IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 17, 2019, accepted November 19, 2019, date of publication December 2, 2019, date of current version December 16, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2956918

Fuzzy Inference System Framework to Prioritize the Deployment of Resources in Low Visibility Traffic Conditions

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ABSTRACT Transportation managers and engineers are often required to make decisions regarding the use of limited resources that directly affect public safety, costs, and the overall performance of transportation systems. One important decision involves prioritizing the deployment of resources (e.g., personnel and variable signs) to low visibility areas due to fog or other environmental and road conditions. Due to the lack of proper approaches to characterize and incorporate weather and road condition parameters in the decision-making process, transportation managers depend mainly on personal experience to make these types of decisions. To help them prioritize the deployment of resources to low visibility areas, this research presents a fuzzy inference system (FIS) framework composed of three fuzzy systems that characterize fog occurrence, road risk conditions, and deployment of resources. Preliminary experiments to evaluate the developed fog occurrence FIS against four methods presented in the literature using data from two weather stations showed that the FIS model outperformed three of the other methods in accuracy. These results are very promising given that the other methods represent more expensive solution approaches that require large amounts of data, significant time-consuming data preparation, network architecture design tasks, and high processing power.

INDEX TERMS Fog, fuzzy inference system, fuzzy logic, low visibility conditions.

I. INTRODUCTION

Transportation managers and engineers are often required to make decisions regarding the use of limited resources that directly affect public safety and costs. A particular situation commonly faced by transportation decision-makers involves prioritizing the deployment of resources –such as personnel and variable signs– to areas with low visibility due to fog, rain, smoke, or other types of environmental and road conditions. These decisions are critical given that low visibility conditions create highly unsafe environments and threaten the operation and performance of transportation systems. Among the various factors affecting roadway visibility, fog stands out as a major contributor to severe crashes nationwide. In fact, statistics from the Federal Highway Administration show that almost 39,000 yearly vehicle crashes occur during fog conditions, resulting in over 600 fatalities and 16,000 injuries [1].

The current process to prioritize the deployment of resources to low visibility traffic areas relies on operational tools (e.g., simulation models) and standards that assume clear environmental conditions; therefore, transportation managers depend mainly on personal experience to make these types of decisions when faced with inclement weather of varying intensities [2]. This limitation increases the risk of ineffective use of resources, which inevitably results in higher project costs and the probability of developing unreliable solutions [2]– [5]. Another key factor that directly impacts the effectiveness of the current decision-making process has to do with the fact that some environmental and road parameters are vague by nature and difficult to quantify. These parameters are highly imprecise; therefore, they should be considered as imprecise parameters within a decision-making framework. One weather parameter that significantly impacts traffic volumes and increases the likelihood of accidents on the road is fog [5]–[7]. Fog is one of the least predictable and most imprecise weather variables because it fluctuates in terms of time and position, both horizontally and vertically.

Enhanced methodologies to prioritize the deployment of resources to low visibility traffic areas can significantly improve the effectiveness of associated resource assignment

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

policies. These improvements can lead to positive impacts on key performance measures related to public safety and costs. Therefore, it is necessary to follow a continuous improvement approach by pursuing further research to enhance the process of deploying resources to low visibility traffic areas.

This paper presents a fuzzy inference system (FIS) framework to assist transportation managers with prioritizing the deployment of resources to areas of low visibility due to fog and other environmental and road condition parameters. Given that these prioritization decisions depend on parameters that are of a highly imprecise nature, a fuzzy logic approach is employed as it is considered an appropriate decision-making technique to manage imprecise and complex variables [8]–[12]. The proposed FIS framework is composed of three FIS models. The first model determines the occurrence of fog. The second model outputs the risk conditions of a road. The last model determines the priority to deploy resources to low visibility areas due to fog.

While fuzzy systems have been developed for forecasting purposes within the transportation and weather literature (e.g., [7] and [8]), a framework to determine the priority of resource deployments based on fog occurrence, road risk conditions, and other road parameters has not yet been proposed. The development of this framework represents a significant contribution to the literature related to transportation and resource assignment.

This paper consists of six sections. Section II describes literature related to four main areas: overview of techniques considered for dealing with uncertainty and imprecise parameters in the decision-making process; modeling imprecise weather variables; application of fuzzy logic within the transportation field; and resource allocation decisions based on imprecise parameters. Section III provides a background related to fuzzy logic. Section IV describes the approach involved to develop the three inference systems, as well as a description of each of them. Section V evaluates the proposed framework. Finally, Section VI provides concluding remarks and identifies areas for future research.

II. RELATED LITERATURE

Effective consideration of weather variables and road conditions are essential for the correct implementation of traffic and transportation solutions. However, many of the variables and parameters involved are characterized by uncertainty, subjectivity, imprecision and ambiguity [13]. Traditional statistical techniques have been found to be ineffective when dealing with problems in which the dependencies of the variables are complex, non-linear, or when the variables are difficult to quantify. Moreover, traditional statistics techniques typically require variables to be independent and normally distributed. When dealing with non-linear dynamic processes (e.g., fog), it is necessary to look into data driven methodologies that can handle the inherit uncertainty in the analysis and perform better than the traditional methods [14]. Among those data driven methods are decision trees, fuzzy logic, and machine learning algorithms (e.g., support vector machines, Naïve Bayes, and neural networks). Table I shows an overview of the techniques considered for this paper.

A decision tree is a graphical representation that follows decision paths based on a set of comprehensible rules. Despite the popularity of this approach in various fields, its application for transportation related problems such as the one addresed in this paper is limited. One reason for this lack of applications is the difficulty in defining accurate rules due to the complexity and subjective nature of environmental parameters [15].

Many studies have used fuzzy logic as a tool to deal with imprecise, complex, and ambiguous variables [11], [16]–[19]). This technique has proven to be successful in a variety of traffic and transportation problems when the data structure is characterized by linguistic parameters, e.g., cloudy, foggy, slippery, clear, dry, wet, etc. These problems can often be formulated in linguistic terms based on descriptive rules, which are simple for processing and execution but complicated when it comes to the use of other data driven methodologies [9]. Fuzzy logic is based on user knowledge and interpretation; therefore, its main downside is subjectivity.

