Advances in Fuzzy Systems

Applications of Fuzzy Multicriteria Decision Making to Complex Engineering Problems

Lead Guest Editor: Hanbo Zheng
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Editorial Board

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Editorial

Applications of Fuzzy Multicriteria Decision Making to Complex Engineering Problems

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As a major research topic of decision making, multicriteria decision making (MCDM) has extensive applications in practical decision making. It is a modeling and methodological tool for dealing with complex engineering problems. Decision makers need to solve many issues with incomplete and uncertain information in the MCDM problems. The MCDM is dealing with structuring and solving decision and planning problems involving multiple criteria to support decision-makers. Typically, there does not exist a unique optimal solution for such problems, and the decision-maker usually differentiates the solutions based on their tools, in which fuzzy set theory plays an important role.

The fuzzy set theory is recognized as an important technique for problem modeling and solving. Fuzzy sets were introduced by Zadeh in 1965 as the extension of the classical notion of sets [1]. Almost all early interests in fuzzy set theory pertained to representing uncertainty in human cognitive processes, and now the fuzzy set theory has been extended to problems in engineering, business, medical and related health sciences, and the natural sciences [2, 3].

The MCDM has been broadly used in the world and more theories were proposed to solve the MCDM problems, such as the paper by R. Liao and H. Zheng et al. introduced an integrated model based on the fuzzy theory and evidential reasoning decision-making approach to the condition assessment of power transformers [4]. Their experimental results indicated that the integrated model could accurately assess the operating conditions of power transformers. Hence, this integrated method can be regarded as a radical innovation in the monitoring of electric devices. Another successful application of MCDM is in the face recognition. Ramalingam described an application of MCDM for multimodal fusion of features in a 3D face recognition system [5]. The fuzzy interval-valued TOPSIS (IVFT) approach for fusing multimodal features in a 3D face recognition system was proposed, which significantly improved recognition accuracy.

This special issue collects eight papers involved in the MCDM, which is in accordance well with the main features summarized above. Their investigations were applied to diverse disciplines (electrical engineering, computer science, economics, transportation, and gemstone identification) to assist the decision-makers to make the optimal choice.

First, the paper by N. A. Sedova et al. provides a neural-fuzzy approach to solve the problem of ship collision prevention in a heavy traffic zone. The authors presented the technique of using a maneuvering board to form the elements of learning samples by generating 192 different simulating models of neural fuzzy ship collision prevention systems through the lattice-free clustering method, as well as 288 neural-fuzzy ship collision prevention systems, where the network was generated through the subclustering method. Simulation studies show that the hybrid optimization method has the best performance. The testing of the most effective neural-fuzzy ship collision prevention systems proved that they can accurately determine the value of changing the ship-operator course to avoid the ship collision.

Next paper by B. Erdebilli et al. entitled "Using Intuitionistic Fuzzy TOPSIS in Site Selection of Wind Power Plants in Turkey" discussed how to select an appropriate site to build a wind power plant. They employed the TOPSIS method

combined with the intuitionistic fuzzy numbers which are reflecting the judgments of decision makers and dealing with the complexity in the decision process, so that more accurate results can be achieved. Wind potential, location, cost, and social benefits were defined as the dimension of criterion, and the ten selected criteria were collected under these dimensions. The weights of the criterion importance were decided in the establishment of the wind power plant and the selection was made. Based on the calculated data, the most appropriate site for the wind farm was determined.

A. Guleria and R. K. Bajaj in the paper entitled "Pythagorean Fuzzy (R, S)-Norm Information Measure for Multicriteria Decision-Making Problem" propose a new parametric (R, S)-norm information measure for Pythagorean fuzzy set along with the proof of its validity and discuss its maximality and the monotonic behavior with respect to parameters under consideration. Further, an algorithm for the MCDM problem has been proposed and implemented with the help of two different kinds of numerical examples where weights are partially known or entirely unknown. Finally, the work has been concluded by providing the scope for future work.

The study by H. Hui et al. entitled "Ultra-Short-Term Prediction of Wind Power Based on Fuzzy Clustering and RBF Neural Network" shows that the precision of predicts wind generation by using fuzzy clustering and RBF neural networks. The power output of the wind farm is affected by, for example, wind speed, wind direction, the tail flow effect of units, and so on. Each unit's output has a certain influence on the others. According to the output of the wind turbines and the uncertain relationship between these factors, fuzzy clustering and RBF neural network are combined to establish a two-step prediction model. Different contributions of the wind turbines at different spatial positions to the power of wind farm and the correlation of wind power time series are also considered. Compared to the ARIMA forecast model and single RBF model, it was verified that the two-step forecasting method can effectively improve the precision in the ultra-short-term power prediction.

A. Janjic in the paper entitled "Distribution Network Risk Assessment Using Multicriteria Fuzzy Influence Diagram" proposes a new methodology for the multicriteria risk assessment of the distribution network assets, based on influence diagrams and fuzzy probabilities. The influence diagram has been used to determine all relevant factors concerning risks and their interdependencies. And the fuzzy probabilities are represented by triangular fuzzy numbers with constraints on the feasibility of elicited probabilities. This methodology enables the decision process in an uncertain environment, with the impact evaluation of each particular distribution asset or the asset component. The methodology was verified by the case study of selecting the maintenance strategy of distribution substation circuit breakers.

M. S. D. Putra et al. in the paper entitled "Fuzzy Analytical Hierarchy Process Method to Determine the Quality of Gemstones" utilized a fuzzy analytical hierarchy process (F-AHP) method to choose and assess the quality of gemstones to be traded. It is well known that the gemstone identification needs not only relevant professional knowledge but also abundant experience. By using the F-AHP method, the decision-maker can make more efficient, flexible, and realistic decisions based upon the available criteria and alternatives.

A. Basu and S. Ghosh in the paper entitled "Implementing Fuzzy TOPSIS in Cloud Type and Service Provider Selection" use multicriteria decision-making method to find out the best service provider among the top existing four companies and choose the deployment model as per requirement. As one of the leading-edge technological advances in the IT industry, cloud computing has been extensively applied to various industries. However, consumers often face difficulties in selecting the most suitable one from numerous cloud providers as per their requirements. This paper analyzes different criteria for choosing the suitable service provider along with the deployment model using the MCDM concept. The evaluation is carried out by using the technique for order preference by similarity to an ideal solution (TOPSIS) method. The MCDM method helps decision makers in integrating objective measurements with value judgments based on collective group ideas other than individual opinions. The best alternative is deduced based on the shortest distance from the fuzzy positive ideal solution and farthest distance from the fuzzy negative ideal solution.

The study by T. O. Fahad and A. A. Ali entitled "Multiobjective Optimized Routing Protocol for VANETs" adopts an optimized integrated multicast, multicriteria, adaptive route lifetime as a routing protocol for VANETs, whereby only an optimal subset of neighbor vehicles is chosen to relay route request (RREQ) messages based on distance, direction, speed, and future direction information in a combined sender-receiver manner. Fuzzy controllers were employed to assess routes' costs and their lifetimes. Furthermore, artificial bee colony (ABC) algorithm was used to concurrently optimize all used fuzzy systems and obtain the optimal highest rank of links' cost values within which the neighbors could be selected as relay nodes in a route discovery process. And the simulation results prove that the proposed routing scheme significantly improves the network performance in both urban and highway scenarios, under different situations of vehicle density.

Conflicts of Interest

The editors declare that they have no conflicts of interest regarding the publication of the special issue.

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Research Article

Multiobjective Optimized Routing Protocol for VANETs

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Guest Editor: Jiefeng Liu

Vehicular ad hoc network (VANET) routing protocols have been attracting a considerable attention of both research and industrial communities, due to their significant role in intelligent transportation system applications. The present paper adopts an optimized integrated multicast, multicriteria, adaptive route lifetime as a routing protocol for VANETs. Whereby only an optimal subset of neighbor vehicles is chosen to relay route request (RREQ) messages based on distance, direction, speed, and future direction information in a combined sender-receiver manner. Among those selected optimal paths for route discovery, the best route with lowest cost will be chosen for forwarding data packets for a specified duration assigned depending on the obtained cost and number of intermediate vehicles of that route. Fuzzy controllers were employed to assess routes' costs and their lifetimes. Furthermore, artificial bee colony (ABC) algorithm was used to concurrently optimize all used fuzzy systems and obtain the optimal highest rank of links' cost values within which the neighbors could be selected as relay nodes in route discovery process. Simulation results prove that the proposed routing scheme significantly improves the network performance in both urban and highway scenarios, under different situations of vehicle density.

1. Introduction

The vehicular networks [1, 2] are a promising technology that enables smart vehicles to exchange wireless messages among themselves, in order to achieve more convenient and safer transportation system. These messages may include information about traffic flow condition, adaptive trip assistance, warnings and alarms, and parking or gas station availability, as well as infotainment applications.

These numerous VANET applications substantially rely on VANET routing protocols [3, 4], which are originated from preceding wireless mobile ad hoc network (MANET) algorithms but have been extensively reformed to cope with VANET characteristics and requirements.

The unique VANET characteristics of highly mobile vehicles, limited coverage area, intermittently wireless connection, and traffic density, in addition to restriction of movement within road patterns and traffic rules, make providing more reliable and efficient routing protocol for these challenging networks is still an open research topic; some of these recently related studies attend.

Li et al. [5] propose an adaptive QoS routing by using terminal intersections and an ant colony algorithm to search the optimal route based on connectivity probability, packet delivery ratio, and delay.

Al-Kharasani et al. [6] propose a particle swarm optimization tuned optimized link state routing protocol considering multiple objectives of throughput, packet delivery ratio, delay, and normalized routing overhead to evaluate the fitness function.

Latif et al. [7] offer an algorithm to select the next forwarder vehicle by using multicriteria based mathematical formulation considering direction, position, and distance of vehicles with respect to source vehicle.

Zhang et al. [8] suggest multicast routing protocol based on microartificial bee colony, in which energy consumption and transmission delay are considered to measure the quality.

Miao et al. [9] present fuzzy logic based routing scheme that forward broadcasted packets depending on fuzzifying two factors regarding distance and time delay.

Nabil et al. [10] propose a scheme to select the most stable route and predict its lifetime by calculating the link stability

time of vehicle's neighbors according to mathematical equations taken into account four cases of same or opposite direction of movement with same velocity or not.

However, the essential uniqueness of the current study represents by addressing the main three critical issues of routing in VANET in associative form; the first problem is the blind broadcasting of route request (RREQ) messages in route discovery phase, which result in high control messages overhead and packet collision problem especially in high dense network, or even in a sparse network with high packet transmission rate.

While the second issue regards high route breakage as a result of the omission of some affecting criteria in route selection process, resulting in high number of error messages and lost data packets.

Whereas the third issue treats the dilemma of using fixed route lifetime, regardless of the situation of the selected route, which might lead to disrupt some valid routes or consider some others as valid while they were broken.

Even though there are a number of works concerning the above first two problems [7–9, 11–13], they mostly consider only two or three factors in their studies. And some are completely based on sender to specify the relay nodes [11, 12], which typically require exchanging periodic hello messages, while the others are completely based on receiver to determine whether to rebroadcast the packet or not [9, 13], and as a consequence some redundant broadcasts are still not eliminated.

On the other hand, few works attend the third mentioned dilemma of routing in VANET environment [10, 14]; they mainly depend on mathematical models that take into account only two factors.

Particularly, this proposed protocol incorporates the principles of fuzzy systems to improve the decision-making processes of ad hoc on demand distance vector (AODV) routing protocol for vehicular network environment by evaluating the link cost of every neighbor in a combined sender-receiver fashion, taking the information of distance and direction into account at sender, in addition to considering speed and future direction information at receiver. This is in order to select only a subset of optimal relay neighbors for route discovery process, as well as select the best route for carrying data. Additionally, it could predict the lifetime of each selected route considering its obtained cost, besides number of its involved hops. Moreover, ABC optimized algorithm is used to generate the proposed fuzzy memberships' vertices and rules, aside from thresholds of selected relay neighbors' link cost.

More specifically, the main contribution keys of the proposed scheme in the present work can be summarized as follows:

(i) Three-step optimization using fuzzy systems in route discovery phase, regarding choosing relay nodes and appropriate route considering the most effective stability factors, in addition to specifying each route lifetime.

