificial neural network to build a prediction model is more suitable and useful for traffic management and control.

Both fuzzy logic and neural networks are commonly used for various tasks within ITS, such as recognition, classification, or prediction. The choice between fuzzy logic and neural networks depends on the specific problem at hand and the available data. A neural network, comprises of different layers of interconnected neurons, attempts to incorporate the thinking process to solve problems without mathematical modeling. Each neuron receives inputs, performs weighted computations, and applies an activation function to generate an output. Generally, a neural network involves a learning process that utilizes learning algorithms and requires a large amount of training data. On the other hand, fuzzy logic is a mathematical framework for dealing with vague or ambiguous information. It allows for the representation of imprecise data and the use of linguistic variables. Fuzzy logic systems employ fuzzy rules to capture expert knowledge and express connections between factors. Hence, fuzzy logic is suitable used in systems where precise mathematical modeling is difficult.

In this paper, we propose a fuzzy logic system based on the Greenshields model for predicting highway traffic congestion. Our system integrates a fuzzy logic system with two inputs: vehicle speed and traffic flow, and a single output, which represents traffic density. Each input is associated with specific membership functions, facilitating the conversion of inputs into meaningful information through the fuzzification process. The fuzzy inference module subsequently, guided by the Greenshields model, utilizes logical rules to make decisions based on the input information. At the output stage, the defuzzification module converts the conclusions from the inference mechanism to an output, offering a prediction of the level of traffic congestion. This system is designed to adapt rapidly to real-time situations, tailoring itself to different road conditions in each segment of the highway. Experimental results obtained from our system will be compared with those generated by a regression method using data collected from roadside sensors to highlight the advantages of the proposed fuzzy logic systems. Our contributions are briefed as follows:

1. We propose a Greenshields model-based fuzzy system to predict traffic congestion on a highway road segment using vehicle speed and traffic flow as inputs. The output, traffic density, is expressed as a percentage of the maximum capacity. To the best of the authors' knowledge, no such scheme has applied the Greenshields model directly in a fuzzy system for congestion prediction.

2. The proposed system operates in two distinct modes: jam mode and non-jam mode. Each mode is specifically designed to address realistic traffic conditions by adjusting input membership functions, fuzzy rules, and output membership functions. These adjustments are based on Greenshields models of vehicle speed, traffic flow, and density, derived from a cross-analysis of practical traffic data collected by roadside equipment. This approach allows for the quick generation of accurate results without the need for complex computations or extensive data training, ensuring efficiency in comparison with regression methods.

3. Each fuzzy system operates on a specified highway road segment and can be integrated as a component of the designated road segments for predicting traffic status. These systems can be cascaded sequentially to provide a comprehensive prediction of traffic congestion along the entire section.

In the following sections of this paper, the relevant methodologies and corresponding theories for forecasting traffic congestion are explored in Section II. Moving on to Section III, the design process of the proposed fuzzy logic system for predicting traffic jams is presented. In Section IV, simulations are conducted through the actual cases, and the outcomes will be analyzed and discussed. The results obtained from our fuzzy system are compared with those derived from the regression method. The simulation results will serve to validate the benefits and efficacy of the proposed system. Section V will provide concluding remarks along with a summary of the accomplishments of the proposed scheme.

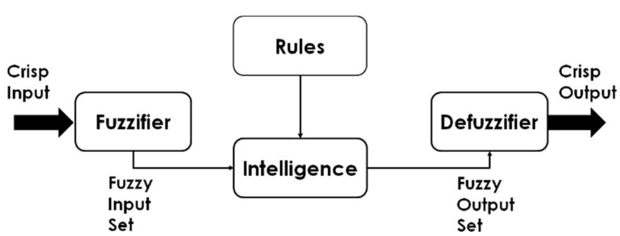

FIGURE 1. **Fuzzy logic system architecture.**

II. PREPARATIONPREDICTION RELATED TECHNICAL METHODS AND THERETICAL BASIS

The establishment of an efficient prediction system has the potential to enhance highway safety and utilization efficiency, ultimately leading to more seamless and enjoyable travel experiences for everyone. In this section, each respective subsection delves into the fuzzy logic method, Greenshields model, and time series forecasting technologies as applied to the proposed system for predicting congestion on highways.

A. FUZZY LOGIC METHOD

The utilization of fuzzy logic in our system offers a flexible and intuitive method for handling uncertainty and imprecise information in various decision-making processes. Fuzzy logic allows for degrees of truth, representing uncertainty through a range of values between 0 and 1. It enables more human-like, adaptable, and context-aware reasoning in ITS applications. This is accomplished through the utilization of linguistic variables and fuzzy sets, which assign membership values to elements based on their degree of belonging to a particular set. By employing fuzzy rules and inference mechanisms, this approach enables the synthesis of imprecise inputs to generate precise and actionable outputs. A general fuzzy logic system is shown in Fig.1.

Fuzzification is the process of converting crisp input data into fuzzy sets in a fuzzy logic system. It entails mapping inputs to fuzzy sets using membership functions. A fuzzy set A comprises elements $(x, \mu A(x))$, where x belongs to the universe of discourse X, and $\mu A(x)$ is the membership function assigning a value between 0 and 1 to each element x, representing its degree of membership in A. Commonly used membership functions during fuzzification include trapezoidal, Gaussian, triangular, and others. These functions determine the degree of membership in a fuzzy set, enabling the representation of uncertainty and imprecision in the input data. Two widely used membership functions are the trapezoidal function and the Gaussian function [60]. Other potential membership functions can be formulated based on existing formulas and functions. The selection of membership function shape is problem-specific and requires experience with the given situation to tune-up achieve the best fit.