In the past few years, machine learning algorithms have achieved great success and recognition. Artificial neural networks (ANN) are among the most popular machine learning approaches for solving non-linear problems. They are very popular in classification tasks, particularly in the field of image processing and computer vision. Typically, ANN algorithms focus on very large datasets and their performance highly depends on the quality of the training data. One downside of ANN is the lack of interpretability compared to methods like decision tress or fuzzy logic. Another popular data driven approach is Naïve Bayes (NB), which is a classification algorithm based on Bayes Theorem. NB classifiers are a type of probabilistic classifiers, where the probability of each class and the conditional probability of each class given each instance value are calculated to determine the likelihood that a new instance will belong to a class [14]. However, when dealing with uncertainties and fuzzy parameters, collecting and estimating all the prior conditional and joint probabilities might not be possible. Another machine learning algorithm able to deal with complex non-linear data is Support Vector Machines (SVM). SVM algorithms have been successfully employed for various classification and forecasting problems. However, just like with ANN, they often require time-consuming data preparation tasks and their implementation can be slow. Despite the fact that data driven approaches have proven to be able to handle complex data, not all of them can cope with fuzzy concepts and uncertainties.

Decision makers dealing with the task of prioritizing deployment of resources to low visibility areas due to fog face multiple challenges. The first challenge is to address the uncertainty related to fog, (i.e., determining the likelihood of fog occurrence). The second challenge deals with effectively determining if road conditions are risky or not based on traffic and environmental parameters. The third challenge involves determining priority levels for resource allocation based on

TABLE 1. Overview of techniques considered for this research.

Technique/Approach		*Overview*	*References*
Traditional Approaches	*Linear & Logistic Regression*	• Models may be too general or too specific • Useful to understand linear relationships among variables • Simple to understand and interpret • Not appropriate for complex non-linear variables	[30], [31]
Data Driven Approaches	*Decision Trees*	• Graphical representation • Difficult to deal with quantitative variables • Definition of rules can be highly challenging • Hard to update • Simple to understand	[17]–[19]
	Fuzzy Logic	• Consider uncertainty in qualitative variables • Definition of membership functions and rules require expert knowledge • Simple to implement and interpret • Tend to be subjective • Can handle categorical variable	[8], [34], [35]
	Machine Learning	Artificial Neural Networks • Capable of capturing nonlinear and complex relationships • Usually require large amount of data • Computationally expensive • Slow implementation • Difficult to interpret • Might require extensive data preparation	[14], [21]–[23]
		Support Vector Machines • Slow implementation • Difficult to interpret • Relatively memory efficient • Handle non-linearity • Might require extensive data preparation	[14], [39]
		Naïve Bayes • Fast and simple to implement • Assumption of independent predictors	[14], [40]

all the parameters involved. In order to assist decision-makers with resource deployment tasks in low visibility traffic conditions, it is necessary to develop a framework that can handle these three challenges.

Fuzzy logic has achieved promising results in tasks similar to the ones related with prioritizing the deployment of resources in low visibility traffic conditions. Furthermore, despite the popularity of neural networks and their proven potential to tackle complex problems, generally, they often result in a more expensive solution approach than fuzzy logic because they require great amounts of data and processing power. In addition, implementing effective neural network solutions often require significant time-consuming data preparation and network architecture design tasks. On the other hand, fuzzy logic systems do not require large amount of data and are relatively easy to implement and interpret. Moreover, fuzzy logic can handle categorical variables without data transformation and can cope adequately with fuzzy concepts. Table II shows a list of relevant research studies found in the literature that considered fuzzy logic for applications related to this paper, including weather forecasting, transportation, resource allocation, and others (e.g., project prioritization and scheduling).

A. WEATHER FORECASTING

Various studies in the literature have evaluated the impact of weather variables on the transportation sector, in particular

TABLE 2. Recent literature on fuzzy logic.

Fuzzy Logic Applications	*Related Literature*
Weather forecasting	[7], [8], [16]
Transportation	[9], [10], [41]–[43]
Deployment/allocation of resources	[3], [11], [24], [25]
Other	[44]–[47]

the effects of such variables on roadways [2], [12], [20]. These studies concluded that different weather conditions significantly affect traffic operations, safety, traffic demand, traffic flow, and traffic intensity.

Various researchers make use of fuzzy logic to forecast weather variables. For example, one study described the development of a forecasting system based on a multi-network approach to evaluate data initiating from electronic sensors and satellite observations using fuzzy logic to calculate the probability of fog formation [7]. The study showed that the increased complexity of the global system required more data originating from different sources; nonetheless, it resulted in good reliability. It was concluded that the use of fuzzy logic was a potential tool for meteorological forecasting. The concept of a weather FIS is also presented in [8], where a fuzzy logic system was used to predict fog formation. The study revealed that dew point spread and rate of change were the most important factors to predict fog formation. The authors concluded that the use of a FIS could be a promising tool for fog forecasting. In [16], the authors used fuzzy logic to develop a weather event prediction system. Temperature, pressure, dew point, and humidity were used as weather parameters to predict the following weather events: clear weather, fog, scattered clouds, thunderstorm, partly clouds, rain, and rain-thunderstorm. Performance tests of the overall fuzzy system resulted in a 96.9% level of accuracy.

B. TRANSPORTATION

The literature shows various studies that use fuzzy logic to model complex traffic and transportation processes such as traffic control, vehicle routing, accident analysis, and vehicle scheduling. In [21], the authors present a comprehensive overview of literature on fuzzy logic systems used in traffic management, as well as a chronology of the evolution of the fuzzy models. The authors concluded that in most cases, fuzzy logic systems provide considerable improvements in the efficiency of traffic junctions' management compared to traditional adaptive and non-fuzzy systems. In [22], the authors presented a literature review and discussed potential applications of fuzzy logic in the transportation planning field (e.g., trip generation, trip distribution, modal splits, and route choice problem). The authors concluded that when dealing with highly complex non-linear transportation systems, the use of fuzzy logic could present a more effective and practical solution than other types of complex mathematical models.

Another example of an approach based on fuzzy logic includes the use of fuzzy set theory to develop safety inference rules for driving assistance maneuvers [16]. In this study, the authors developed a framework that can be used to comprehensively view and assess the crash risk for a set of driving maneuvers. The authors used fuzzy set theory to perform a risk evaluation of maneuvers such as driving on curves, overtaking, and lane changing. The main idea behind this research was that, given information about the driving situation and the knowledge about the driver's behavior, it was possible to infer the maneuvers that a driver was most likely to have performed. A fuzzy approach based on car velocity is proposed to model traffic flow and incident recognition [23]. The authors developed a fuzzy system for road-traffic evaluation using traffic volume and velocity as inputs. The authors verified the accuracy of the system by comparing the outputs of the system with experts who analyzed the traffic video. Results showed that the fuzzy logic system achieved 88.79% accuracy. However, the authors reported that the accuracy of fuzzy logic systems depends highly on how rules were defined.