(ii) Combined sender-receiver-based multicast routing protocol without the overhead of using periodic Hello packets, as well as mitigating the shortcoming of completely receiver-based forwarding decider.

(iii) A novel stability factor regarding next direction of vehicles considered in route discovery phase, without transferring this datum to keep security of vehicles' future movements.

(iv) Multiple factors of distance, direction, speed, future direction, and number of hops considered in the proposed scheme.

(v) Automatic-extracted fuzzy controllers using artificial bee colony optimization.

(vi) Four objectives of optimization process considered: maximizing packet delivery ratio and throughput, and minimizing delay and number of control packets.

The rest of the paper is organized as follows: Section 2 describes the optimization algorithm used in the present study. Section 3 gives details about the proposed routing scheme. Simulation parameters and comparative results are presented in Section 4. Finally, conclusions and suggested future works are conferred in Section 5.

2. Employed Optimization Method

2.1. Artificial Bee Colony (ABC) Optimization. ABC optimization [15–17] is a swarm intelligent based scheme that simulates the foraging behaviour of honey bee colonies.

It is simple and flexible algorithm, requiring few parameters to be tuned; moreover, it could be hybridized with other intelligent algorithms easily.

Furthermore, many studies [18–20] have proven the efficiency and accuracy of using ABC optimization and hybridization over many other popular optimization methods.

The general structure of ABC optimization algorithm consists of three groups of artificial bees: employed, onlooker, and scout bees.

Each employed bee is associated with a food source (possible solution) and shares the position information and nectar amount (quality or fitness cost) of these sources with onlooker bees for further processing. The onlooker bees decide the best profitable source food according to a probability selection process. When a food source does not improve up to a predefined number of trials, the food source is rejected by the bees and the corresponding employed bee becomes a scout bee.

More details about ABC algorithm are given below:

First, let $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$ denote the ith solution in the population, where $i = 1, 2, \ldots, SN$; however, SN reflects the size of solutions in the population and is taken as half of the bee colony (equals number of employed bees or onlooker bees), while D represents the number of optimization parameters.

2.1.1. ABC Initialization Phase. The ABC generates a randomly distributed initial population of SN solutions within

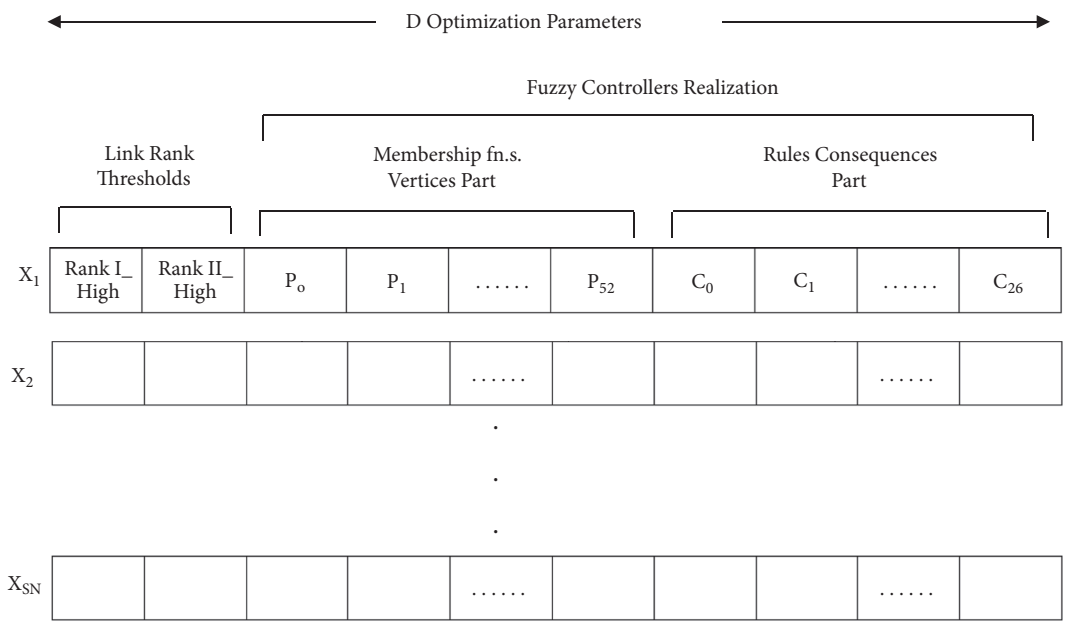

Figure 1: Food sources structure.

the range of boundaries according to the following equation:

$$x_{ij} = x_j^{min} + \left(x_j^{max} - x_j^{min}\right) * \text{rand}\,(0, 1) \tag{1}$$

where x_j^{min} and x_j^{max} are the lower and upper bounds of x_{ij}.

After solutions generation, the fitness function fit_i for all initial solutions in the population is evaluated.

2.1.2. ABC Employed Bee Phase. In this phase, each solution is assigned to an employee bee, which produces a modification on the position of the solution as follows:

$$v_{ij} = x_{ij} + \varphi_{ij}.\left(x_{kj} - x_{ij}\right) \tag{2}$$

where v_{ij} is the mutant solution of the original solution, φ_{ij} is a random number in the range [-1, 1], and k is a neighbor of i, k ≠ i.

After that, a greedy selection is performed by the employed bee between the original solution and its mutant according to their fitness evaluation values.

2.1.3. Probability Calculation Phase. For each solution, a probability value p_i which is proportional to its quality is calculated as

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{3}$$

2.1.4. ABC Onlooker Bee Phase. The onlooker bee evaluates the information taken from the employed bees and selects the solution with the highest probability value. Next, the same as employed phase mechanism of position adjustment and greedy selection are applied by the onlooker bees to memorize the better solutions.

2.1.5. ABC Scout Bee Phase. If a solution does not improve up to a predefined number of trials (exceeds a control parameter called **Limit**), the solution is abandoned, and its corresponding employed bee becomes a scout bee which replaces it with a new randomly solution using (1).

The execution of the above four phases will be repeated until reaching the maximum number of cycles for search, and the best obtained solution is given as the optimized output.

2.2. ABC Optimized Fuzzy System. Fuzzy logic [21, 22] has been widely employed for supporting many intelligent based real world systems especially under imprecise and uncertain information.

Typically, the knowledge base unit which consists of data base and rule base represents the heart of any fuzzy system.

However, the manual generation of the fuzzy knowledge base depending on system knowledge and trial and error process is a very tedious and time consuming task. Moreover, it does not guarantee the construction of an optimal system.

As a solution, ABC optimization is proposed to automatically extract the optimal rule set, with "do not care" condition exploration for more compact rules acquiring and tuning the membership functions for all the proposed fuzzy controllers.

Since all the proposed fuzzy controllers are depended, a collection of all membership function vertices for fuzzy inputs and outputs, in addition to linguistics for consequents of the rules, is encoded into the food source as shown in Figure 1 to guarantee the simultaneous upgrowth of the whole model parameters within the given search space.

In order to reduce number of optimization parameters to speed up the optimization process, the membership functions which were used for the proposed fuzzy controllers were set to triangular type, since it has proven more efficiency than other types in such network model [23–26].

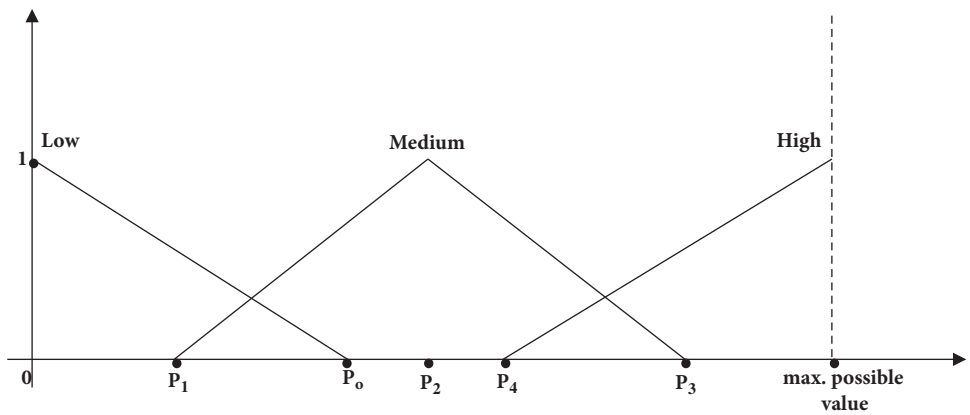

Figure 2: Fuzzy input optimized membership points.

Three linguistic terms were associated with each fuzzy input (Low, Medium, and High) and five for the output (Very Low, Low, Medium, High, and Very High) to get more accuracy.

As will be presented in next section, most fuzzy inputs were put in a ratio form, so that the first and last membership points were fixed and did not need to optimize. This gives a total of five membership optimized points which are required to represent each fuzzy input as shown in Figure 2.

Similar to the above mechanism, a total of eleven membership optimized points are required to represent the first two fuzzy controllers output, and an extra point are added in the last fuzzy controller output to get the optimal maximum route lifetime point.

In other respect, to generate the optimal rule base set, the fuzzy output linguistic terms are coded into real numbers from 1 to 5, and '0' value is used to represent the rule absence. Hence, each rule antecedent may take an integer value ranging from 0 to 5, such that '1' represents 'Very Low', '2' represents 'Low', and so on.

Furthermore, the objective of the optimization process in this work is to explore the best fuzzy models besides link rank thresholds that would be incorporated in the proposed routing algorithm to meet the best network performance outcomes through multiple objectives of maximizing packet delivery ratio (PDR) and throughput (Th) and minimizing delay (D) and number of control packets (C).

This requires integrating between the network simulation and the optimization process to evaluate the network performance response for a specific time interval (t) in respect to each available solution.

A weighted sum is used to aggregate these multiple objectives into a single objective function as

$$\begin{aligned} \text{Maximize} \quad & F(x_i) = w_1 . f_{PDR}(x_i) + w_2 . f_{Th}(x_i) \\ & + w_3 . \frac{1}{f_D(x_i)} + w_4 . \frac{1}{f_C(x_i)} \end{aligned} \tag{4}$$

where each individual objective factor term is qualified as a ratio between theobtained performance metric in response to the applied solution (x_i) with respect to the original achieved result by means of the traditional protocol, in order to quantify the efficiency of change in each evaluation term under using the available solution model in the proposed routing protocol as

$$f_{PDR}(x_i) = \frac{PDR_{OFAODV}(x_i)\big|_{t=0}^{t=100s}}{PDR_{AODV}\big|_{t=0}^{t=100s}} \tag{5}$$

$$f_{Th}(x_i) = \frac{THROUGHPUT_{OFAODV}(x_i)\big|_{t=0}^{t=100s}}{THROUGHPUT_{AODV}\big|_{t=0}^{t=100s}} \tag{6}$$

$$f_D(x_i) = \frac{MEAN\ DELAY_{OFAODV}(x_i)\big|_{t=0}^{t=100s}}{MEAN\ DELAY_{AODV}\big|_{t=0}^{t=100s}} \tag{7}$$

$$f_C(x_i) = \frac{No.\ OF\ CONTROL\ PACKETS_{OFAODV}(x_i)\big|_{t=0}^{t=100s}}{No.\ OF\ CONTROL\ PACKETS_{AODV}\big|_{t=0}^{t=100s}} \tag{8}$$

Meanwhile, in light of the facts that the four performance metrics are equally substantial and all the measured factors fall within the same range, 0.25 has been assigned to each weight value (w_k).

3. Proposed Routing Scheme

At first assume that each vehicle is equipped with GPS navigation system facility [27, 28] to get updated information about vehicle position, road map, and traffic information, besides multiplanned destination directions. Moreover, assume an array antenna [29, 30] is utilized in each vehicle to get location and angle of movements of neighbor vehicles.