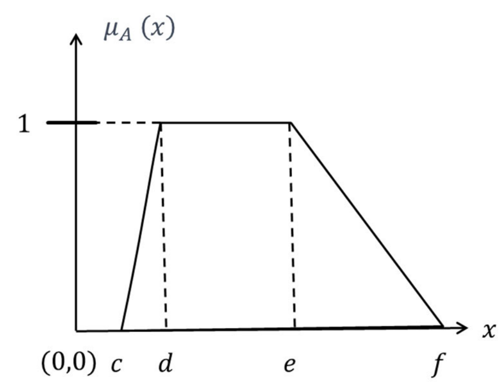

FIGURE 2. **Membership function-trapezoidal function.**

The trapezoidal function is defined by four parameters (c, d, e, f), where $c \leq d \leq e \leq f$. These parameters determine the shape and membership values of the fuzzy set, as shown in (1) and graphically represented in Fig. 2 [60].

$$\mu_A(x) = \begin{cases} \frac{x-c}{d-c}, & c \le x \le d \\ 1, & c \le x \le d \\ \frac{f-x}{f-e}, & e \le x \le f \\ 0, & x \ge f. \end{cases} \quad (1)$$

The Gaussian function expressed in (2) has two parameters, g and σ. Parameter g determines the center and peak value of the curve, while parameter σ controls the width. The definition and graph of the Gaussian membership function is shown in Fig. 3 [60].

$$\mu_A(x) = e^{-\frac{1}{2}\left(\frac{x-g}{\sigma}\right)^2}. \quad (2)$$

Fuzzy rules are vital in fuzzy logic systems, modeling decision-making based on fuzzy logic principles. They connect input and output variables using linguistic variables and fuzzy sets, often using if-then statements with logical operators. These rules capture relationships between inputs and outputs, enabling flexible decision-making in areas like control systems and artificial intelligence applications [61].

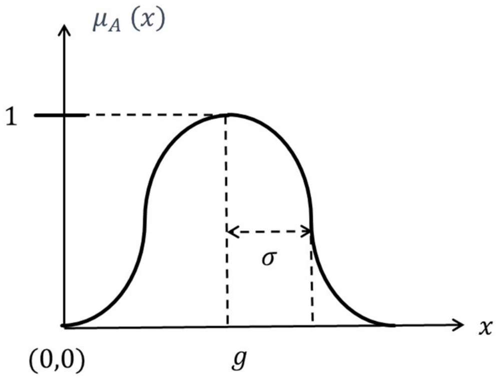

FIGURE 3. Membership function-gaussian function.

A fuzzy logic reasoning system is a computational framework that mimics human thinking using fuzzy logic principles to make decisions based on fuzzy rules and input data. It consists of three main components: the rule base (defining fuzzy rules), the database (containing membership functions used in the rules), and the reasoning mechanism (deriving logical conclusions from the rules and facts). The system's operation involves fuzzification (converting inputs to fuzzy sets), applying fuzzy rules to determine the output set, and then using defuzzification to extract crisp values representing the fuzzy set.

The defuzzifier is the final stage in a fuzzy logic system, converting a fuzzy output set into a clear output value. Common defuzzification methods include the centroid method, bisector method, maximum mean method, and weighted average method. Each method has its use cases and depends on the characteristics of the fuzzy output set and application requirements. The defuzzifier produces a crisp output value for further decision-making processes.

B. GREENSHIELDS MODEL

Greenshields macroscopic traffic flow theory focuses on the speed-density relationship in traffic flow. It establishes connections between speed and density, flow and density, and speed and flow. This theory is represented graphically through speed-density, flow-density, and speed-flow diagrams. Congestion occurs when traffic density approaches or exceeds a critical level, resulting in inefficient flow and reduced speed. These relationships are widely used in traffic flow models of highway and transportation planning to assess traffic conditions, estimate capacity, and design efficient transportation systems [59].

Graphical representations of speed-density, flow-density, and speed-flow relationships offer insights into how changes in traffic speed and flow impact traffic density impact. Transportation planners and engineers use these relationships to make informed decisions on road design, traffic management, and congestion mitigation. The speed-density relationship curve shows the connection between traffic speed and density. As the number of vehicles per unit of road length increases, the average speed of vehicles decreases linearly. This is because higher vehicle density reduces maneuvering space, leading to decreased speeds.

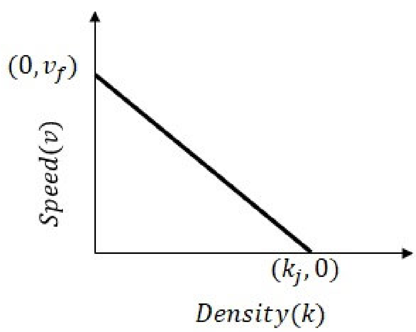

FIGURE 4. Relationship between speed and density.

The relationship between the mean velocity v and the density k can be expressed by [59]

$$v = v_f - \left(\frac{v_f}{k_j}\right) k, \quad (3)$$

where v_f represents the free speed parameter and k_j stands for the density parameter. This relationship is visually depicted in Fig. 4. As the density approaches to zero, speed will also converge toward to zero.

The flow-density relationship curve illustrates how traffic flow changes with varying traffic density and can be expressed as follows [59]:

$$q = v_f.k - \left(\frac{v_f}{k_j}\right) k^2. \quad (4)$$

At lower densities, traffic flow increases as density rises, but it eventually levels off and decreases when density reaches a tipping point, indicating congestion. Fig. 5 visually portrays this relationship. This curve aids in estimating road capacity and determining the maximum sustainable flow under different density conditions.