C. DEPLOYMENT AND ALLOCATION OF RESOURCES

Various researchers have used fuzzy logic to develop models for optimal resource assignments. One example involves the application of fuzzy logic to assign four different vehicles to four different demands that needed to be satisfied [24]. The demands represented the input fuzzy variables of the system (load capacity, cargo space, type, and purpose). The system had one output, suitability. The output parameter of the system represented the suitability of each vehicle to a specific demand. The authors stated that the main advantage of the fuzzy approach was the much higher flexibility in the definition of demands. Another study proposed a methodology based on fuzzy logic to allocate resources in the manufacturing industry [25]. The purpose of this study was to extract valuable business rules by using genetic algorithm and fuzzy inferences techniques. The fuzzy inference model in this study had as output a parameter called "tardiness", which was defined as the absolute value of the difference between assigned due date of a certain test and actual completion date of that test. The inputs considered were: product, inter-arrival time, due date, and size. The results of the fuzzy system were used in the genetic algorithm to perform capacity allocations. Researchers have also used fuzzy logic to develop adaptive prioritization assignments, where a fuzzy reasoning-based algorithm was used to rank targets and sectors of surveillance in dynamically changing tactical environments [26]. The results suggested that the fuzzy approach was a valid means for evaluating the relative importance of tasks.

The related literature indicates that the impact of weather variables on roads, traffic flow, and operations is a significant matter of concern. Furthermore, the fuzzy set theory approach could be customized for the resource assignment problem in low visibility scenarios. The development of a framework based on fuzzy logic that can potentially assist transportation managers in assigning limited resources to low visibility areas is extremely appealing. A methodology that incorporates fog occurrence, road risk conditions, and priority of deployment as imprecise parameters has not yet been proposed in the literature.

III. BACKGROUND

Logic is the study of methods for reasoning. Classical logic relies on the premise that propositions are either true or false. On the other hand, fuzzy logic relies on the assumption that propositions are true to some degree. Thus, fuzzy logic allows logical reasoning with partially true imprecise statements [27]. This section provides a brief background of fuzzy logic concepts that are key in the understanding of the proposed framework.

A. FUZZY SETS AND MEMBERSHIP FUNCTIONS

Fuzzy logic allows reasoning for ambiguous, imprecise, and vague variables using linguistic terms (e.g., high, low) and associating each of them with a membership function (MF) to form a fuzzy set. MFs map elements from any universal set into real numbers. The resulting values represent the degrees of membership of elements to particular fuzzy sets. Degrees of membership are determined by MFs defined subjectively

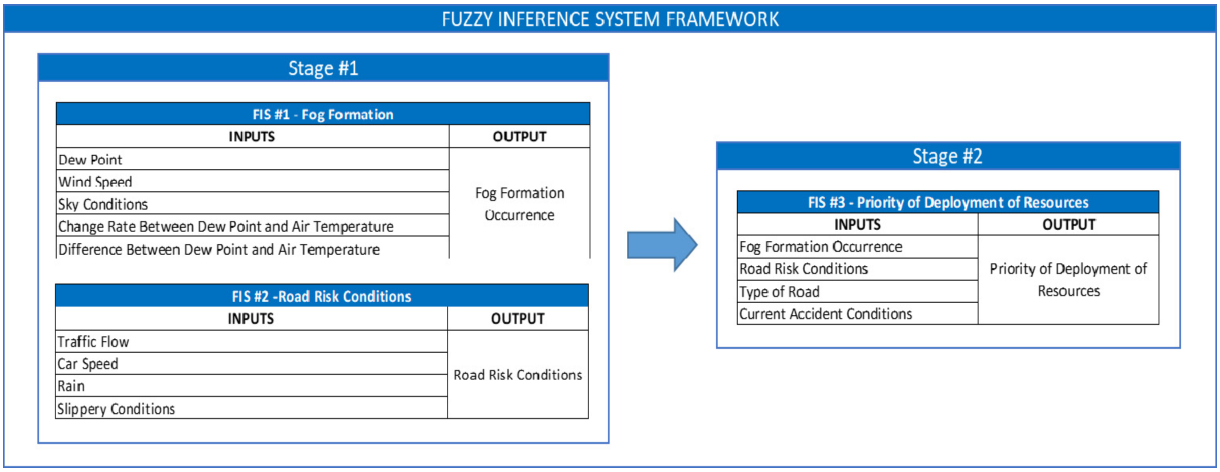

FIGURE 1. **Fuzzy inference system framework.**

based on approaches such as literature reviews and expert opinions.

B. FUZZY REASONING: IF-THEN RULES

Fuzzy sets are used to formulate conditional statements in the form of IF-THEN rules. These sets of rules are used to provide output responses in an inference system. The order of the rules does not affect output responses because they are all evaluated in parallel using fuzzy reasoning. A single fuzzy IF-THEN rule, where A and B are linguistic values defined by fuzzy sets based on established ranges for input_1 and output_1, has the form of:

$$\text{IF input\_1 IS } A, \quad \text{THEN output\_1 IS } B \tag{1}$$

The first part of the rule, (the IF part) is denoted as the antecedent, whereas the second part (the THEN part) is denoted as the consequent. The interpretation of a rule implicates that the reasoning is deduced in two parts. First, the antecedent needs to be evaluated, which involves fuzzifying the input and applying the necessary fuzzy operators. Second, the results of the antecedent evaluation are applied to the consequent.

Complex systems that are modeled with fuzzy logic usually involve more than one rule. The process of obtaining the overall consequent from the individual consequents contributed by each rule is known as aggregation [18]. Through the aggregation process, all the fuzzy sets that represent the output of every single rule are combined into a single fuzzy set.

C. MAMDANI INFERENCE SYSTEM

One of the most popular methods of deductive inference for fuzzy systems is the Mamdani approach. To illustrate this inference method, consider a two-rule system where each rule is composed of two antecedents and one consequent. A fuzzy system comprised of two inputs, $x1$ and $x2$, which represent the antecedents, and a single output, y, is described by a collection of n linguistics IF-THEN rules in the Mamdani form as: IF $x1$ IS $A1k$ and $x2$ IS $A2k$, THEN yk is Bk, for $k = 1, 2, \ldots,$ n where $A1k$ and $A2k$ are the fuzzy sets representing the kth antecedent pairs and Bk is the fuzzy set representing the kth consequent [28].

D. DEFUZZIFICATION

Defuzzification is the process of converting fuzzy sets obtained from the aggregation process into a single crisp value. The output is represented by the logical union of two or more fuzzy MFs. The input for this process is a fuzzy set, whereas the output is a single number. Several methods are available for defuzzification. Some of the most popular methods are the centroid and the weighted average methods [16].