Apart from assumption issue, the proposed routing scheme **Optimized Fuzzy AODV (OFAODV)** is looking up

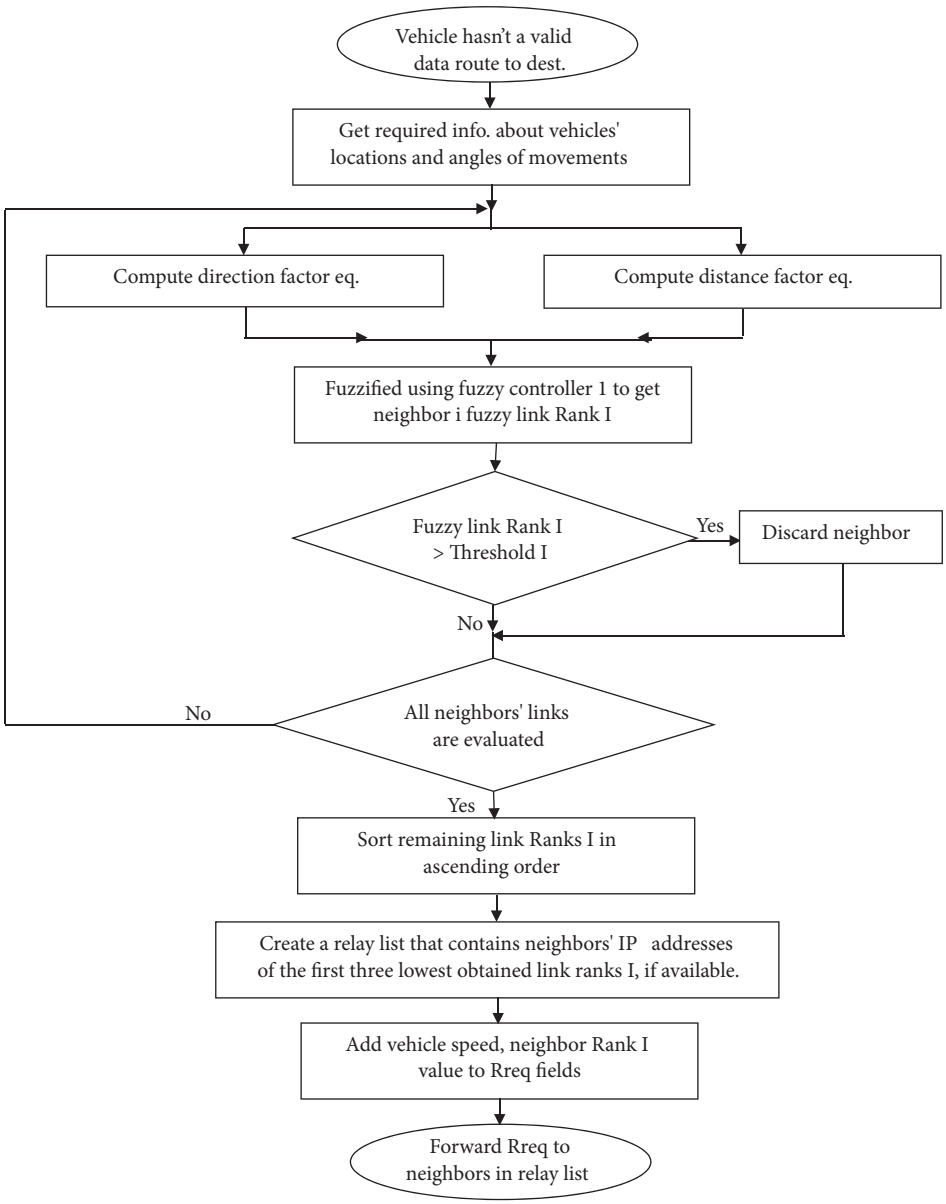

Figure 3: Additional steps of OFAODV before RREQ send/forward.

to tune the most used routing protocol in literature: AODV routing protocol [31, 32] within three stages during the route discovery phase. The first two stages are carried out before sending the (RREQ) packet, while the last stage is regarding specifying the selected route lifetime in the route reply packet.

In the first modification stage (Figure 3), each vehicle evaluates every one-hop neighbor link rank (**Rank I**) before attempting to send the RREQ packet using fuzzy logic that combines two factors of direction of neighbor vehicle with respect to destination direction, besides distance factor, which is calculated as a ratio between next node distance to destination as a ratio to current node distance to destination as follows:

$$\textit{Direction Factor} = \frac{\left|\textit{Neighbor Direction Angle} - \textit{Dest.Direction Angle}\right|}{180^0} \quad (9)$$

$$\textit{Distance Factor} = \frac{\textit{Distance from Neighbor to Dest.}}{\textit{Distance from Current node to Dest.}} \quad (10)$$

Consequently, up to only three neighbors with the fewest link rank are specified to be as relay nodes, only if their obtained links' rank is less than a particular value of **Rank1_High (Threshold I)**.

The second tuning stage (Figure 4) starts upon arriving the RREQ packet to the relay node, which assesses **Rank**

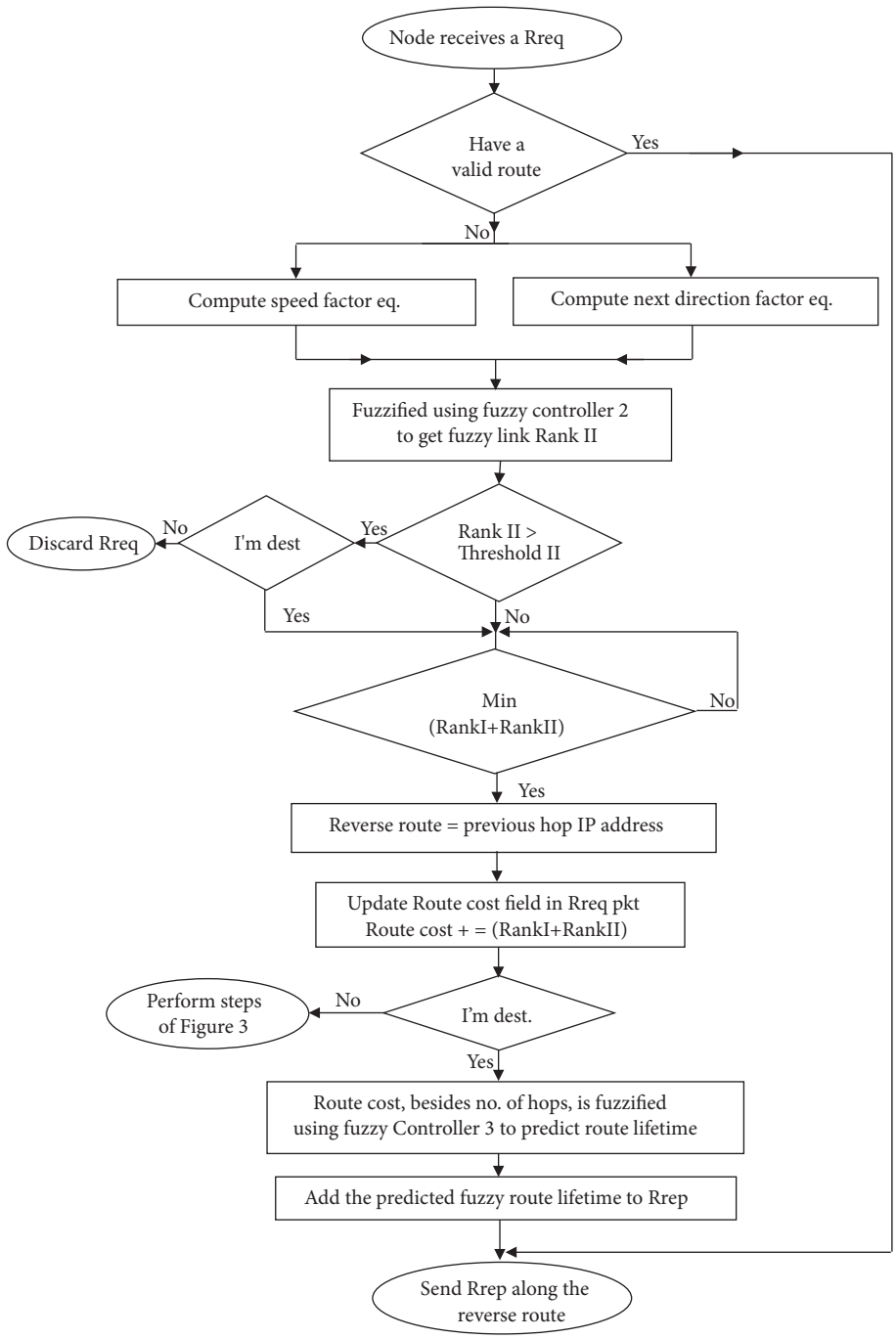

Figure 4: Additional steps of OFAODV upon RREQ receiving.

II value of link cost using other fuzzy system joints, other two factors of change in next direction of that vehicle and speed variance between current and previous vehicle as follows:

$$Next\ Direction\ Factor = \frac{|Node\ Next\ Direction\ Angle - Node\ Current\ Direction\ Angle|}{180^0} \tag{11}$$

$$Speed\ Factor = \frac{|Node\ Speed - Previous\ Node\ Speed|}{Max\ Allowable\ Speed} \tag{12}$$

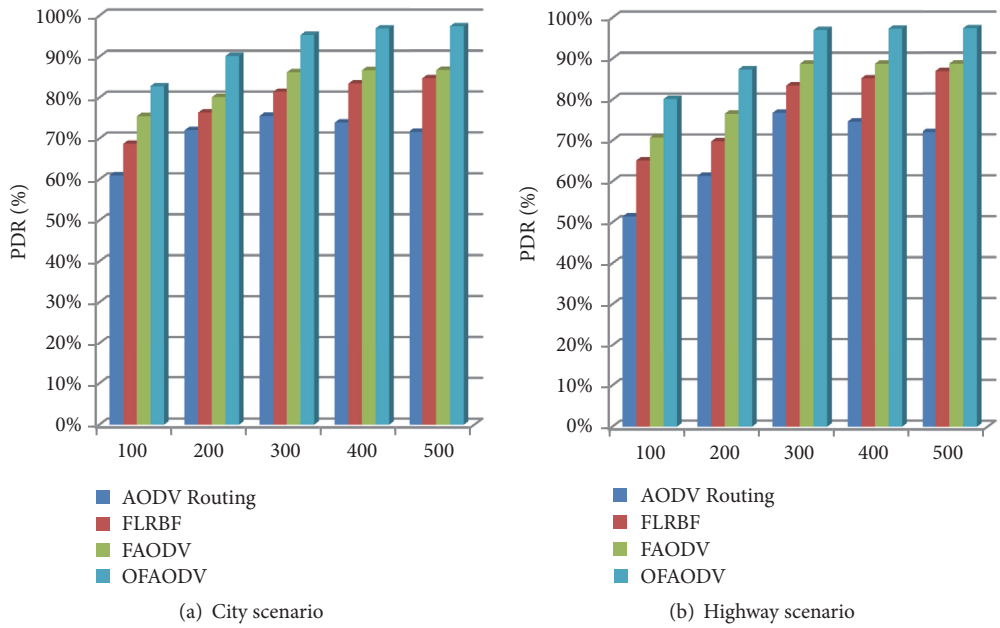

Figure 5: Packet delivery ratio (%) vs. no. of vehicles.

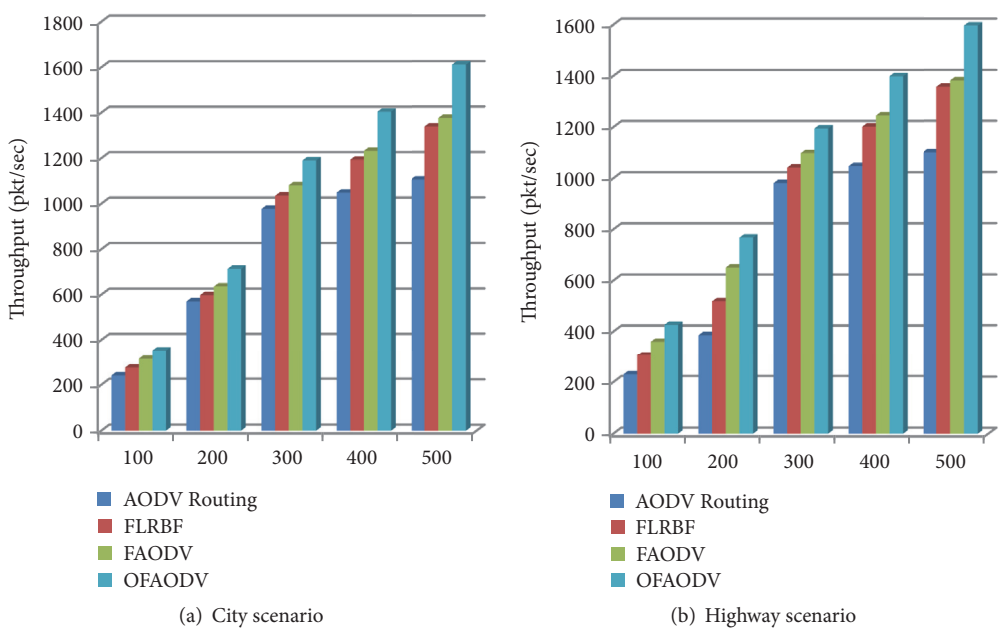

Figure 6: Throughput (pkt/sec) vs. no. of vehicles.