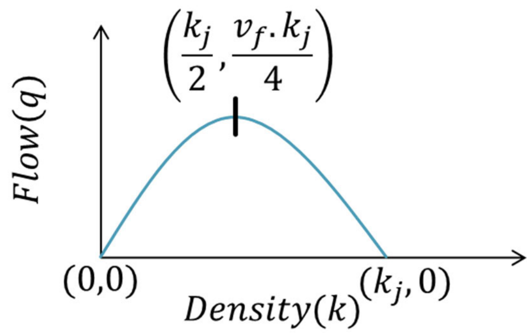

FIGURE 5. Relationship between flow and density.

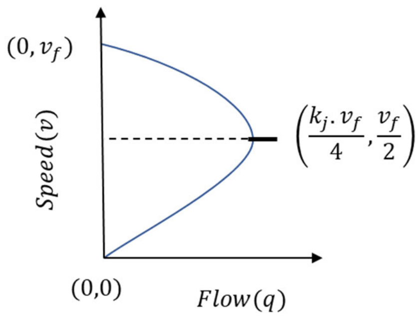

FIGURE 6. Relationship between speed and flow.

The speed-flow relationship curve demonstrates how traffic speed decreases as traffic volume increases. It is influenced by factors such as congestion, vehicle interactions, and road capacity. This relationship can be derived from equations (3) and (4) and expressed in (5) [59]. A visual representation is provided in Fig. 6.

$$q = k_j.v - \left(\frac{k_j}{v_f}\right) v^2. \tag{5}$$

C. TRAFFIC DATA COLLECTION AND TIME SERIES FORECASTING

The traffic flow within the highway network is influenced by factors such as vehicle entry and exit ramps, the road structure, and the traffic flow of adjacent interconnected road sections. Collecting, integrating, and processing multi-modal traffic data for congestion forecasting, performing accurate travel time estimation, and managing hidden information are essential steps in optimizing traffic control and enhancing overall management.

Although determining exact free-flow speed and jam density directly from the field is changing, approximate values can be derived from multiple observations of speed and density, followed by fitting a suitable equation between them. Acquiring traffic flow data involves gathering information about the current road network to formulate effective traffic control strategies. Traffic management units utilize various types of detectors, including circular vehicle detectors, image detectors, microwave detectors, and radar detectors, to collect real-time traffic flow data. Vehicle detectors play a crucial role in estimating travel time and facilitating demand analysis for traffic management. These fixed detectors are permanently installed on the pavement, roadside, or above driveways, using different measurement methods with sensors such as loop coils, electronic tags, and microwave sensors for data collection. As illustrated in Fig. 7, loop coil detectors are commonly employed by Taiwan highway bureaus, but other types like video vehicle detectors, license plate readers, and electronic toll collection systems are also used [62].

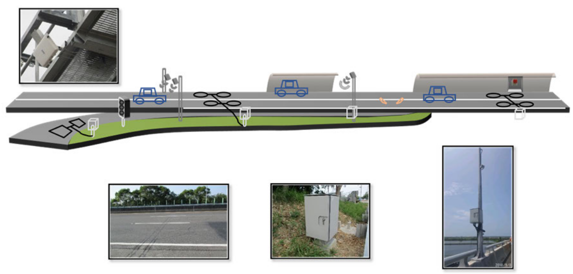

FIGURE 7. Illustrated diagram for the placement of various vehicle detectors.

To establish Greenshields models in each segment of Taiwan highways, regression analysis in time series forecasting is used and experimentally validated according collected traffic flow data. Specifically, polynomial regression methods are applied to approximate a function by fitting a polynomial equation to the data points. The goal is to find a smooth curve that can be expressed by a polynomial with the degree n as follows [26]:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \ldots + \beta_n X^n + \epsilon, \tag{6}$$

where Y represents the dependent variable, X represents the independent variable, and β_i, $i = 0, \cdots, n$, are the coefficients of the polynomial and ϵ is the error term. Polynomial regression fits a polynomial equation to the data, allowing estimation of the dependent variable for any given independent variable value within the data range. Although the method is simple, but may overfit the data if the polynomial degree is too high, capturing noise and leading to a poor representation of the relationship. The choice of polynomial degree should be carefully considered based on data characteristics and desired precision. For smoother curves or irregularly spaced data, spline regression could be a better alternative. The procedure to establish a model by the regression method is shown in Fig. 8.

III. SYSTEM FOR HIGHWAY TRAFFIC CONGESTION PREDICTION BASED ON GREENSHIELDS MODEL

The Greenshields model offers insights into how changes in vehicle speed and flow traffic impact traffic density. The proposed scheme for addressing highway traffic congestion involves a two-input, one-output fuzzy system. Input parameters, namely vehicle speed and traffic flow, are employed, and a fuzzification process is implemented using established membership functions to transform these inputs into meaningful information. Subsequently, a fuzzy inference module, based on the Greenshields model, is devised to interpret,

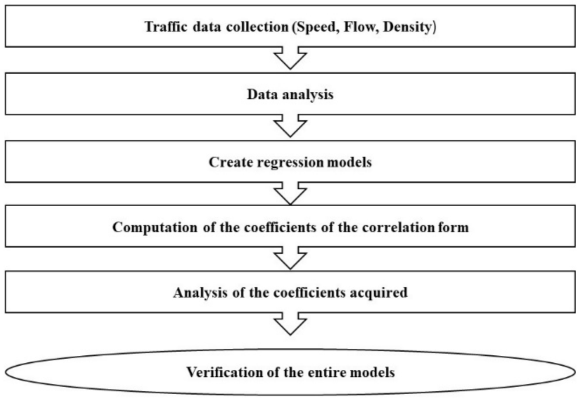

FIGURE 8. Procedure of creating regression models.