IV. FUZZY INFERENCE SYSTEM FRAMEWORK

The proposed framework is composed of three fuzzy systems. The first FIS models fog occurrence. The second FIS models road risk conditions, and the last FIS models the priority of deployments of resources. As shown in Figure 1, the proposed framework can be viewed as a two-stage approach because the outputs of the first two fuzzy systems are inputs of the last FIS.

A. FIS PROCESS

This section describes the stepwise flow of the data within the FIS framework, which involves five steps: fuzzification of user inputs, application of fuzzy operators, implication method, aggregation of outputs, and defuzzification.

1) PRE-CONDITIONS

Following the solution approach suggested by [26], three pre-conditions need to be satisfied. First, decision-makers must agree on a crisp rating scale of the parameters of each FIS. Second, linguistic terms must be established to denote the levels of these parameters. Third, fuzzy sets must be created for each linguistic term to determine the degrees of membership of crisp values in each fuzzy set.

TABLE 3. Inputs and outputs of the fog occurrence FIS.

Input Name	Description	Fuzzy Sets	Crisp Range
Inputs			
Dew Point	Temperature at which water vapor in the air condenses.	Dry Medium Wet Very Wet	10F – 70F
Wind Speed	Wind flow caused by air moving from high pressure to low pressure.	Light Medium Strong	0Kn – 16Kn
Sky Conditions	Numerical description of sky conditions where the lower the input the clearer the sky.	Light Medium	0 – 100
Change Rate Between Dew Point and Air Temperature	Numerical value that indicates if the atmosphere shows a saturating trend (negative rate) or a drying trend (positive rate).	Saturating Drying	-5F/hr – 10F/hr
Difference Between Dew Point and Air Temperature	The number of degrees of difference between the air temperature and the dew point.	Saturated Moderate Unsaturated	-5F – 15F
Output			
Fog Formation Occurrence	Numerical value that indicates the likelihood of fog formation where the lower the value the less likely.	Very Low Low Medium High Very High	0 – 100

2) STEP 1: FUZZIFICATION OF USER INPUTS

The first step involves converting crisp quantities into fuzzy ones based on their respective membership functions. This conversion process is known as fuzzification.

3) STEP 2: APPLICATION OF FUZZY OPERATORS

After the inputs have been fuzzified, the antecedent of the fuzzy if-then rule is known. In general, the antecedent of a given rule has more than one part. The fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. The fuzzy operators are the Boolean Operators AND, NOT, and OR.

4) STEP 3: IMPLICATION METHOD AND FUZZY RULES

Before analyzing the implication from the antecedent to the consequent, the weight of each rule is determined. The weight of each rule varies between 0 and 1. The input of the implication method is a single number, truth-value obtained from the application of the fuzzy operators, whereas the output is a fuzzy set. Based on a set of pre-determined fuzzy rules, the system evaluates each parameter set to make inferences about its fuzzy effect in a specified output.

5) STEP 4: AGGREGATION OF OUTPUTS

Decisions are based on the testing of all the rules in a FIS; thus, all of the rules must be combined in order to obtain a single fuzzy set. Through the aggregation process all of the fuzzy sets that represent the output of every single rule are combined into a single fuzzy set.

6) STEP 5: DEFUZZIFICATION

The framework employs the centroid defuzzification method to convert the fuzzy sets into crisp values.

B. FIS MODELS

This section provides a description of the three FIS of the proposed framework. The selection of input variables and definition of the MFs were based on results from the literature review effort. The resulting FIS models were developed using the Mamdani approach.

1) FOG OCCURRENCE FIS

This FIS consists of a single output (i.e., fog occurrence) and five input variables (i.e., dew point, wind speed, sky condition, difference between dew point and air temperature, and change rate between the difference of the dew point and air temperature). The inputs were carefully chosen after reviewing the literature related to fog formation. Several studies agree that dew point spread and rate of change of dew-point are the most important parameters for the formation of fog ([5], [7], [8]). The studies also highlight that wind and sky conditions play an important role in fog formation. Table III shows the inputs, output, corresponding fuzzy sets, and crisp ranges for each parameter of the fog occurrence FIS. There are four sets associated with dew point, three with wind speed, two with sky condition, two with change rate between the air temperature and dew point, and three with the difference between the air temperature and dew point. Thus, the total number of rules that define this system is $4 \times 3 \times 2 \times 2 \times 3 = 144$. The rules are defined in such a way that the

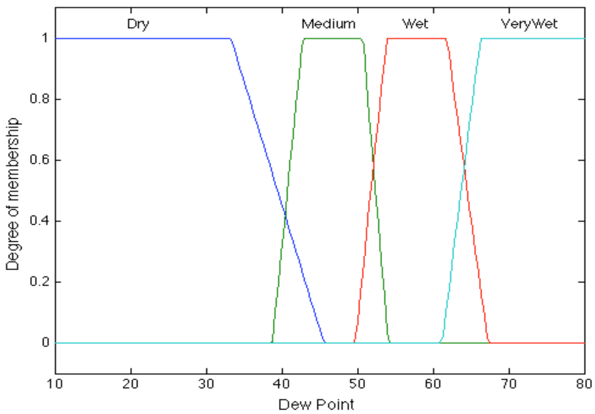

FIGURE 2. Fuzzy sets for dew point.

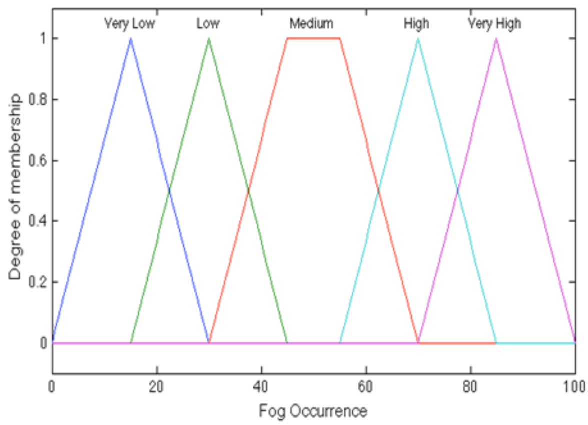

FIGURE 3. Fuzzy sets for fog occurrence.

output "fog occurrence" will belong to the fuzzy set "Very High" if the following conditions apply: dew point is "Very Wet"; wind speed is "Light"; sky condition is "Clear"; change rate is "Saturating"; and difference between air temperature and dew point is "Saturated". Figure 2 shows the corresponding fuzzy sets for dew point, while Figure 3 shows the fuzzy sets for the output of the system, fog occurrence.