The RREQ packet will be forwarded only if the obtained Rank II value of the link cost is less than a specific value of **Rank2_High (Threshold II)**.

Moreover, the link with the fewest integrated Rank I plus Rank II cost will be selected to construct the optimal route to the destination.

Last modification stage executed before the destination sends the route reply packet, and the information of route cost and number of hops in the received RREQ packet are incorporated using fuzzy logic to predict the selected route lifetime.

Furthermore, the values of Rank1_High, Rank2_High, all fuzzy membership functions' vertices, and fuzzy rules are optimized using ABC algorithm (as described in previous section) aiming to improve the most important network performance outcomes.

4. Simulation Model and Results

A simulated area of 3km by 3km of real maps of Basra city and i95 highway is generated using bidirectional coupling of

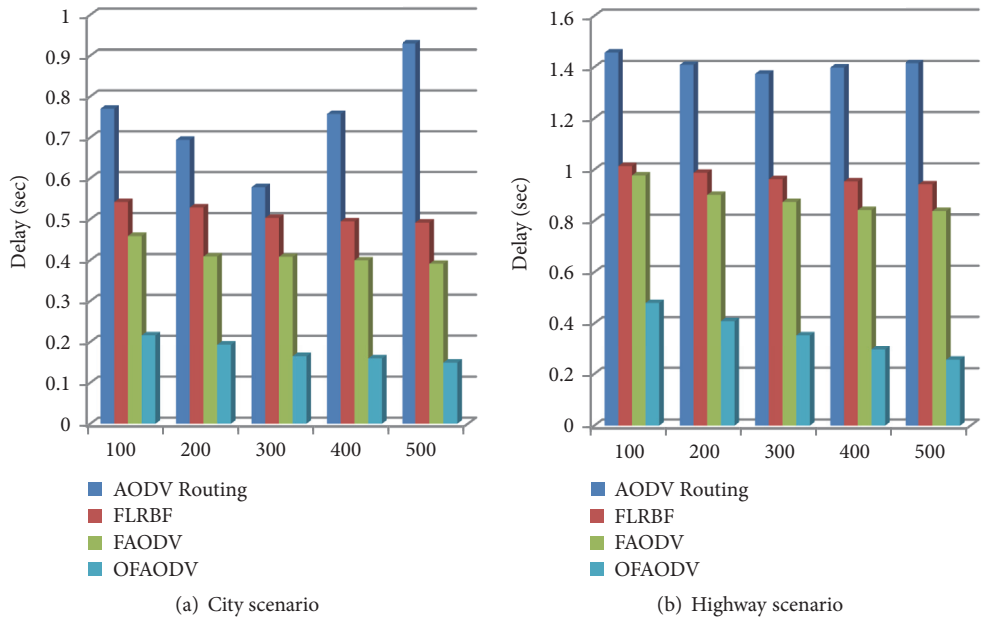

Figure 7: Mean delay (Sec) vs. no. of vehicles.

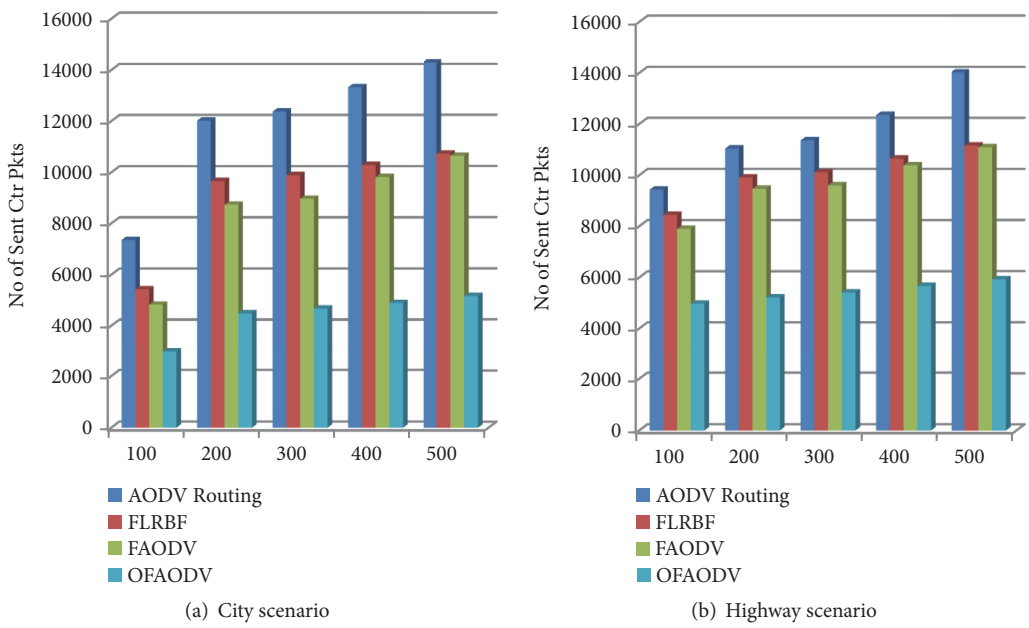

Figure 8: No. of sent control packets vs. no. of vehicles.

SUMO and OMNeT++ simulators to allow direct interaction between vehicular traffic dynamics and network communication system. Along 1000 simulated seconds, a number of 100, 200, 300, 400, and 500 vehicles are simulated to move within each simulated map with TraCI mobility model, each vehicle has a transmission range of 250 m, IEEE 802.11p was used as a medium access control protocol, and UDP data traffic was generated with 512B in size for each sent packets.

On the other hand, the present proposed routing protocol **(OFAODV)** has been simulated and compared with other three protocols: **AODV** routing protocol, Fuzzy Logic Routing Based on forwarding optimization **(FLRBF)** [9], and Fuzzy based AODV routing **(FAODV)**, whereby three criteria regarding number of relay vehicles, distance, and speed of movement of vehicles are considered in route selection decision using fuzzy logic.

The performance evaluation of all the simulated protocols is carried out in terms of packet delivery ratio (Figure 5), throughput (Figure 6), mean delay (Figure 7), and number of sent control packets (Figure 8).

The obtained results have clearly demonstrated the significant improvement of network performance when using

the proposed method (OFAODV routing) by an average of 23.15%, 45.77%, 75.15%, and 57.65% over the traditional AODV protocol in PDR, throughput, delay, and number of sent ctrl packets, respectively as compared with 13.84%, 27.56%, 40.22%, and 22.43%, percentage of achieved improvement by means of FAODV protocol, and an upgrading average of 9.47%, 17.14%, 30.38%, and 18% under FLRBF protocol.

5. Conclusion

The present work introduces an optimal routing method that eliminates the dissemination of RREQ packets; also it could reduce routes error and contention overhead by augmenting the efficiency of the selected routes, with the ability to predict their optimal lifetime.

In order to accommodate that, three two-inputs fuzzy systems are employed based on multiple criteria of distance, direction, speed, future direction, and number of hops information.

Furthermore, artificial bee colony optimization algorithm is used to automatically extract these fuzzy systems' memberships and rules, as well as obtaining link cost limitations within which relay nodes are selected.

Simulation results verified that the proposed routing protocol significantly improves the network performance in terms of packet delivery ratio, throughput, end to end delay, and number of control packets in both urban and freeway environments under different conditions of vehicle density.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Implementing Fuzzy TOPSIS in Cloud Type and Service Provider Selection

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Cloud computing can be considered as one of the leading-edge technological advances in the current IT industry. Cloud computing or simply cloud is attributed to the Service Oriented Architecture. Every organization is trying to utilize the benefit of cloud not only to reduce the cost overhead in infrastructure, network, hardware, software, etc., but also to provide seamless service to end users with the benefit of scalability. The concept of multitenancy assists cloud service providers to leverage the costs by providing services to multiple users/companies at the same time via shared resource. There are several cloud service providers currently in the market and they are rapidly changing and reorienting themselves as per market demand. In order to gain market share, the cloud service providers are trying to provide the latest technology to end users/customers with the reduction of costs. In such scenario, it becomes extremely difficult for cloud customers to select the best service provider as per their requirement. It is also becoming difficult to decide upon the deployment model to choose among the existing ones. The deployment models are suitable for different companies. There exist divergent criteria for different deployment models which are not tailor made for an organization. As a cloud customer, it is difficult to decide on the model and determine the appropriate service provider. The multicriteria decision making method is applied to find out the best suitable service provider among the top existing four companies and choose the deployment model as per requirement.

1. Introduction

Cloud computing (CC) provides service to users adopting the distributed computing model. It provides computing resources and service to the users as per demand. Cloud computing enhances user's opportunity who can access infrastructure and software applications in a ubiquitous manner [1]. Hardware and licensing costs can be leveraged by utilizing cloud computing and customers can be served in an efficient manner with the aid of scalability attribute. Service offerings in cloud are complex and are constantly evolving. On-demand resource provisioning, broad network access, resource pooling, rapid elasticity, and measured services are some of the key characteristics in cloud computing. Various organizations are trying to adopt cloud from their existing IT infrastructure. The scalability and potential cost effectiveness are attracting various organizations to shift to cloud environment. Recent surveys have revealed that various organizations are willing to transfer their applications to cloud to avail the diverse advantages it offers. The cloud computing market has been growing over the years and the service providers are trying to gain foot hold in the market with various offers in terms of services [2]. There are several cloud service providers in current scenario who are providing services almost identical in nature but with variation in characteristics and offerings. The consumers often face difficulty in selecting the best cloud provider as per their requirement. Cloud providers including Amazon Web Services (AWS) and Microsoft give customers the choice to deploy their applications over a pool of virtual services with practically no upfront investment and with an operating cost proportional to their actual usage [3]. The cloud service providers help the companies to concentrate on their core business areas, but there are certain factors and parameters which customers need to consider during choice of service [4]. Cloud has different deployment models (Public, Private,

and Hybrid) and different service models like SaaS, PaaS, and IaaS. Big IT organizations like Google, IBM, Microsoft, Amazon, etc., are offering various cloud services to users. It becomes an uphill task for a cloud customer or user to determine which company to choose [5, 6]. Also it becomes complex to decide on the deployment model. Customers are lacking relevant experience and information to assess the service providers capability in various occasions.

This paper analyzes the different criteria for choosing the suitable service provider along with the deployment model using the Multi Criteria Decision Making (MCDM concept). The evaluation will be done using the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method [7]. MCDM method helps decision makers (DMs) in integrating objective measurements with value judgments that are based on collective group ideas instead of individual opinions.

The best alternative is deduced based on the shortest distance from the fuzzy positive ideal solution (FPIS) and farthest distance from the fuzzy negative ideal solution (FNIS). FPIS refers to maximization of benefit criteria while minimizing cost criteria whereas FNIS will maximize cost criteria and minimize benefit criteria. Utilizing the concept of Fuzzy TOPSIS, FPIS, and FNIS was defined and distance from each alternative from FPIS and FNIS was calculated. In final stage the closeness coefficient will help in determining the ranking order of the alternatives [6].

The current research work deals with the application of TOPSIS in the two most critical areas of concern, viz., selection of the suitable cloud service provider from the top 3 in current fiercely competitive cloud industry and most suitable cloud based on its type. Section 2 deals with related works. Section 3 describes the different cloud service providers and cloud types. Section 4 describes the MCDA techniques. Section 5 deals with fuzzy TOPSIS. Section 6 has two parts dealing with cloud service provider selection and cloud type selection using TOPSIS. Section 7 concludes the paper.

MCDA technique has found its application in several research areas to determine the best alternative among numerous alternatives with different set of criteria. In the current scenario there are multiple cloud service providers offering numerous attractive benefits to customers. Similarly, it is very difficult to determine the suitable cloud type for an organization. Fuzzy TOPSIS has been applied in this paper to determine the most suitable service provider and also the cloud type for an organization.