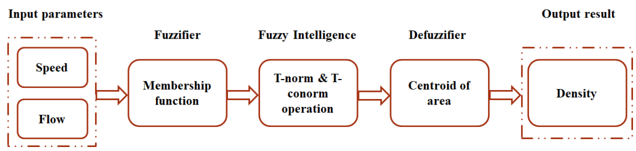

FIGURE 9. Block diagram of designing highway traffic congestion fuzzy system.

and apply the input information using logical rules to facilitate optimal decision-making. To predict traffic congestion conditions, a defuzzification module is employed to convert the outcomes of the interference mechanism. Fig. 9 provides a visual representation of the step-by-step procedure for designing the desired fuzzy logic system.

The traffic data collected for model verification was sourced from the southbound section of the Sun Yat-Sen Freeway in Taiwan, extending from Yongkang District to Gangshan District [60]. This segment comprises three lanes to facilitate efficient traffic flow, with a maximum speed limit of 110 km/h and a buffer range up to 120 km/h. These specifications are essential for designing a fuzzy system that accurately reflects real-world traffic conditions. Additionally, a polynomial regression model was developed using this data to validate the proposed system.

A. MEMBERSHIP FUNCTION CONSTRUCTION

Speed and traffic flow are selected as the input and output parameters. Three types of membership functions-namely, trigonometric, Gaussian, and trapezoidal-are respectively chosen to model ambiguous regions based on the collected data, range of domain, and limitations for each segment of Taiwan Freeway. This choice will determine which function aligns best with Greenshields theoretical values. The selected membership function should aptly capture uncertainty and imprecision while remaining consistent with the theory.

The fuzzy system comprises two modes: jam mode and non-jam mode. In the jam mode, the fuzzy domain of the membership function for vehicle speed is categorized into several levels: Extremely Slow (ES), Very Slow (VS), Slow (S), Steady (St), Quite Slow (QS), Moderate Slow (MS), and Moderate (M), as detailed in Table 1. Fig. 10 shows the membership function of vehicle speed and its range values for jam mode.

TABLE 1. Tabular membership function of vehicle speed for jam mode.

Vehicle speed (km/hour)	Mapping interval (km)
Extremely Slow speed	0~10
Very Slow speed	4~20
Slow speed	16~32
Steady speed	27~42
Quite Slow speed	36~55
Moderate Slow speed	47~64
Moderate speed	59~85

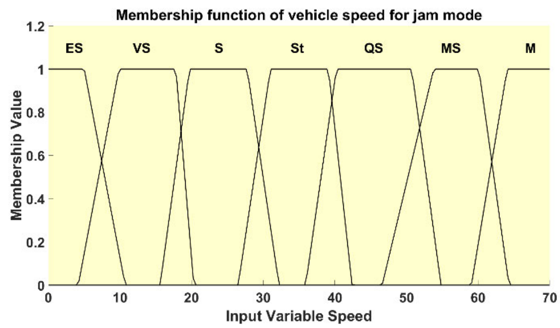

FIGURE 10. Membership function of vehicle speed for jam mode.

Similarly, the fuzzy domain of the membership function for traffic flow in jam mode is segmented into various levels: Extremely Low (EL), Very Low (VL), Low (L), Sparse (Sp), Quite Low (QL), Moderate Low (ML), Moderate (M), Moderate High (MH), Quite High (QH), Dense (De), High (H), Very High (VH), and Extremely High (EH), as presented in Table 2. Fig. 11 illustrates the membership function of traffic flow and its range values for jam model.

TABLE 2. Tabular membership function of traffic flow for jam mode.

Traffic Flow (number/hour)	Percentage of flow (%)
Extremely Low flow	0~10
Very Low flow	4~16
Low flow	12~25
Sparse flow	20~31
Quite Low flow	28~43
Moderate Low flow	38~50
Moderate flow	46~56
Moderate High flow	55~65
Quite High flow	62~74
Dense flow	72~80
High flow	77~89
Very High flow	84~97
Extremely High flow	92~100

For the non-jam mode, the fuzzy domain of the membership functions for vehicle speed is categorized into several levels: Moderate (M), Moderate Fast (MF), Quite Fast (QF), Speedy (Sp), Fast (F), Very Fast (VF), Extremely Fast (EF),

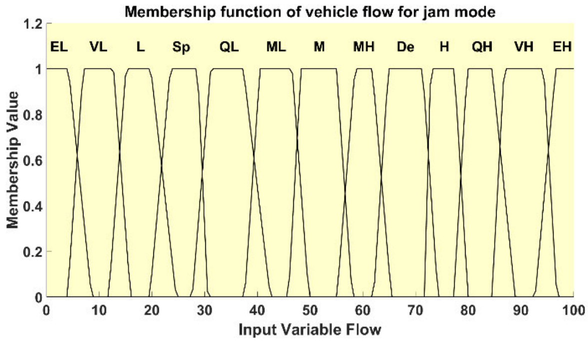

FIGURE 11. Membership function of traffic flow for jam mode.

as detailed in Table 3. The membership function of vehicle speed and its range values are designed as shown in Fig. 12, while the membership function of traffic flow and its range values are designed as shown in Fig. 13.

TABLE 3. Tabular membership function of vehicle speed for non-jam mode.