2) ROAD RISK CONDITIONS FIS

The second FIS is composed of a single output (i.e., road risk conditions) and four input variables (i.e., traffic flow, car speed, rain, and slippery conditions). Based on academic literature (e.g., ([1], [2], [5], [9]), traffic flow, car speed, rain and road conditions are significant parameters of roads. Collision risk usually increases during precipitation [20]. Moreover, studies have shown that drivers tend to underestimate the slipperiness of a road they are driving on, driving at speeds higher than the speed limit and considering it safe ([1], [2]). Table IV shows the inputs and output of this FIS, and the corresponding fuzzy sets and crisp ranges of each parameter. There are four fuzzy sets associated with traffic flow, three with car speed, four with rain, and two with road conditions. Therefore, the total number of rules that define this system is $4 \times 3 \times 4 \times 2 = 96$. The rules are defined in such a way that the output "Road Risk Conditions" will belong to the set "Very High" if the following conditions apply: traffic flow is "Very Heavy"; car speed is "Fast"; rain is "Heavy Rain"; and road conditions is "Slippery". Figures 4 and 5 show the corresponding fuzzy

TABLE 4. Inputs and outputs of the road risk conditions FIS.

Inputs			
Input Name	***Description***	***Fuzzy Sets***	***Crisp Range***
Traffic Flow	Numerical description of traffic severity.	Light	0 – 100
		Normal	
		Light Heavy	
		Heavy	
Car Speed	Numerical description of the average car speed where the lower the input, the slower the speed.	Slow	0 mi/h – 100 mi/h
		Medium	
		Fast	
Rain	Numerical description of rain conditions where low values indicate no rain or light rain, while high values indicate rain occurrence.	No Rain	0 – 100
		Light Rain	
		Rain	
		Heavy Rain	
Slippery Conditions	Numerical description of how slippery a road is where the lower the value, the less slippery.	Not Slippery	0 – 100
		Slippery	
Output			
Road Risk Conditions	Numerical value that indicates the risk conditions of a road where the lower the value the less risky.	Very Low	0 – 100
		Low	
		Medium	
		High	
		Very High	

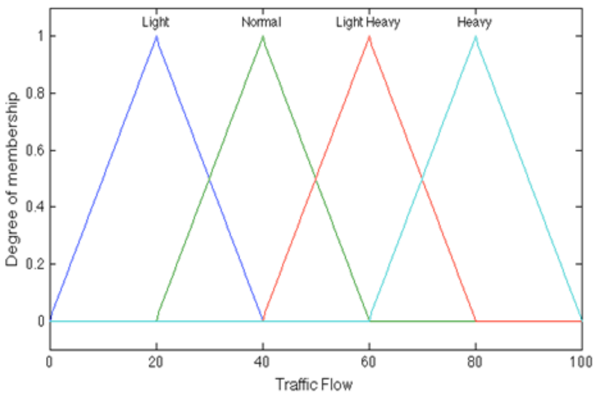

FIGURE 4. Fuzzy sets for traffic flow.

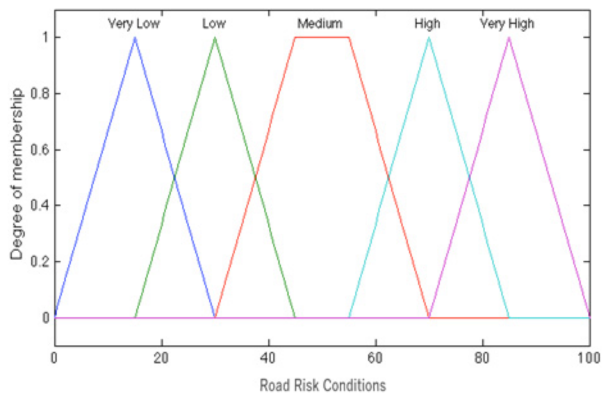

FIGURE 5. Fuzzy sets for road risk conditions.

sets for the traffic flow input and road risk conditions output.

3) PRIORITY OF DEPLOYMENT FIS

The third and last FIS consists of a single output (i.e., priority of deployment of resources) and four input parameters (i.e., fog formation occurrence, road risk conditions, type of road, and the current accident conditions of the road). Note that two of the inputs are the outputs of the previous two fuzzy inference systems, fog occurrence and accident occurrence. The type of road, which refers to the priority and traffic flow on the road, is composed of the following three fuzzy sets: principal arterial, minor arterial, and local arterial. The ‘‘current accident conditions’’ input considers unexpected accidents such as pileup and vehicle crashes. Table V shows the inputs and output of this system and the corresponding 56 fuzzy sets and ranges of each parameter. There are five fuzzy sets associated with fog occurrence, five with road risk conditions, three with type of road, and two with current conditions of the road. The total number of rules that define this system is $5 \times 5 \times 3 \times 2 = 150$. The rules are defined in such a way that if the four inputs have the values shown in

TABLE 5. Inputs and outputs of the priority of resources deployment FIS.

Inputs			
Input Name	***Description***	***Fuzzy Sets***	***Crisp Range***
Fog Formation Occurrence	Numerical value that indicates the likelihood of fog formation where the lower the value the less likely.	Very Low Low Medium High Very High	0 – 100
Road Risk Conditions	Numerical value that indicates the risk conditions of a road where the lower the value the less risky.	Very Low Low Medium High Very High	0 – 100
Type of Road	Numerical value that describes the hierarchy of the road according to its function and capabilities.	Local Arterial Minor Arterial Principal Arterial	0 – 100
Current Accident Conditions	Numerical value that describes the current accident conditions of the road. The higher the value, the higher the severity of an accident, e.g., a multiple-vehicle collision. Low values indicate no accidents at all or a minor single vehicle accident low.	Normal Accident	0 – 100
Output			
Priority of Resources Deployment	Numerical value that indicates the priority of resources deployment where low values indicate low priority, while high values (>75) indicate critical priority	Low Moderate High Critical	0 – 100

TABLE 6. Rules when the priority of deployment is critical.

Rules				
Fog Occurrence	*Road Risk Conditions*	*Type of Road*	*Current Accident Conditions*	*Priority*
Very High	High	Principal	Accident	Critical
Very High	Very High	Local	Accident	Critical
Very High	Very High	Minor	Accident	Critical
Very High	Very High	Principal	Accident	Critical

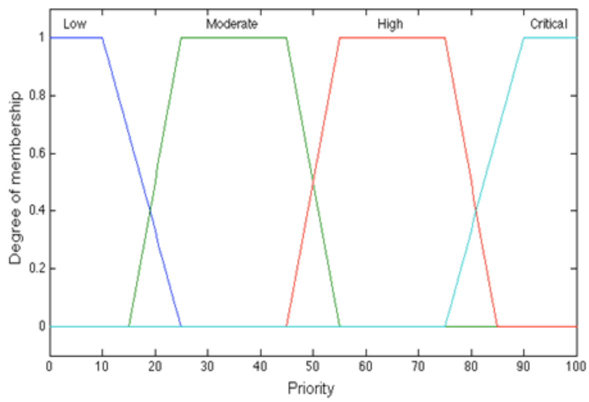

FIGURE 6. Fuzzy sets for priority of deployment.