2. Related Work

In recent years there had been numerous studies on cloud service provider selection and cloud type selection. There are top cloud service providers offering plethora of services at different rate and multiple features. It becomes extremely difficult for a company to decide the best service provider and also the type of cloud to choose [8]. Kumar and Rai (2016) have studied IaaS with 3 different sets of criteria and provided a framework on cloud simulation. Costa (2013) has worked on selection of cloud service providers using MACBETH MCDA technique. Park and Jeong (2013) proposed a new MCDM approach and applied the same on SaaS based ERP. Rad et al. have studied cloud service platforms and its salient features. Li et al. have worked on the issues related to cloud application performances. Peng et al. have done survey on cloud middleware.

Chen et al. applied constraint programming in cloud provider selection and provided inputs on enterprise policies and its conflicts with users expectations. Chung and Seo (2015) applied ANP technique while working on evaluation on cloud services. Lee and Seo (2013) applied AHP in their research on cloud IaaS.

Godse and Mulik (2009) applied MCDA technique on 3 companies for comparison.

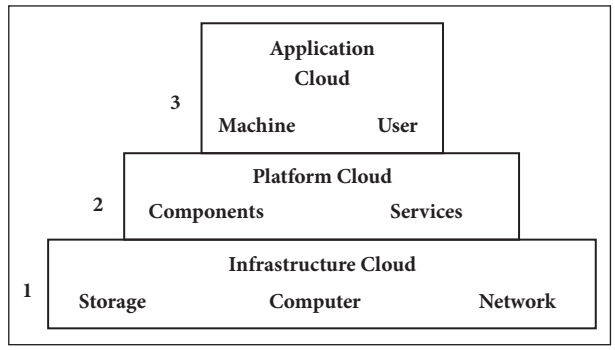

Figure 1: Cloud computing models.

3. Cloud Computing and Cloud Service Providers

3.1. Cloud Computing Overview. Cloud computing refers to storing of data in a remote place and accessing it via Internet instead of doing it in the local machine. So, the greatest advantage is that we need not require a hard drive or dedicated network for data storage and access. One well-known application is Office 365 by which user can store, access, and edit their MS Office documents online without the installation of software in their local machine. The architecture of cloud computing mainly comprises front-end device, back-end platform, cloud-based delivery, and network. The storage in cloud includes three options like public, private, and hybrid. In case of public cloud, it is available to the general public whereas infrastructure is owned and operated by service providers like Google and Microsoft. For private cloud, it is dedicated to a specific organization which can use it for storing organization's data, hosting business application, etc. Other organizations are not able to access the same. Advantages of both public and private cloud are present in hybrid cloud. Organizations can utilize private clouds for sensitive application, while public clouds are meant for nonsensitive applications.

3.2. Cloud Computing Models. Cloud computing models can be mapped against the layers of business value pyramid. Figure 1 depicts the same.

(i) SaaS. The top most layer of the above pyramid is SaaS or functional layer. This specific cloud type is responsible for delivering a single application with the help of a browser to various users through multitenant architecture. It is basically a "pay-as-you-go" model where provider sells an application based on license. The users need not have to take the hazards of maintaining servers or any software which basically reduces the cost. Service providers can also handle it easily as one application needs to be maintained here. Thus, it is cost effective for both sides, users and providers. Few well-known applications are Salesforce.com, SRM, ERP, etc. Few major characteristics of SaaS are listed in the following:

(I) Centralized web-based access to company and commercial software

(II) Providing superior services to client

(III) No software maintenance required from user's perspective

(IV) Integration with different applications possible through Application Programming

(V) Interfaces (APIs)

(ii) PaaS. PaaS or Platform as a service delivers development or operating environments as a service. It is a combination of tools and services designed for coding and deploying the applications in an effective and efficient manner. The major difference with SaaS model is that PaaS is a platform for development/deployment of the software instead of readymade software delivered over the Internet. Few major examples include Salesforce.com's Force.com, Azure from Microsoft, and Google App Engine. The major characteristics are the following:

(a) A one stop solution for developing, testing, deploying, hosting, and maintaining applications

(b) Web-based UI designing tools to create, modify, test, and deploy different UI scenarios

(c) Multitenant architecture facilitating concurrent users

(d) Load balancing, security, and failover capabilities for application to be deployed

(e) OS and cloud programming APIs to create new apps for cloud or to cloudify the current apps

(f) Tools to handle billing and subscription

(iii) IaaS. The infrastructure cloud is responsible for storage and compute resources as a service which is basically used by various IT organizations for providing business solutions. Complete flexibility is provided in this approach to the user; users can choose among desktops, servers, and network resources. The entire infrastructure package can be customized by choosing anything from the list of CPU hours, storage space, bandwidth, etc. This cloud type has different categories like private, public, and hybrid. Public cloud consists of shared resources whereas private cloud is responsible for providing secure access to the resources and is managed by the organization it serves [9]. This type of cloud is maintained by both internal and external providers. Some notable characteristics are the following:

(a) Resources distributed as a service

(b) Dynamic, on-demand scaling of resources

(c) Utility based pricing model

(d) Concurrent users on a single piece of hardware

3.3. Cloud Computing Benefits. Cloud computing provides different benefits. Cloud services offer scalability. Dynamic allocation and deallocation of resources happen based on demand. Cost savings are another major advantage which happens due to cost reduction in capital infrastructure. Applications can be accessed across the globe and without the hardware configuration in the local machine also. Network is simplified, and client can access the application without buying license for individual machine. Storing data on cloud is more reliable as it is not lost easily.

3.4. Challenges behind Cloud Services. Cloud services cover various issues along with its advantages. Few such concerns are listed in the following:

(a) Security and Privacy

(b) Interoperability and Portability

(c) Reliability and Availability

(d) Performance and Bandwidth Cost

3.5. Cloud Service Providers. Cloud service providers refers to different organizations that offer infrastructure, network services, software, hardware components, etc. to different customers and business entities. Cisco, Citrix, IBM, Google, Microsoft, Rackspace, etc. are examples of cloud service providers. In the paper we have considered currently, the top cloud service providers in market are like Amazon Web Services, IBM Bluemix, and Google Cloud Compute. Evaluating the cloud service provider is not an easy activity, but it requires thorough analysis. This has been dealt with in this research article in detail. Cost cannot be the single criteria for selecting a service provider, but different offerings should also be considered in detail. The different fine prints in the agreement need to be analyzed by customers before selecting the provider.

3.6. Public Cloud. In a public cloud a service provider manages resources such as infrastructure, application, and storage and makes it available to cloud consumers via Internet. The service providers like Microsoft, Amazon, Google, etc. own and operate their infrastructure from their own data centers [10]. With the increase in demand of service, users do not need to purchase hard ware as public cloud providers manage the infrastructure. Public clouds are owned by third party organizations and are made available to organizations. Google, Amazon, and Microsoft are notable examples of public cloud vendors.

Some advantages of public cloud are

(i) seamless data availability,

(ii) all round technical support,

(iii) scalability on demand,

(iv) limited investment,

(v) proper resource utilization.

Limitations of public cloud are

(i) data security and privacy.

3.7. Private Cloud. Private cloud as the name suggests refers to infrastructure which is linked to a concern either managed by an organization or third party. It may be present on premise or off site. In private cloud the service is offered to a specific organization and is not meant for public use. In terms of security private clouds are providing highest amount of security service. Private clouds can be built and managed by companies own infrastructure or by cloud service provider.

Some advantages of public cloud are

(i) control over data and information assets,

(ii) high level security,

(iii) superior performance due to intranet and network performance,

(iv) easier to achieve compliance.

Limitations of private cloud are

(i) underutilization of resources

(ii) costliness

3.8. Hybrid Cloud. Hybrid cloud deployment model involves composition of two or more clouds like private, public, etc. The combination of public cloud provider and private cloud platform can also be referred to as a hybrid cloud where they operate independently. Organizations can store sensitive data on private cloud environment and leverage the computational services from public cloud. The hybrid environment ensures minimum data exposure while taking advantage of public cloud platform. Some advantages of public cloud are

(i) private infrastructure to ensure easy accessibility,

(ii) reduction of access time and efficient resource utilization,

(iii) advantage of using computational infrastructure.

Limitations of hybrid cloud are

(i) higher cost,

(ii) security aspects,

(iii) compatibility issues.

4. Multicriteria Decision Analysis (MCDA)

4.1. Background of MCDA. Multicriteria Decision Analysis (MCDA) or Multi Criteria Decision Making is a subbranch of operational research which helps in decision making where several decision making criteria exist. Finding out the best option from the available alternatives is known as decision making. In real world scenario decision making is difficult where there are conflicting goals, different constraints, and unpredictable end results [11]. Here the fuzzy set theory can be used where we are unable to conclude precisely. In 1951 the vector maximum problem was first introduced by Harold William Kuhn and Albert William Tucker. This can be considered as the basics of MCDA. Later in 1972 "Multiple Criteria Decision Making" conference was held in Columbia University. MCDA has been growing in rapid space in the following decades since then.

The MCDA uses the mathematical and computational tools in selection of the best alternative among different choices which may have conflicting criteria. MCDA helps in finding the best alternative among different available choices with respect to specific criteria by decision maker.

We human beings face difficulty in finding the best alternative if there exists multiple criteria and in such situation MCDA can guide in proper decision making. As an example we may consider our current scenario where we have different cloud providers. All the cloud providers are competing against each other to gain the top position and have been trying to draw customers by providing different attractive and cost competitive features. There are distinctive features like control interface features, support services availability, and server OS types which are being offered by the cloud service providers. A customer needs to take decision on the distinctive features being offered by the cloud providers and select the one which is the best alternative among them. MCDA is developed based on the human thinking and their approach in decision making. There are several MCDA methods and techniques available, but the basic methodology is similar based on existing diverse set of criteria and decision making. MCDA consists of methodologies, application of theories, and techniques aiding and dealing with decision making problems. Decision making theory has been applied to solve various real-life problems where multiple conflicting criteria can exist.

4.2. MCDA Methods. MCDA is part of operational research which aims to select the suitable or best alternative among several options with the aid of mathematical and computational tools. It consists of two main categories: Multiattribute Decision Making (MADM) and Multiobjective Decision Making (MODM). MCDA can also be categorized into 2 types, viz., (a) Multiattribute Utility Theory (MAUT) and (b) outranking methods. Using MAUT we try to find a function which determines the utility or usefulness of an alternative. Every action is linked with a marginal utility and a real number will represent the preference in the considered action. The resultant utility represents the addition of the marginal utilities. Outranking method helps