Vehicle speed (km/hour)	Mapping interval (km/)
Moderate speed	70~76
Moderate Fast speed	74~86
Quite Fast speed	83~96
Speedy speed	94~104
Fast speed	102~111
Very Fast speed	109~121
Extremely Fast speed	115~130

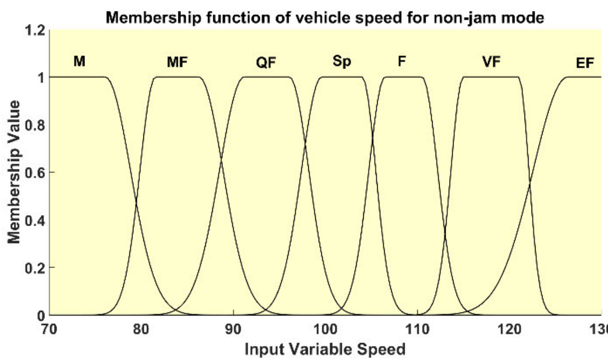

FIGURE 12. Membership function of vehicle speed for non-jam mode.

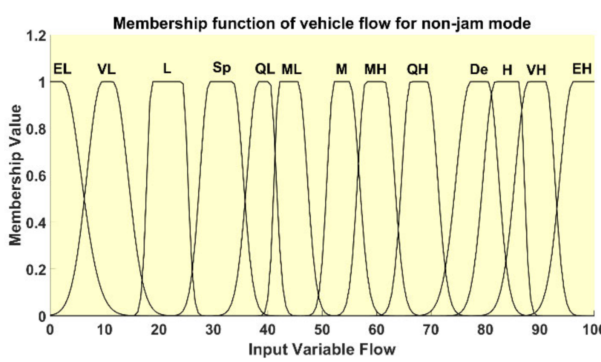

FIGURE 13. Membership function of traffic flow for non-jam mode.

The output variable is traffic density, which is utilized to assess the level of road congestion. Its fuzzy domain is divided into several levels: Extremely Low (EL), Very Low (VL), Low (L), Sparse (sp), Quite Low (QL), Moderate Low (ML), Moderate (M), Moderate High (MH), Quite High (QH), Dense (De), High (H), Very High (VH), and Extremely High (EH). The membership function of traffic density and its range values in jam mode are depicted in Fig. 14, whereas the membership function of traffic density and its range values in non-jam mode are designed as shown in Fig. 15.

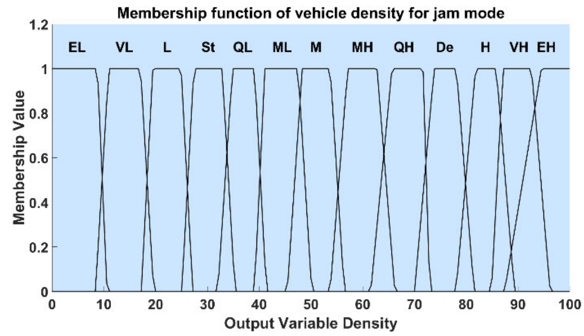

FIGURE 14. Membership function of vehicle density for jam mode.

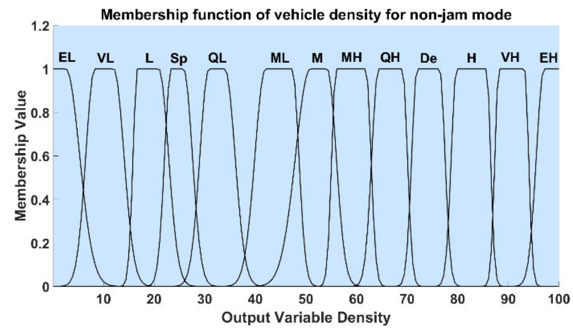

FIGURE 15. Membership function of vehicle density for non-jam mode.

B. RULE CONSTRUCTION AND DEFUZZIFICATION

The rule base of the proposed system, which defines the relationship between input variables (vehicle-speed and traffic-flow) and output variables (traffic-density), significantly influences subsequent model generation and its predictive ability for real-world traffic conditions. The design of logical and reasonable fuzzy rules within the proposed system for generating traffic density, which is essential for congestion prediction and travel time estimation, involves capturing data, adhering to regulations, and incorporating expert knowledge to reflect realistic traffic scenarios. Tabular representations of possible sets of rules are employed to prevent contradictory or illogical rules that do not align with real-world traffic conditions on Taiwan freeways, ensuring consistency for accurate predictions of traffic density. Based on the relationship between traffic density and traffic flow, the fuzzy system operates in two modes: jam mode, and non-jam mode. Consequently, two tabular representations of possible rule sets are defined, as presented in Table 4 and Table 5.

In Tables 4 and Table 5, the two operators - AND and OR - are respectively applied according to T-norms and T-conorms to combine rules and determine system behavior.

TABLE 4. Traffic density rule table for jam mode.

	Vehicle speed		Traffic flow		Vehicle density
If	ES	OR	EL	Then	EH
If	ES	OR	VL	Then	EH
If	ES	OR	L	Then	EH
If	VS	OR	Sp	Then	VH
If	VS	AND	QL	Then	VH
If	VS	OR	ML	Then	H
If	S	OR	ML	Then	H
If	S	OR	M	Then	H
If	S	AND	MH	Then	H
If	St	AND	MH	Then	H
If	St	OR	QH	Then	De
If	St	OR	De	Then	De
If	QS	OR	De	Then	De
If	QS	AND	H	Then	QH
If	QS	OR	VH	Then	QH
If	MS	OR	H	Then	QH
If	MS	OR	VH	Then	MH
If	MS	AND	EH	Then	M
If	M	OR	H	Then	QH
If	M	AND	VH	Then	MH
If	M		EH	Then	M

TABLE 5. Traffic density rule table for non-jam mode.