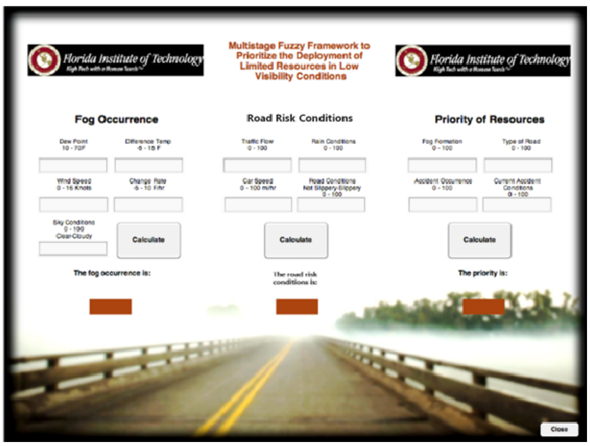

FIGURE 7. Fuzzy inference system interface.

Table VI, the output (i.e., priority of resource deployments) will belong to the "Critical" fuzzy set. Figure 6 shows the fuzzy sets for the output variable of this FIS.

V. DEMONSTRATION OF THE FRAMEWORK

The model was developed using the Fuzzy Logic Toolbox of MATLAB. A graphical user interface, shown in Figure 7, was created using GUIDE (Graphical User Interface Developing Environment) of MATLAB. This section shows the functionality of the three fuzzy systems of the framework. For the fog occurrence FIS, the crisp values of the inputs are shown in Table VII. For these values, the dew point input belongs to the "Very Wet" MF, and the wind speed input partially belongs

TABLE 7. Inputs for the fog occurrence FIS.

Inputs				
Dew Point	*Wind Speed*	*Sky Condition*	*Change Rate*	*Difference Between Temperatures*
70	6	9	2	3

TABLE 8. Inputs for the road risk conditions FIS.

Inputs			
Traffic Flow	*Car Speed*	*Rain*	*Slippery Conditions*
75	65	80	70

TABLE 9. Inputs for the priority of resource deployments FIS.

Inputs			
Fog Formation	*Road Risk Conditions*	*Type of Road*	*Current Accident Conditions*
85	77.5	65	55

to the "Light" MF. The sky condition input fully belongs to the "Clear" MF, the change rate between the dew point and the air temperature input partially belongs to both the "Saturated" and "Drying" MFs, and the difference between the dew point and the air temperature input fully belongs to the "Saturated" MF. Based on the defined fuzzy sets, these input values should produce a fog occurrence output that belongs to the "High" or "Very High" MFs. The fog occurrence is 85, a value that fully belongs to the "Very High" MF. For this case, only two rules of the entire set of 144 rules have non-zero values. The dew point, wind speed, sky conditions, and difference between temperatures each involve one fuzzy set, whereas change rate involves two fuzzy sets ($1 \times 1 \times 1 \times 2 \times 1 = 2$).

The input variables for the "Road Risk Conditions" fuzzy system are shown in Table VIII. The input value for traffic flow partially belongs to the "Light Heavy" and "Heavy" MFs. The input value for car speed partially belongs to the "Medium" and "Fast" MFs. The value for the rain input fully belongs to the "Heavy Rain" MF, while the value for road conditions fully belongs to the "Slippery" MF. Based on the defined fuzzy sets, these input values should produce an output that partially belongs to the "High" and "Very High" MFs of road risk conditions. The output of the system indicates a value of 77.5. Only four rules of the entire set of 96 rules have non-zero values. Traffic flow and car speed each involves two fuzzy sets, whereas rain and slippery conditions involve a single fuzzy set ($2 \times 2 \times 1 \times 1 = 4$).

The input variables of the last FIS are shown in Table IX. The input value for fog formation fully belongs to the "Very High" MF, while the road risk conditions input partially belongs to the "High" and "Very High" MFs. The input value for the type of road partially belongs to the "Principal

TABLE 10. Performance scores – Station: Melbourne Airport.

H	F	M	BIAS	Accuracy
947	52	97	1.045	0.864

TABLE 11. Performance scores – Station: Orlando Airport.

H	F	M	BIAS	Accuracy
767	138	191	1.059	0.700

Arterial'' MF, and the current accident conditions input partially belongs to both the ''Normal'' and ''Accident'' MFs. Under the considered scenario, the resources' deployments output has a priority value of 80.39 out of 100, partially belonging to the ''High'' and ''Critical'' MFs. Out of the entire set of 150 rules, only four have non-zero values. Fog occurrence and type of road involve one fuzzy set, while road risk conditions and current accident conditions involve two fuzzy sets ($1 \times 2 \times 2 \times 1 = 4$).

A. PERFORMANCE OF THE FOG OCCURRENE FIS

This section evaluates the performance of the fog occurrence FIS. Local climatological data (LCD) collected from two land-based stations located in Florida were retrieved from the National Oceanic and Atmospheric Administration (NOAA) website. For both stations, 1096 cases (i.e., observations) of fog were evaluated. Each observation was composed of five input features, i.e., dew point, wind spend, sky condition, change rate, and difference between temperatures. If the output of an observation corresponded to a value belonging to either the ''high'' or the ''very high'' fuzzy set, then that scenario had forecasted fog occurrence. Furthermore, a BIAS score was calculated for both datasets. The bias score indicates whether the forecast system has a tendency to under-forecast (if it is less than the unity) or over-forecast (if it is greater than one). Equation (2) depicts the BIAS score where H is the number of hits (i.e., events forecast correctly), F is the number of false alarms (i.e., events forecasted to occur, but did not occur) and M is the number of missing alarms (i.e., events forecasted to not occur, but did occur).

$$BIAS = \frac{H + F}{H + M} \tag{2}$$

Both the accuracy and the bias skill score for the two stations are shown in Tables X and XI. These tables show promising results from the FIS, with the forecasts being slightly bias towards over-forecast (i.e., BIAS scores are greater than 1). The results also show that the proposed fog FIS performs better with data from the Melbourne Airport Station. Thus, modification of the membership functions and/or the fuzzy rules may lead to better results of the framework for the Orlando dataset. Furthermore, as an attempt to show the effectiveness of the proposed fog occurrence FIS, the authors investigated the performance of previous proposed studies. However, it is important to mention that the results of each method will vary depending on the dataset used.

TABLE 12. Skill scores from [8].