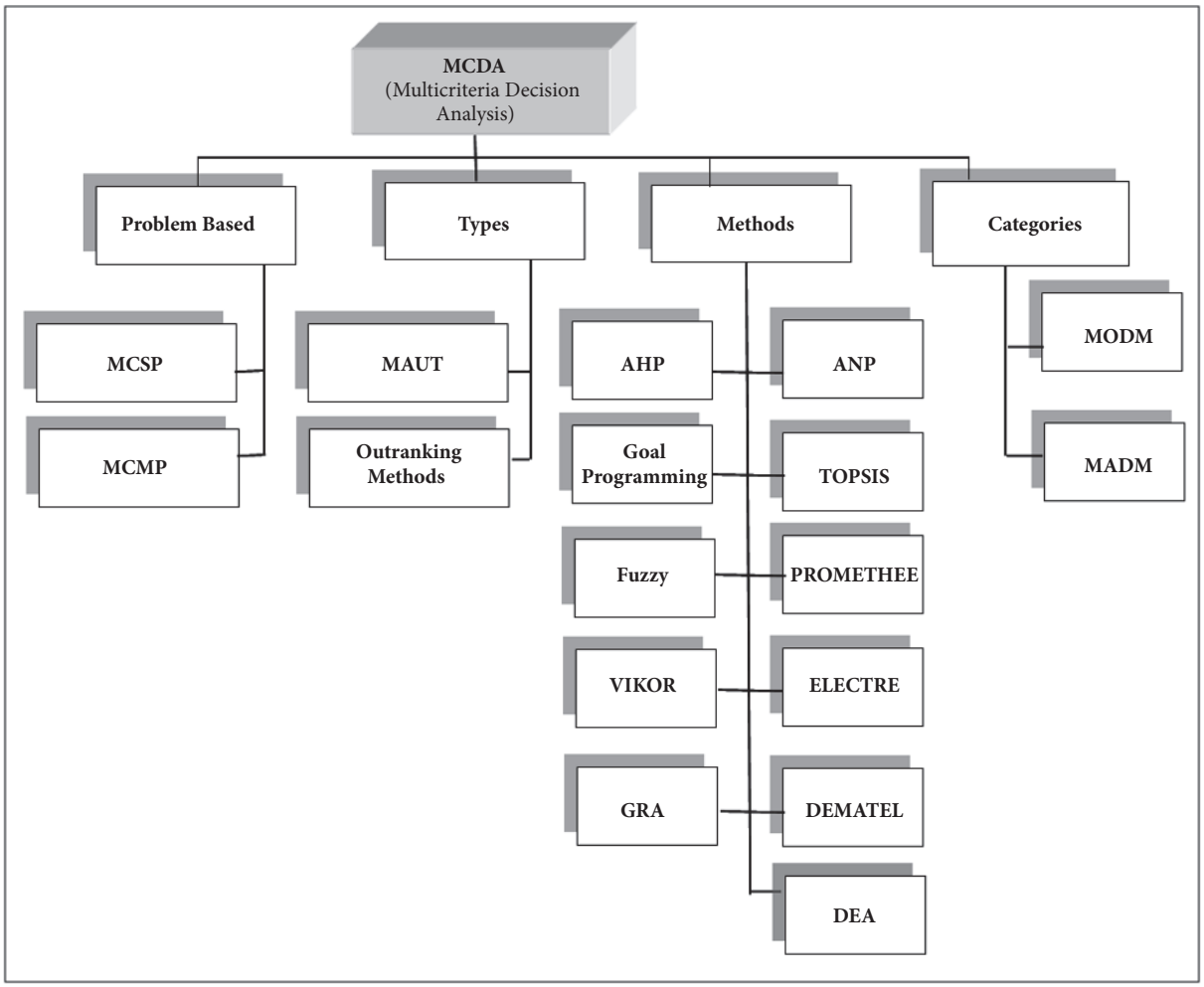

Figure 2: Different branches of MCDA.

in finding the alternative which is ranked higher when compared pairwise. Figure 2 shows the different branches of MCDA.

4.2.1. Analytic Hierarchical Process (AHP). Analytic Hierarchical Process (AHP) was introduced by Thomas L Satty in 1980. This is a popular and widely used method for MCDA. Complex MCDM problems are divided into system of hierarchies. In final stage AHP deals with an M X N matrix where M refers to number of alternatives and N represents number of criteria. The matrix is formed considering the relative importance of alternatives against each criterion. Both qualitative and quantitative criteria are used in AHP to find the alternatives and attributes are not entirely independent of each other [12]. Pair wise comparison is used in AHP and the attributes are structured into a hierarchical relationship. Hierarchy starts from top level and then proceeds towards the goal. Criteria, subcriteria, etc., represent the lower levels. The process execution in hierarchy tree initiates from the leaf nodes and it proceeds to the top level. Output level represents hierarchy related to the weight or the influence of different branches which originated at that level. In final stage the comparison is done and best alternative against each attribute is selected.

4.2.2. Analytic Network Process (ANP). Analytic Network Process (ANP) can be referred to as an extension or generalization of Analytic Hierarchy Process (AHP). ANP decision making technique is designed using unidirectional hierarchical relationships between different levels and taking upon the problem of dependence and feedback on different criteria. ANP considers interrelationships within decision levels and attributes using unidirectional hierarchical relationships. It models the decision problem by implementing ratio scale measurements based upon pair wise compare. The interdependence between elements is effectively handled by ANP using composite weights and "super matrix". In many real world scenarios of decision making, ANP has been successfully applied. It has been observed that many decision making problems cannot be hierarchically structured as there is involvement of interaction and dependence between higher and lower level elements [13]. Thus ANP is represented as a network instead of hierarchy. The feedback structure is devoid of the top-to-bottom form in hierarchy. It rather

looks like a network with cycles connecting its component of elements which cannot be referred as levels and it loops to connect a component to itself. ANP has sources and sinks. Source node is the origin of paths of influence and is not the destination of paths. Sink node is a destination of paths of influence and is not an origin of paths. A full network may consist of source nodes, intermediate nodes which appear on the paths from source nodes and lie or fall on path to sink nodes and finally sink nodes.

4.2.3. Technique for Order of Preferences by Similarity to Ideal Solutions (TOPSIS). In multicriteria decision making (MCDM) methods we know the ratings and weights of the criteria. TOPSIS was first developed by Hwang and Yoon for solving issues where multicriteria exist and decision making becomes a complex affair. In TOPSIS the performance ratings and weights of the criteria are provided with crisp values. C.T. Chen developed TOPSIS methodology further in solving multiperson and multicriteria decision issues in real world environment where fuzzy exists. Linguistic variables are used to determine weights of all existing criteria and ratings given on each alternative linked to each criterion as there exists fuzziness in decision data and group decision.

In Fuzzy TOPSIS we define the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS). Then calculation is done on distance of each alternative from FPIS and FNIS. Finally ranking order of alternatives is determined using closeness coefficient.

4.2.4. Elimination and Choice Expressing Reality (ELECTRE). Elimination and Choice Expressing Reality (ELECTRE) was introduced initially in 1966. This deals with "outranking relations" by performing pairwise comparison among alternatives under each criterion separately. Later several versions were developed like ELECTRE I, ELECTRE II, ELECTRE III, ELECTRE IV, and so on. ELECTRE belongs to the class of outranking methods and it involves up to 10 steps. Pairwise comparison is done between alternatives to find out the outranking relationships. The relationships in turn help in identifying and removing the alternatives which are dominated by others, resulting in a smaller set of alternatives.

ELECTRE method handles discrete criteria that are both qualitative and quantitative and provides ordering of alternatives. Ranking of alternatives is obtained by using graphs in an iterative procedure. This method starts comparing pair wise of alternatives under each criterion. The ELECTRE method finds a whole system of binary outranking relations among the alternatives. ELECTRE method at times is unable to identify the preferred alternative since the systems are not necessarily complete ones. It yields the core of leading alternatives. This method eliminates the less favorable ones thus giving a clear understanding of the alternatives. In cases where we need to deal with few criteria and large alternatives, this ELECTRE method will be useful.

4.2.5. Fuzzy. Fuzzy set theory has been initially proposed by Zadeh in 1965 and is applied in areas of uncertain data or there is lack of precise information. Fuzzy can help in multicriteria decision making where there exist several uncertainties in available information. The decision pools help in finding selected alternative criteria using the fuzzy MCDA model. Weights are assigned to criteria which are evaluated in terms of linguistic values. Linguistic values are then assigned fuzzy numbers. Inside fuzzy set, fuzzy terms are described by linguistic variables which in turn are used to map the linguistic variables to numeric variables [14].

4.2.6. Goal Programming. Goal Programming is a MODM tool proposed by Charnes in 1955. In areas of multiple conflicting objects the Goal Programming is applied. This is an extension of Linear Programming. Multiple conflicting objective measures can be handled by the Goal Programming optimization procedure. Mathematical programming is combined with the logic of optimization in order to take decisions involving several objectives in different multicriteria decision making problems.

4.3. Motivations in Selecting TOPSIS Method. TOPSIS is one of the most popular multicriteria decision making (MCDM) methods. It deals with the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution while determining the best alternative. TOPSIS is a well-known method due to the following reasons: (a) theoretical stringency, (b) effective usage of human thinking in selection process, (c) guides in decision making using rank alternatives in fuzzy environment, (d) proper implementation of subjective and objective criteria, (e) crisp values assigned to performance ratings and also to the weights of the criteria which helps in dealing with MCDM problems.

5. Brief Overview of TOPSIS Method

TOPSIS stands for Technique for Order Preference by Similarity to Ideal Solution. Here two artificial alternatives are hypothesized which are Ideal Alternative and Negative Ideal Alternative. Ideal Alternative is the one which has the best attribute values like maximum benefit attributes and minimum cost attributes. Similarly Negative Ideal Alternative includes the worst attribute values like minimum benefit attributes and maximum cost attributes. The TOPSIS method chooses the alternative which is nearest to the ideal solution and farthest from the negative ideal solution [15, 16]. The outline of the TOPSIS method is presented in the following.

Step 1. Evolution matrix is formed of m alternatives and n criteria, using the intersection of each alternative and criteria given as x_{ij}, and then we have a matrix $(x_{ij})_{\mathrm{m\ x\ n}}$

Step 2. The matrix $(x_{ij})_{mxn}$ is then normalized to form the matrix.

$\mathrm{R} = (r_{ij})_{m\ x\ n}$ using the normalization method $r_{ij} = X_{ij}/\sqrt{\sum_{i=1}^{m} x_{ij}^2}$, i = 1, 2, ... m, j = 1, 2, ..., n

Step 3. Calculate the weighted normalized decision matrix

$t_{ij} = r_{ij}.\, w_j$, i = 1, 2, ..., m, j = 1, 2 . . . . . , n

where $w_j = W_j / \sum_{j=1}^{n} W_j$, j = 1, 2 . . . ..n so that $\sum_{j=1}^{n} w_j = 1$ and W_j is the original weight given to the indicator v_j, j = 1, 2 . . . ..n

Step 4. Determine the worst alternative (A_w) and the best alternative (A_b)

$A_w = \{(\max(t_{ij} \mid i = 1, 2 \ldots, m) \mid j \in J_-), (\min(t_{ij} \mid i = 1, 2 \ldots m)\ j \in J_+)\} \equiv \{t_{wj} \mid j = 1, 2 \ldots n\}$,

$A_b = \{(\min(t_{ij} \mid i = 1, 2 \ldots, m) \mid j \in J_-), (\max(t_{ij} \mid i = 1, 2 \ldots m)\ j \in J_+)\} \equiv \{t_{bj} \mid j = 1, 2 \ldots n\}$,

where

$J_+ = \{j = 1, 2, \ldots, n \mid j$ associated with the criteria having a positive impact and

$J_- = \{j = 1, 2, \ldots, n \mid j$ associated with the criteria having a negative impact

Step 5. Calculate the L2 – distance between the target alternative i and the worst condition A_w

$$d_{iw} = \sqrt{\sum_{j=1}^{n} \left(t_{ij} - t_{wj}\right)^2}, \quad i = 1, 2 \ldots\ldots, m \tag{1}$$

and the distance between the alternative i and the best condition A_b

$$d_{ib} = \sqrt{\sum_{j=1}^{n} \left(t_{ij} - t_{bj}\right)^2}, \quad i = 1, 2 \ldots\ldots, m \tag{2}$$

where d_{iw} and d_{ib} are L2 – norm distances from the target alternative i to the worst and the best conditions, respectively.

Step 6. Calculate the similarity to the worst condition:

$s_{iw} = d_{iw}/(d_{iw} + d_{ib})$, $0 \le s_{iw} \le 1$, i = 1, 2 . . . . . m.

$s_{iw} = 1$ if and only if the alternative solution has the best condition.

$s_{iw} = 0$ if and only if the alternative solution has the worst condition.

Step 7. Rank the alternative according to s_{iw} (i = 1, 2 . . . ..m).

6. Applying MCDM Topsis in Cloud

6.1. Evaluation of Cloud Service Provider Using TOPSIS. Three experts evaluate three types of cloud service providers A, I, G and find their evaluations in linguistic variables with respect to objectives, i.e., criteria $C_1 \ldots\ldots C_9$.

The decision makers use seven point scale linguistic variables which are represented by triangular fuzzy numbers to express importance of weight/priority to *Nine* criteria given by Box 1

The criteria are assessed by decision makers which are represented in Table 1.

The three different decision makers are represented in Table 1 by D1, D2, and D3.

Very Low (VL)	(0,0,0.1)
Low (P)	(0,0.1,0.3)
Medium Low (ML)	(0.1,0.3,0.05)
Medium (M)	(0.3,0.5,0.7)
Medium High (MH)	(0.5,0.7,0.9)
High (H) (0.7,0.9,1.0)	
Very High (VH)	(0.9,1.0,1.0)

Box 1

Table 1: Criteria assessed by decision makers.