	Vehicle speed		Traffic flow		Vehicle density
If	EF	OR	EL	Then	EL
If	EF	OR	VL	Then	EL
If	EF	AND	L	Then	EL
If	VF	OR	L	Then	VL
If	VF	OR	Sp	Then	VL
If	VF	OR	QL	Then	VL
If	F	OR	ML	Then	L
If	F	AND	M	Then	L
If	F	AND	MH	Then	Sp
If	Sp	AND	MH	Then	Sp
If	Sp	AND	QH	Then	Sp
If	Sp	AND	De	Then	Sp
If	QF	OR	De	Then	Sp
If	QF	AND	H	Then	QL
If	QF	OR	VH	Then	QL
If	MF	AND	H	Then	QL
If	MF	OR	VH	Then	ML
If	MF	AND	EH	Then	M
If	M	AND	H	Then	QL
If	M	AND	VH	Then	ML
If	M	OR	EH	Then	M

The T-norm operation identifies the intersection of processing rules, employing the minimum operation to calculate the minimum value between two fuzzy sets, A and B, as shown below [61]:

$$\mu_{A\cup B}(x) = min\left[\mu_{A,}\mu_{B}\right] = \mu_A(x)\, AND \mu_B(x)\,, \quad \forall x \in U, \tag{7}$$

where x is an element of the universe of discourse U, and μ_A and μ_B are the membership functions associated with their respective fuzzy sets A and B.

The OR operator corresponds to the maximum operation applied to the fuzzy sets A and B, respectively. The fuzzy set operation for OR operator can be expressed by [61]

$$\mu_{A\cup B}(x) = max\left[\mu_{A,}\mu_{B}\right] = \mu_A(x)\, or \mu_B(x)\,, \quad \forall x \in U. \tag{8}$$

Defuzzification plays a crucial role in transforming fuzzy outcomes into precise, understandable values. This process employs the centroid of area method, which determines the central point of the block within the fuzzy region. By doing so, it yields a definitive and interpretable value for the traffic density. This step is pivotal in ensuring that the information extracted from the proposed fuzzy system is not only accurate but also readily comprehensible, thereby enhancing its applicability and effectiveness in real-world traffic management scenarios.

IV. SIMULATION RESULTS AND DISCUSSIONS

In this segment, we utilize real-world vehicle speed and traffic flow data from the specified segment of the Sun Yat-Sen Highway in Taiwan. These values are applied to both our fuzzy system and the model using the regression method, enabling us to evaluate the traffic density. We then conduct a detailed comparison of the simulation results, providing a comprehensive analysis that ultimately affirms the validity and precision of our systems. The simulations clearly demonstrate that our system's adaptable nature allows for seamless implementation across different segments of the highway.

A. UTILIZING POLYNOMIAL REGRESSION FOR GREENSHIELDS MODEL

For comparison with the proposed fuzzy inference system, a conventional approach was employed, entailing the establishment of a Greenshields model using the polynomial regression. This process leveraged comprehensive traffic data collected from detectors installed along the Yongkang to Gangshan segment of the Sun Yat-Sen Highway in Taiwan [62]. Through polynomial regression analysis of the traffic data, a set of models was generated. These models comprise the relationship diagram between speed and traffic density shown in Fig. 16, the relationship diagram between traffic flow and density shown in Fig. 17, and the relationship diagram between speed and traffic flow shown in Fig. 18. Each of these visual representations provides valuable insights into the complex dynamics among velocity and density, flow and density, as well as velocity and flow. Clearly, these figures establish the Greenshields model for the specified road section.

Using regression analysis to establish parametric models for traffic status evaluation and prediction involves capturing the key characteristics of traffic data for specified problems. The requisite functions for prediction can be derived through

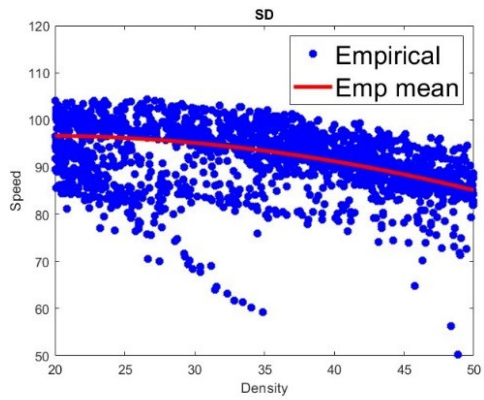

FIGURE 16. Relationship between speed and traffic density: realistic data and polynomial regression, respectively.

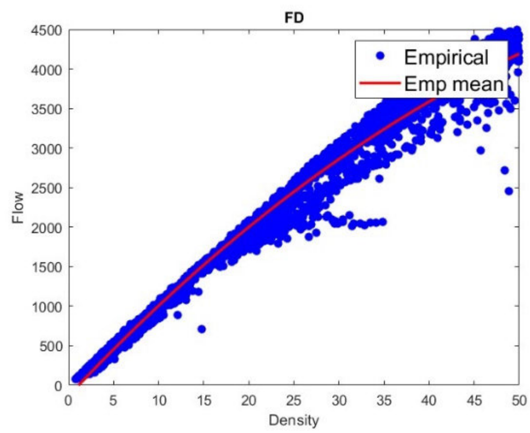

FIGURE 17. Relationship between traffic flow and density: realistic data and polynomial regression, respectively.