H	F	M	BIAS
178	20	30	0.95
41	10	11	0.98

TABLE 13. Accuracy results of other studies.

Method	Average Accuracy%
Naïve Bayes [14]	79.02%
SVM [14]	86.01%
ANN [14]	89.71%
Decision Tree [30]	77.00%

The skill scores of a fog forecasting approach using a rule-based FIS are shown in Table XII [8]. The BIAS scores indicate that the model is bias towards under-forecast. In addition, the number of samples used is smaller than the one used in this paper, and no accuracy scores were reported. In [14], the authors used machine learning algorithms to classify visibility into three classes: low visibility, moderate visibility, and good visibility. The average accuracy of these three approaches to forecast visibility is shown in Table XIII. This table also shows the accuracy of another study that employed a decision tree approach to forecast the occurrence of sea fog [29]. As shown in Table XIII, the fuzzy model proposed in this paper for fog occurrence was able to achieve better results than three other methods.

VI. CONCLUSION AND FUTURE RESEARCH

This paper presents a fuzzy system framework for detecting fog occurrence, determining road risk conditions, and determining the priority of deployment of resources under certain conditions. Preliminary experiments to evaluate the developed fog occurrence FIS against four methods presented in the literature using data from two weather stations showed that the FIS model outperformed three of the other methods in accuracy. These results are very promising given that the other methods represent more expensive solution approaches that require large amounts of data, significant time-consuming data preparation, network architecture design tasks, and high processing power.

There are two major contributions that this paper makes to the transportation decision-making body of knowledge. The first significant contribution is the full incorporation of imprecise parameters in this transportation application related to resource assignments in low visibility scenarios. The parameters used in the framework are considered to be naturally imprecise and they are defined using fuzzy concepts. The use of fuzzy logic provides decision makers the flexibility to add, modify or even delete parameters and MFs based on their particular needs without having to incur in expensive architectural system modifications of the framework.

The second significant contribution from this work is the approach used to determine the priority of resource deployments in low visibility conditions, which takes into consideration fog as well as and road conditions. This framework represents a significant contribution to the academic literature. As future research, models for performance analysis of road risk conditions and deployment of resources should be considered. In addition, different weights of the fuzzy rules and membership functions may be considered to improve the overall performance of the proposed framework.

In order to bridge the gap between theory and field implementation, it may be necessary to re-design the software interface prototype developed in MATLAB (see Figure 7) to facilitate the implementation of the proposed solution approach for practical purposes. Critical to this step will be a robust requirements engineering approach to ensure that critical functional needs are incorporated into the proposed solution [48], [49].