Feature Name	D1	D2	D3
Business Size Support	H	VH	VH
Support for Versatile Industries	VH	H	H
Control Interface Features	H	H	H
Availability of Support Services	VH	VH	VH
Server OS Types	H	H	VH
Preconfigured Operating Systems	MH	MH	MH
Available Runtimes	MH	H	MH
Middleware	H	MH	MH
Native Databases	VH	VH	H

As per above assessment and based on the values of linguistic variables, the fuzzy weight of each criteria j is found as

$$\widetilde{w_j} = \frac{1}{3}\left[w_j^{(1)} + w_j^{(2)} + w_j^{(3)}\right] \tag{3}$$

Thus

$$\begin{aligned} \widetilde{w_1} &= \frac{1}{3}[\mathrm{G} + \mathrm{VG} + \mathrm{VG}] \\ &= \frac{1}{3}[\mathrm{G} + \mathrm{VG} + \mathrm{VG}] \\ &= \frac{1}{3}[(0.7, 0.9, 1.0) + (0.9, 1.0, 1.0) + (0.9, 1.0, 1.0)] \\ &= \frac{1}{3}[2.5, 2.9, 3] \\ &= (0.83, 0.97, 1) \end{aligned} \tag{4}$$

Similarly we can obtain the values of $\widetilde{w_2}, \widetilde{w_3} \ldots\ldots \widetilde{w_9}$

In Table 2 features of different cloud service providers are given along with the reason for the different weightage and motivation behind the weightage.

The three cloud companies are evaluated by three decision makers on a seven point linguistic scale comprising the values in Box 2.

The decision makers' opinion is considered for each criterion in Table 3. The fuzzy decision matrix of 3 cloud service providers is given by the following.

For cloud provider AWS, under the feature F_1, the evaluation is

$$\tilde{x}_{11} = \frac{1}{3}[\mathrm{G} + \mathrm{VG} + \mathrm{VG}]$$

Table 2: Cloud service providers and feature compare.

Feature Name	Cloud Service Providers					
	Amazon Web Services(AWS)	**Major Motivators for Weight Assignment**	**IBM Bluemix (IB)**	**Major Motivators for Weight Assignment**	**Google Compute Engine (GCE)**	**Major Motivators for Weight Assignment**
Business Size Support	Good	Supporting Small-Medium Business	Very Good	Supporting Large - Small-Medium Business	Very Good	Supporting Large - Small-Medium Business
Support for Versatile Industries	Good	Supporting medium range of industries	Very Good	Supporting large set of industries	Poor	Supporting very few industries
Control Interface Features	Very Good	Supporting API, GUI, Web Based Application/Control Panel and Command Line	Poor	Supporting Web Based Application/Control Panel and Command Line	Good	Supporting API, Web Based Application/Control Panel and Command Line
Availability of Support Services	Very Good	Supporting Live Chat, Phone, 24/7, Forums, Online/Self-Serve Resources	Good	Supporting 24/7, Forums, Online/Self-Serve Resources	Good	Supporting 24/7, Forums, Online/Self-Serve Resources
Server OS Types	Very Good	Support Linux and Windows	Good	Supporting Windows	Very Good	Supporting Linux and Windows
Preconfigured Operating Systems	Very Good	Supporting Amazon Linux, Cent OS, Debian, Oracle Enterprise Linux, Red Hat Enterprise Linux, SUSE Enterprise Linux, Ubuntu, Windows Server	Poor	Supporting None	Good	Supporting Cent OS, Debian, Red Hat Enterprise Linux, Ubuntu, FreeBSD, openSUSE Linux
Available Runtimes	Good	Supporting NET, Java, PHP, Python and Ruby	Very Good	Supporting Go, Node, Java, PHP, Python and Ruby	Poor	Supporting None
Middleware	Good	Supports Tomcat	Very Good	Supports Jboss, Tomee	Poor	Supports None
Native Databases	Very Good	Supports CouchDB, Microsoft SQL, MongoDB, MySQL	Good	Supports MySQL and PostGreSQL	Poor	Supports None

Very Poor (VP)	(0,0,1)
Poor (P)	(0,1,3)
Medium Poor (MP)	(1,3,5)
Fair (F)	(3,5,7)
Medium Good (MG)	(5,7,9)
Good (G)	(7,9,10)
Very Good (VG)	(9,10,10)

Box 2

$$= \frac{1}{3}\left[(7,9,10)+(9,10,10)+(9,10,10)\right]$$
$$= \frac{1}{3}(25,29,30) = (8.3,9.6,10) \tag{5}$$

Under Feature F_2,

$$\begin{aligned}\tilde{x}_{12} &= \frac{1}{3}\left[G+MG+MG\right]\\ &= \frac{1}{3}\left[(7,9,10)+(5,7,9)+(5,7,9)\right]\\ &= \frac{1}{3}(17,23,28) = (5.6,7.6,9.3)\end{aligned} \tag{6}$$

Likewise, evaluation is done for AWS for remaining features.

Similarly for other 2 cloud service providers, viz., IB & GCE under 9 Features ($F_1, F_2 \ldots F_9$) the evaluations are done.

Normalized decision matrix for each 9 features is determined against the 3 cloud service providers. Normalized fuzzy decision matrix $\tilde{v} = (\tilde{v}_{ij})$ where $\tilde{v}_{ij} = (\tilde{r}_{ij})(.)(\tilde{w}_j)$.

Table 3: Cloud service provider features and decision makers analysis.

Feature Name	Cloud Providers	Decision Makers		
		D_1	D_2	D_3
Business Size Support (F_1)	AWS	G	VG	VG
	IB	VG	G	G
	GCE	VG	VG	BG
Support for Versatile Industries (F_2)	AWS	G	MG	MG
	IB	VG	G	VG
	GCE	P	F	MP
Control Interface Features (F_3)	AWS	VG	VG	G
	IB	P	F	MP
	GCE	G	G	MG
Availability of Support Services (F_4)	AWS	VG	G	VG
	IB	G	G	MG
	GCE	G	G	G
Server OS Types (F_5)	AWS	VG	VG	VG
	IB	G	MG	G
	GCE	VG	VG	VG
Preconfigured Operating Systems (F_6)	AWS	VG	G	G
	IB	P	MG	MP
	GCE	G	G	G
Available Run Times (F_7)	AWS	G	G	VG
	IB	VG	G	G
	GCE	P	F	P
Middleware (F_8)	AWS	G	MG	MG
	IB	VG	G	VG
	GCE	P	MP	F
Native Databases (F_9)	AWS	VG	VG	VG
	IB	G	G	G
	GCE	P	F	F

Weighted normalized fuzzy decision matrix is determined next.

The fuzzy positive and fuzzy negative ideal solutions are

$$P^* = (\widetilde{V}_1{}^*, \widetilde{V}_2{}^* \ldots\ldots \widetilde{V}_9{}^*)$$

$$\overline{N} = (\overline{\widetilde{V}}_1, \overline{\widetilde{V}}_2 \ldots\ldots \overline{\widetilde{V}}_9) \text{ respectively such that}$$

$$\widetilde{V}_j{}^* = (1, 1, 1) \text{ and } \overline{\widetilde{V}}_j = (0, 0, 0)$$

The distance of the alternatives from B_i from positive solution is calculated by

$$d_i{}^+ = \sum_{j=1}^{n} d\left(V_{ij}, V_j{}^*\right) \tag{7}$$

This is done for all the 3 cloud service providers.

Similarly, the distance from the alternatives from (0,0,0) is calculated.

The separation measures from positive ideal solution and negative ideal solution are calculated [17]. Table 4 depicts the same.

Table 4: Separation measures.

Cloud Providers	$d_1{}^+$	$d_1{}^-$
AWS	3.6759	6.0917
IB	4.285	5.56645
GCE	3.78625	6.0728

In Table 4 the separation measures are provided. The closeness coefficient will be calculated based on the separation measures obtained in Table 4.

The closeness coefficient CC_i is given by $d_i{}^-/(d_i{}^+ + d_i{}^-)$

$$CC_1 = \frac{6.0917}{(3.6759 + 6.0917)} = 0.6237$$

$$CC_2 = \frac{5.56645}{(4.285 + 5.56645)} = 0.5650 \tag{8}$$

$$CC_3 = \frac{6.0728}{(3.78625 + 6.0728)} = 0.6159$$

Very Low (VL)	(0,0,0.1)
Low (P)	(0,0.1,0.3)
Medium Low (ML)	(0.1,0.3,0.05)
Medium (M) (0.3,0.5,0.7)	
Medium High (MH)	(0.5,0.7,0.9)
High (H)	(0.7,0.9,1.0)
Very High (VH)	(0.9,1.0,1.0)

Box 3

Very Poor (VP)	(0,0,1)
Poor (P)	(0,1,3)
Medium Poor (MP)	(1,3,5)
Fair (F)	(3,5,7)
Medium Good (MG)	(5,7,9)
Good (G)	(7,9,10)
Very Good (VG)	(9,10,10)

Box 4

Table 5: Assessment criteria by decision makers.

Feature Name	D1	D2	D3
Cloud environment	H	VH	H
Data center location	VH	H	H
Resource sharing	H	H	H
Cloud storage	VH	VH	VH
Scalability	H	H	VH
Pricing structure	MH	MH	MH
Cloud security	MH	H	MH
Performance	H	MH	MH

The ranking order is now determined based on the closeness coefficient and its found AWS>GCE>IB. Hence the best alternative cloud service provider is AWS, i.e., Amazon Web Services.

6.2. Evaluation of Suitable Cloud Types Based on Notable Features. Evaluations are done in linguistic variables by cloud experts to evaluate suitable cloud platforms with respect to the different features like cloud environment, data center location, resource sharing, cloud storage, scalability, pricing structure, cloud security, and performance [18, 19].

Cloud experts use seven points linguistic variable scale based on the triangular fuzzy numbers and express the weightage/priority to 8 unique features (Box 3).

A committee is formed with decision makers to identify the evaluation criteria, which is shown in following Table 5. The committee of decision makers is represented by D1, D2, and D3 and assessment of criteria importance is shown in Table 5.

The fuzzy weight of each criterion j is determined with the help of given values of linguistic variables. These are provided below.

$$\widetilde{w_j} = \frac{1}{3}\left[w_j^{(1)} + w_j^{(2)} + w_j^{(3)}\right] \tag{9}$$

Thus

$$\begin{aligned}\widetilde{w_1} &= \frac{1}{3}[\mathrm{H} + \mathrm{VH} + \mathrm{H}]\\ &= \frac{1}{3}[\mathrm{H} + \mathrm{VH} + \mathrm{H}]\\ &= \frac{1}{3}[(0.7, 0.9, 1.0) + (0.9, 1.0, 1.0) + (0.7, 0.9, 1.0)]\\ &= \frac{1}{3}[2.3, 2.8, 3]\\ &= (0.77, 0.93, 1)\end{aligned} \tag{10}$$

Similarly, we can obtain the values of $\widetilde{w_2}, \widetilde{w_3} \ldots\ldots \widetilde{w_9}$

The three cloud platforms are evaluated by three decision makers on a seven point linguistic scale comprising the values in Box 4

The decision makers' opinion is combined for each criterion in Table 6. The fuzzy decision matrix of 3 cloud platforms is given by

For Cloud Platform Public, under the feature CE, the evaluation is

$$\begin{aligned}\widetilde{x}_{11} &= \frac{1}{3}[\mathrm{G} + \mathrm{VG} + \mathrm{G}]\\ &= \frac{1}{3}[(7, 9, 10) + (9, 10, 10) + (7, 9, 10)]\\ &= \frac{1}{3}(23, 28, 30) = (7.6, 9.6, 10)\end{aligned} \tag{11}$$

Under feature DC,

$$\begin{aligned}\widetilde{x}_{12} &= \frac{1}{3}[\mathrm{G} + \mathrm{G} + \mathrm{MG}]\\ &= \frac{1}{3}[(7, 9, 10) + (7, 9, 10) + (5, 7, 9)]\\ &= \frac{1}{3}(19, 25, 29) = (6.3, 8.3, 9.6)\end{aligned} \tag{12}$$

Likewise, evaluation is done for public cloud for remaining features.

Similarly for the other 2 cloud platforms, viz., Private and Hybrid under 8 features (CE, DC. . .PR) the evaluations are done.

Normalized decision matrix for each 8 features is determined against the 3 cloud platforms.