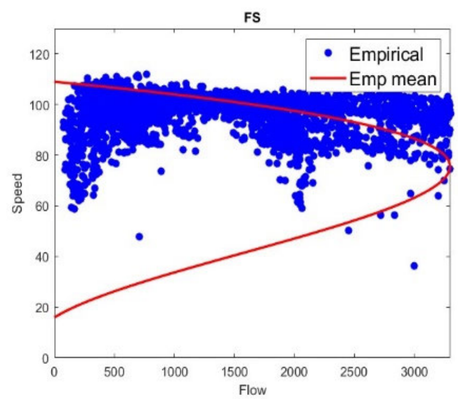

FIGURE 18. Relationship betweenvehicle speed and traffic flow: realistic data and polynomial regression, respectively.

correlation operations and the least-squares method on empirical data. In general, regression models need large data sets to obtain accurate results but may suffer from overfitting. For specific predictions, it may require several related models to achieve the results through mutual computations among them. Furthermore, once the environment and conditions change, it is necessary to correct a large amount of new data for training to obtain the new parameters. Obviously, this process is a time-consuming and tedious works.

B. GREENSHIELDS MODEL-BASED FUZZY SYSTEM

This section centers on the practical implementation of designing a fuzzy system based on the Greenshields model for a specific segment of the Sun Yat-Sen Highway in Taiwan. The goal is to accurately capture the relationship between vehicle speed, traffic flow, and traffic density in real-world scenarios. To ensure the accuracy and reliability of the model, practical traffic data from the Yongkang to Gangshan segment of the Sun Yat-Sen Highway is utilized as a reference point. This empirical data forms the basis for parameterizing the model, aligning it with the observed actual behavior on the highway [62].

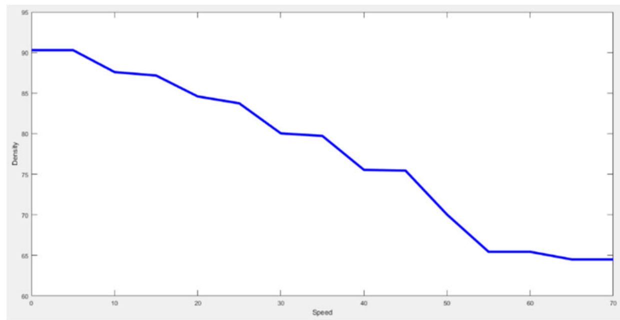

FIGURE 19. Relationship between vehicle speed and density for the fuzzy system in jam mode.

To construct an effective fuzzy system, it is crucial to define the range of each variable. In this case, vehicle speed ranges from 0 to 130 km/h, traffic flow is represented as a percentage ranging from 0% to 100%, and traffic density is also expressed as a percentage, ranging from 0 to 100%. The designed fuzzy system operates in two distinct modes: non-jam and jam. Each mode features specific input and output membership functions, as well as a set of rules for system operation. This dual-mode approach allows for a comprehensive understanding of traffic dynamics under varying conditions.

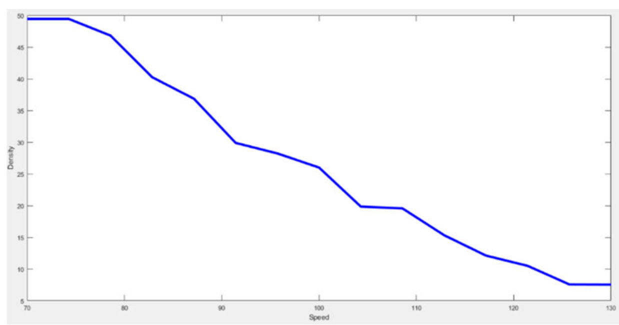

FIGURE 20. Relationship between vehicle speed and density for the fuzzy system in non-jam mode.

The simulations are conducted using MATLAB, which allows for precise modeling and analysis, providing a robust foundation for evaluating the performance of the designed fuzzy system. Fig. 19 illustrates a linear correlation between vehicle speed and traffic density within the jam mode. Similarly, Fig. 20 presents a comparable relationship between vehicle speed and traffic density for the non-jam mode. Furthermore, Fig. 21 and 22 depict the relationship between traffic flow and density in both jam and non-jam modes, respectively. These figures demonstrate how the fuzzy system accurately captures the relationship among vehicle speed traffic flow, and traffic density. The Greenshields model-based fuzzy rules generate the output according to the degrees obtained from the inputs to validate its effectiveness. These simulations provide additional insights into the behavior of traffic under different conditions, further affirming the applicability and flexibility of the designed fuzzy system.

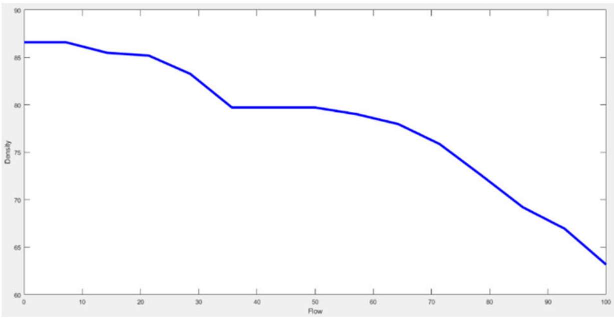

FIGURE 21. Relationship between traffic flow and the upper density for the fuzzy system in jam mode.

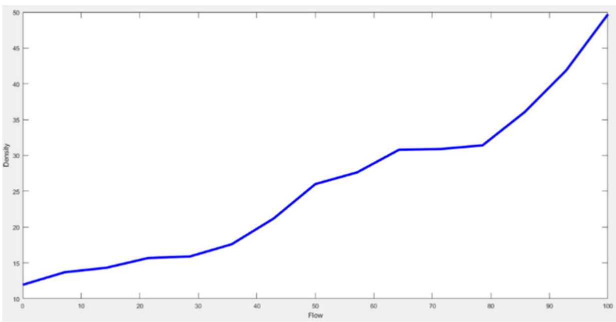

FIGURE 22. Relationship between traffic flow and the lower density for fuzzy system in non-jam mode.