REFERENCES

[1] *Low Visibility*, USDOT Federal Highway Admin., Washington, DC, USA, 2017.
[2] T. H. Maze, M. Agarwal, and G. Burchett, "Whether weather matters to traffic demand, traffic safety, and traffic operations and flow," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1948, no. 1, pp. 170–176, 2006.
[3] L. D. Otero, G. Centeno, A. J. Ruiz-Torres, and C. E. Otero, "A systematic approach for resource allocation in software projects," *Comput. Ind. Eng.*, vol. 56, no. 4, pp. 1333–1339, May 2009.
[4] N. E. Fenton and M. Neil, "A critique of software defect prediction models," *IEEE Trans. Softw. Eng.*, vol. 25, no. 5, pp. 675–689, Sep./Oct. 1999.
[5] L. Musk, "Climate as a factor in the planning and design of new roads and motorways," in *Highway Meteorology*, L. J. Perry and A. H. Symons, Eds. London, U.K.: Spon Press, 1990.
[6] P. O. Wanvik, "Effects of road lighting: An analysis based on dutch accident statistics 1987–2006," *Accident Anal. Prevention*, vol. 41, no. 1, pp. 123–128, Jan. 2009.
[7] E. Pasero, W. Moniaci, and T. Meindl, "Intelligent systems for meteorological events forecast," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, vol. 5, Jul. 2005, pp. 2686–2688.
[8] A. K. Mitra, S. Nath, and A. K. Sharma, "Fog forecasting using rule-based fuzzy inference system," *J. Indian Soc. Remote Sens.*, vol. 36, no. 3, pp. 243–253, Mar. 2009.
[9] D. Teodorović, "Fuzzy logic systems for transportation engineering: The state of the art," *Transp. Res. A, Policy Pract.*, vol. 33, no. 5, pp. 337–364, Jun. 1999.
[10] H. Malik, G. S. Larue, A. Rakotonirainy, and F. Maire, "Fuzzy logic to evaluate driving maneuvers: An integrated approach to improve training," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1728–1735, Aug. 2015.
[11] P. Wanke, H. Alvarenga, H. Correa, A. Hadi-Vencheh, and M. A. K. Azad, "Fuzzy inference systems and inventory allocation decisions: Exploring the impact of priority rules on total costs and service levels," *Expert Syst. Appl.*, vol. 85, pp. 182–193, Nov. 2017.
[12] M. J. Koetse and P. Rietveld, "The impact of climate change and weather on transport: An overview of empirical findings," *Transp. Res. D, Transp. Environ.*, vol. 14, no. 3, pp. 205–221, May 2009.
[13] D. Teodorovic and M. Janic, *Transportation Engineering: Theory, Practice and Modeling*. Portsmouth, NH, USA: Heinemann, 2016.
[14] L. Ortega, L. D. Otero, and C. Otero, "Application of machine learning algorithms for visibility classification," in *Proc. IEEE Int. Syst. Conf. (SysCon)*, Apr. 2019, pp. 1–5.
[15] J. R. Colquhoun, "A decision tree method of forecasting thunderstorms, severe thunderstorms and tornadoes," *Weather Forecasting*, vol. 2, no. 4, pp. 337–345, Dec. 1987.
[16] M. S. K. Awan and M. M. Awais, "Predicting weather events using fuzzy rule based system," *Appl. Soft Comput.*, vol. 11, no. 1, pp. 56–63, Jan. 2011.
[17] G. Klir and B. Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, 1st ed. Upper Saddle River, NJ, USA: Prentice-Hall, 1995.
[18] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965.
[19] K. Abhishek, M. Singh, S. Ghosh, and A. Anand, "Weather forecasting model using artificial neural network," *Procedia Technol.*, vol. 4, pp. 311–318, Jan. 2012.
[20] M. Cools, E. Moons, and G. Wets, "Assessing the impact of weather on traffic intensity," *Weather, Climate, Soc.*, vol. 2, no. 1, pp. 60–68, Jan. 2010.
[21] M. Koukol, L. Zajčková, L. Marek, and P. Tuček, "Fuzzy logic in traffic engineering: A review on signal control," *Math. Problems Eng.*, vol. 2015, 2015, Art. no. 979160.
[22] A. Sarkar, G. Sahoo, and U. C. Sahoo, "Application of fuzzy logic in transport planning," *Int. J. Soft Comput.*, vol. 3, no. 2, pp. 1–21, 2012.
[23] P. Pongpaibool, P. Tangamchit, and K. Noodwong, "Evaluation of road traffic congestion using fuzzy techniques," in *Proc. IEEE Region 10 Conf. (TENCON)*, Oct. 2007, pp. 1–4.
[24] M. Moškon, Š. Novak, M. Medeot, I. L. Bajec, N. Zimic, and M. Mraz, "Solving the logistic problems with optimal resource assignment using fuzzy logic methods," *J. Adv. Transp.*, vol. 47, no. 4, pp. 447–460, Jun. 2013.
[25] K.-J. Wang, Y.-S. Lin, C.-F. Chien, and J. C. Chen, "A fuzzy-knowledge resource-allocation model of the semiconductor final test industry," *Robot. Comput.-Integr. Manuf.*, vol. 25, no. 1, pp. 32–41, Feb. 2009.
[26] J. Teixeira and P. M. A. Miranda, "Fog prediction at Lisbon airport using a one-dimensional boundary layer model," *Meteorol. Appl.*, vol. 8, no. 4, pp. 497–505, 2001.
[27] L. D. Otero, "A framework for resource assignments in skill-based environments," Tech. Rep., 2009.
[28] T. J. Ross, *Fuzzy Logic With Engineering Applications*, 3rd ed. Hoboken, NJ, USA: Wiley, 2010.
[29] B. L. Lindner, P. Mohlin, A. C. Caulder, and A. Neuhauser, "Development and testing of a decision tree for the forecasting of sea fog along the georgia and South Carolina coast," *J. Oper. Meteorol.*, vol. 6, pp. 47–58, Jun. 2018.
[30] R. L. Vislocky and J. M. Fritsch, "An automated, observations-based system for short-term prediction of ceiling and visibility," *Weather Forecasting*, vol. 12, no. 1, pp. 31–43, 1997.
[31] J. L. Hilliker and J. M. Fritsch, "An observations-based statistical system for warm-season hourly probabilistic forecasts of low ceiling at the San Francisco International Airport," *J. Appl. Meteorol.*, vol. 38, no. 12, pp. 1692–1705, 1999.
[32] H. Almuallim, S. Kaneda, and Y. Akiba, "Development and applications of decision trees," in *Expert Systems*, no. 1. Amsterdam, The Netherlands: Elsevier, 2002, pp. 53–77.
[33] F. Wantuch, "Visibility and fog forecasting based on decision tree method," in *Journal of the Hungarian Meteorological Service*, vol. 105. Hungary: Idojaras, 2001, pp. 29–38.
[34] J. Murtha, "Applications of fuzzy logic in operational meteorology," in *Scientific Services and Professional Development Newsletter, Canadian Forces Weather Service*. 1995, pp. 42–54.
[35] S. Sujitjorn, P. Sookjaras, and W. Wainikorn, "An expert system to forecast visibility in Don-Muang air force base," in *Proc. IEEE Int. Conf. Syst., Man, Humans, Inf. Technol.*, vol. 3, Oct. 1994, pp. 2528–2531.
[36] A. M. Durán-Rosal, J. C. Fernández, C. Casanova-Mateo, J. Sanz-Justo, S. Salcedo-Sanz, and C. Hervás-Martínez, "Efficient fog prediction with multi-objective evolutionary neural networks," *Appl. Soft Comput.*, vol. 70, pp. 347–358, Sep. 2018.
[37] A. Pasini, V. Pelino, and S. Potestà, "A neural network model for visibility nowcasting from surface observations: Results and sensitivity to physical input variables," *J. Geophys. Res., Atmos.*, vol. 106, no. D14, pp. 14951–14959, 2001.
[38] J. B. Bremnes and S. C. Michaelides, "Probabilistic visibility forecasting using neural networks," in *Fog and Boundary Layer Clouds: Fog Visibility and Forecasting*. Springer, 2007, pp. 1365–1381.
[39] G. Mountrakis, J. Im, and C. Ogole, "Support vector machines in remote sensing: A review," *ISPRS J. Photogramm. Remote Sens.*, vol. 66, no. 3, pp. 247–259, 2011.
[40] T. R. Patil and S. S. Sherekar, "Performance analysis of Naive Bayes and J48 classification algorithm for data classification," *Int. J. Comput. Sci. Appl.*, vol. 6, no. 2, pp. 256–261, 2013.
[41] M. Ridwan, "Fuzzy preference based traffic assignment problem," *Transp. Res. C, Emerg. Technol.*, vol. 12, nos. 3–4, pp. 209–233, Jun. 2004.

[42] A. Hegyi, B. De Schutter, S. Hoogendoorn, R. Babuska, H. van Zuylen, and H. Schuurman, "A fuzzy decision support system for traffic control centers," in *Proc. IEEE Intell. Transp. Syst. (ITSC)*, Aug. 2001, pp. 358–363.
[43] F. Milla, D. Saez, C. E. Cortes, and A. Cipriano, "Bus-stop control strategies based on fuzzy rules for the operation of a public transport system," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 1394–1403, Sep. 2012.
[44] E. E. Karsak, "Fuzzy multiple objective programming framework to prioritize design requirements in quality function deployment," *Comput. Ind. Eng.*, vol. 47, nos. 2–3, pp. 149–163, Nov. 2004.
[45] L. Yang and B. Liu, "A multi-objective fuzzy assignment problem: New model and algorithm," in *Proc. 14th IEEE Int. Conf. Fuzzy Syst. (FUZZ)*, May 2005, pp. 551–556.
[46] P. Lorterapong and O. Moselhi, "Project-network analysis using fuzzy sets theory," *J. Construct. Eng. Manage.*, vol. 122, pp. 308–318, Dec. 1996.
[47] L. D. Otero and C. E. Otero, "A fuzzy expert system architecture for capability assessments in skill-based environments," *Expert Syst. Appl.*, vol. 39, no. 1, pp. 654–662, Jan. 2012.
[48] A. Ejnioui, C. E. Otero, and L. D. Otero, "A simulation-based fuzzy multi-attribute decision making for prioritizing software requirements," in *Proc. ACM Res. Inf. Technol. (RIIT)*, 2012.
[49] A. Ejnioui, C. E. Otero, and L. D. Otero, "Prioritisation of software requirements using grey relational analysis," *Int. J. Comput. Appl. Technol.*, vol. 47, no. 2–3, 2013.

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