C. TEST AND DISCUSSIONS

There are two ways to enhance the prediction results of fuzzy systems. The first method involves increasing the number of fuzzy sets in the fuzzy partition of the space for each mode and defining appropriate membership functions for each fuzzy set. The second method classifies the input-output relationships into several modes based on their nonlinearity. Our fuzzy system is based on the Greenshields models. Given the nonlinearity of these models, increasing the number of fuzzy sets is a more convenient and effective approach. The proposed fuzzy system is confirmed to align with the theoretical framework by comparing it to a polynomial regression model. The effectiveness of the system is further demonstrated by comparing real-world data obtained from the fuzzy system to data derived from the polynomial regression model. The validation process involves examining data related to vehicle velocity, traffic flow, and traffic density relationships, all of which are governed by the operational rules.

In Fig. 23, we present the actual simulation results for high-speed conditions in the non-jam scenario. In the input section, the vehicle speed is noted at 105 km/h, and the vehicle flow rate stands at 85%. By feeding these parameters into the fuzzy system, we ascertain that the vehicle density registers at 30.6%, falling precisely within the range of the little and light fuzzy traffic density zones. In Fig. 24, we illustrate the actual simulation results for low-speed conditions in the jam scenario. Within the input section, the vehicle speed is documented as 35 km/h, and the vehicle flow rate remains at 20%. After incorporating these values into the fuzzy system, we determine that the vehicle density reaches 86.5%, precisely matching the congestion levels found in in the high and very high fuzzy traffic zones.

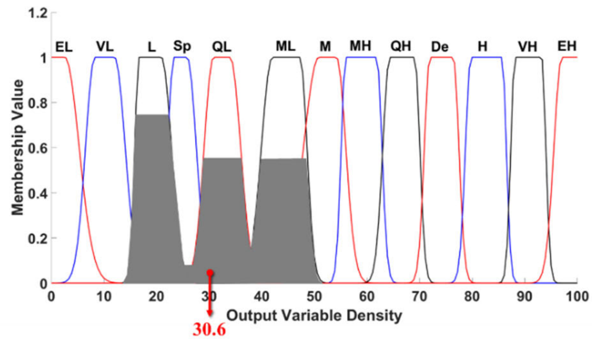

FIGURE 23. Defuzzified traffic density output in high speed and non-jam scenarios.

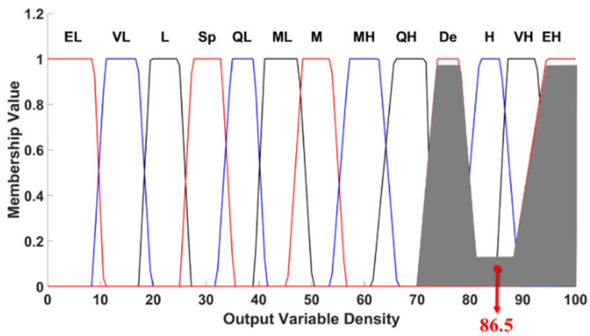

FIGURE 24. Defuzzified traffic density output in low speed and jam scenarios.

Comparing the system with the regression example in Section A, it is evident that at a speed of 95 km/h, Fig. 16 indicates a traffic density of approximately 29%. In our model, the density for non-congested scenarios also hovers around 28%. Turning to the examination of the relationship between flow and density, at a flow rate of 40%, Fig. 17 reflects a non-jam mode traffic density of approximately 20%. Our system closely aligns with this, registering at around 19.5%. Notably, the prediction errors are minimal. Additionally, the proposed system demonstrates distinct advantages in adaptability and flexibility, enabling real-time adjustments, and can be easily implemented across different segments of the highway.

V. CONCLUSION

Traffic congestion not only impacts on social costs through increased fuel consumption and commuting time but also diminishes living quality due to environments pollution. The importance of real-time traffic congestion prediction for efficient traffic management on highways within ITS is undeniable. In this paper, we leverage the Greenshields model, which establishes a critical connection between vehicle speed, traffic flow, and traffic density, to develop a fuzzy inference system for predicting traffic density. By utilizing vehicle speed and traffic flow as input variables, our proposed fuzzy system operates in two modes, effectively quantifying the level of congestion as a percentage of the maximum capacity on highways. Through the analysis of traffic data from Sun Yat-Sen Highway and a comparative study with a polynomial regression model, our consistent prediction results validate the accuracy of our forecasting system. Even with limited existing traffic data, the proposed method still demonstrates remarkable precision.

In contrast to neural network schemes, our fuzzy logic prediction system utilizes fuzzy rules to capture the Greenshields theory as the knowledge base. By utilizing expert-defined linguistic factors and rules, our proposed system can quickly evaluate traffic density without the need for extensive and laborious training. Moreover, the configuration of the system model parameters can be easily adjusted using fuzzy sets, logic rules, and membership functions, allowing it to adapt promptly to changes in real-world traffic situations. Compared to regression models, which typically require extensive training to obtain parameters for various highway segments, the advantages of our system become particularly evident. Additionally, our proposed system can be seamlessly cascaded across multiple segments or the entirety of the highway to provide long-distance predictions of traffic congestion. This unequivocally reaffirms the practicality of our prediction model within ITS, thereby facilitating efficient traffic management, congestion alleviation, and ultimately enhancing overall travel services for road users.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their careful reading, comments, and suggestions of this manuscript.

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