Normalized fuzzy decision matrix $\widetilde{v} = (\widetilde{v}_{ij})$

where $\widetilde{v}_{ij} = (\widetilde{r}_{ij})(.)(\widetilde{w}_j)$.

Weighted normalized fuzzy decision matrix is determined next.

The fuzzy positive and fuzzy negative ideal solutions are

$\mathrm{P}^* = (\widetilde{V}_1{}^*, \widetilde{V}_2{}^* \ldots..\widetilde{V}_9{}^*)$

Table 6: Assessment on different platforms by decision makers.

Feature Name	Cloud Platforms	Decision Makers		
		D_1	D_2	D_3
Cloud Environment CE	Public	G	VG	G
	Private	MG	F	MG
	Hybrid	VG	VG	VG
Data Center Location DC	Public	G	G	MG
	Private	MG	MG	F
	Hybrid	G	VG	G
Resource Sharing RS	Public	VG	G	VG
	Private	MG	MG	F
	Hybrid	G	G	G
Cloud Storage CS	Public	G	VG	VG
	Private	MG	G	G
	Hybrid	MG	G	G
Scalability SC	Public	VG	VG	VG
	Private	F	G	G
	Hybrid	G	VG	VG
Pricing Structure PS	Public	VG	G	VG
	Private	F	MG	F
	Hybrid	G	MG	G
Cloud Security SE	Public	MG	F	F
	Private	VG	VG	VG
	Hybrid	G	G	G
Performance PR	Public	F	F	MG
	Private	VG	G	VG
	Hybrid	G	VG	G

Table 7: Separation measures.

Cloud Types	d_1^+	d_1^-
Public	1.413	3.378
Private	1.645	2.914
Hybrid	2.78625	4.56

$\overline{N} = (\overline{\widetilde{V}}_1, \overline{\widetilde{V}}_2 \ldots\ldots \overline{\widetilde{V}}_9)$ respectively such that

$\widetilde{V}_j^{\,*} = (1,1,1)$ and $\overline{\widetilde{V}}_j = (0,0,0)$

The distance of the alternatives from B_i from positive solution is calculated by

$$d_i^+ = \sum_{j=1}^{n} d\left(V_{ij}, V_j^{\,*}\right) \tag{13}$$

This is done for all the 3 cloud platforms.

Similarly, the distance from the alternatives from (0,0,0) is calculated.

The separation measures from positive ideal solution and negative ideal solution are calculated [20]. This is given in Table 7.

The closeness coefficient CC_i is given by $d_i^- / (d_i^+ + d_i^-)$ based on the separation measures obtained in Table 7. The separation measure in Table 7 is determined based upon the FPIS and FNIS.

The ranking order is determined from the closeness coefficient matrix and it was found Hybrid>Public>Private. The best alternative cloud type is Hybrid.

7. Conclusion

In today's smart era, competition is gradually increasing among the Cloud service providers in the market. It is getting steeper day by day as new entrants are joining in the service provider pool. Top cloud service providers are changing their strategies to retain their position in this volatile market. Hence they are very keen on selection of features which they are providing to the customers. So every provider offers a set of specific features which differ from those of the others. Now it is the client's responsibility to choose the appropriate vendor from the available ones based on their need. This vendor selection requires understanding and analyzing the features in deep, which is quite tedious if done manually. So there is a crying need of some technique which can perform this analysis automatically. This paper deals with TOPSIS methodology which helps us to select the most suitable service provider by analyzing its available offerings and features. It also studied in detail the different MCDA

methods available along with the TOPSIS methodology. The TOPSIS technique is applied in selecting the suitable cloud for an organization which is embracing cloud from on-premise architecture. However, the detailed study will help cloud consumers in selecting the best service provider and cloud service from a set of different offerings and cloud features.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Aveek Basu carried out the research work. Sanchita Ghosh participated as the reviewer and research guide. All authors read and approved the final manuscript.

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Research Article

Fuzzy Analytical Hierarchy Process Method to Determine the Quality of Gemstones

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The selection of quality gemstones requires a special ability to select and assess the quality of gemstones to be traded. The diversity of types of gemstones and consumers becomes an obstacle in itself when the knowledge and ability of individuals to analyze the quality of gemstones is minimal. The decision-making method used is Fuzzy Analytical Hierarchy Process (F-AHP) method which is widely used in various sectors. F-AHP is easy to adapt to many decision issues; the research proposes a decision-making system using the F-AHP algorithm to analyze the quality of gemstones. The results obtained with the use of F-AHP model in the selection of quality gemstones show the highest quality of gemstones of all stones compared, Rubi 1, with a weight value of 0.152942.

1. Introduction

Many times, we are always faced with several options for the right decision-making. It is difficult to determine an accurate choice according to predetermined criteria. Decision-making issues are also experienced when selecting quality gemstones. For the gemstones entrepreneur, special skills are required to select or assess the quality of gemstones to be traded. The diversity of types of gemstones and consumer types in choosing gemstones is certainly a constraint when the data is incomplete and there is a lack of individual knowledge about analyzing the quality of gemstones.

To maintain the consistency of product quality and in accordance with the demands of the market, it is necessary to have quality control on eligible products, so that the error does not happen again. The system to be created is a solution that can assist decision-making for decision-makers in assessing and selecting quality gemstones accurately and effectively.

In previous research, several studies using the F-AHP method have been proven from several previous studies with the conclusion that the F-AHP method can be applied and effective for many problems in real life. Chien-Chang Chou and Ker-Wei Yu [1] propose a hybrid fuzzy AHP to deal with the decision-making problems in an uncertain and multiple-criteria environment choice. The F-AHP adopted by the research [2], which combines the AHP with fuzzy set theory, can not only capture the thinking logic of human beings but also focus on the relative importance of the evaluation criteria. In journal [3], the result obtained shows the best balance of performance for criteria from different categories such as physicochemical properties as well as safety, environmental, and health aspects. The assumption made in F-AHP approach is that all the criteria involved are independent of each other. However, in practice the relationship among criteria is usually complex, and there might be interdependencies.

To control the quality, we need a relevant element and method [4]; fuzzy model can be used with various mcdm methods [5]. F-AHP model is a good referral for decision-makers [6]. The fuzzy AHP method is applicable as a control for the quality and is useful for multicriteria decision-making problems [7]. The criteria people think of are the size that makes the quality of the gemstone better but with other criteria as a comparison can make the quality of smaller stones better than larger ones [8].

By using F-AHP method we can help a decision-maker to make more efficient, flexible, and realistic decisions based

Table 1: Data of gemstones containing specific gravity, color, hardness, cutting, and clarity as the main criteria. The data can be seen from the gemstone certificate.

	Specific gravity	Color	Hardness	Cutting	Clarity
Rubi 1	4.50 ct	AAA	9 mohs	Excellent	I2
Rubi 2	1.60 ct	AA	9 mohs	Excellent	SI2
Rubi 3	0.65 ct	A	9 mohs	Average	I1
Rubi 4	2.25 ct	A	9 mohs	Average	SI1
Rubi 5	1.05 ct	B	9 mohs	Poor	VS

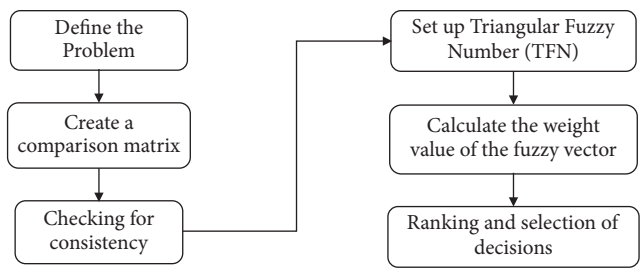

Figure 1: Block diagram has six steps of F-AHP phase process.

upon the available criteria and alternatives [9]. Therefore, the authors wish to apply the F-AHP method to determine the quality of gemstones.

2. Data Availability

The data and criteria in Table 1 were collected by consulting the director of Kantor Promosi Batu Mulia Indonesia. The data can be seen from the stone certificate issued by Kantor Promosi Batu Mulia Indonesia. Every time we buy gemstones we will get certificate of authenticity of stone; in the certificate there are criteria of stone.

3. Materials and Methods

Analytic Hierarchy Process (AHP) is a decision support method developed to complete problem by breaking the solution problems, grouping them, and then arranging them into a hierarchical structure. To obtain priority criteria, this method uses a comparison of criteria paired with a measurement scale that has been determined. The main input of the AHP method is the perception of experts or experts, so there is a factor of subjectivity in retrieval decision. This method also takes into account data validity with inconsistency limits [10]. However, considerable uncertainty and doubt in giving an assessment will have an impact on the accuracy of the data and the results obtained. Based on this, further theory was developed, namely, the method of Fuzzy Analytic Hierarchy Process. Fuzzy Analytic Hierarchy Process is a method of Analytic Hierarchy Process (AHP) developed with fuzzy logic theory. Fuzzy AHP method is used similar to the method of AHP. It is just that the Fuzzy AHP method sets the AHP scale into the fuzzy triangle scale to be accessed priority.

In this section, the F-AHP method was developed. The procedure used in the proposed method is described as follows.

Step 1 (define the problem and determine the desired solution (see Figure 1)). We need to define the problem according to the criteria used to determine the gemstones of quality. Specific gravity, color, hardness, cutting, and clarity are used as the main criteria for determining gemstone quality. This is some data from the gemstone certificate (see Table 1).

The weight of the stone has a unit of carat (ct); the greater the weight of a gemstone, the greater its size. Stone hardness unit is called Mohs because the name of the first person to do research on the hardness of a gemstone was Friedrich Mohs, a geologist and mineralogist from Germany in 1812. The clarity level of a gemstone is divided into IF, VVS1, VVS2, VS1, VS2, I1, I2, etc. The gemstone color level is seen from the level of clarity of color seen by the eye, given the levels of B, A, AA, AAA, and so on. The level of cutting quality is seen from its proportional and symmetrical shape of gemstones pieces.

Step 2 (create a comparison matrix (see Figure 1)). After we know the data and criteria stone in Table 1 we need to create a comparison matrix. The matrix used is simple, has a strong position for the consistency framework, obtains other information that may be required with all possible comparisons, and is able to analyze the overall priority sensitivity for changes in consideration.

Here are the equations used to define pairwise comparisons:

$$a_{ij} = \frac{w_i}{w_j}, \quad i, j = 1, 2, \ldots, n \tag{1}$$

where n denotes the number of criteria compared, W_i are weights for the i criterion, and a_{ij} is the ratio of the weight of the i criterion and j.

After knowing the comparison of its criteria in Table 2, the next thing done is to normalize each column into the

Table 2: Comparison of criteria, as the weighted value of each criterion.

Criteria	Specific Gravity	Color	Hardness	Cutting	Clarity
Specific Gravity	1	3	2	3	3
Color	1/3	1	3	2	3
Hardness	1/2	1/3	1	3	3
Cutting	1/3	1/2	1/3	1	3
Clarity	1/3	1/3	1/3	1/3	1

Table 3: Ratio index.

n	1	2	3	4	5	6	7	8	9	10
RI	0,00	0,00	0,58	0,90	1,12	1,24	1,32	1,41	1,45	1,49

matrix form by dividing each value in the column i and row j with the largest value in column i.

$$a_{ij} = \frac{a_{ij}}{\max a_{ij}}, \quad \forall i, j \tag{2}$$

Then the results of the matrix normalization from Table 2 are obtained as follows:

$$\begin{bmatrix} 0,4 & 0,58 & 0,3 & 0,321 & 0,231 \\ 0,133 & 0,193 & 0,45 & 0,214 & 0,231 \\ 0,2 & 0,064 & 0,15 & 0,3214 & 0,231 \\ 0,133 & 0,096 & 0,05 & 0,107 & 0,231 \\ 0,133 & 0,064 & 0,05 & 0,035 & 0,072 \end{bmatrix} \tag{3}$$

Step 3 (checking for consistency (see Figure 1)). The comparison of the consistency index with a random generator (RI) value is listed in Table 3 set by Saaty [10]. This value depends on the matrix order n.

Consistency is expected to be near perfect to produce a decision that is close to valid.

Here is the equation used to calculate the value of consistency.

First we must recognize the value of the eigenvector which is the weighted value of the criterion. To calculate the eigenvector, we use the following equation:

$$w_i = \frac{\widehat{a}_i}{n}, \quad \forall i \tag{4}$$

w_i is the eigen vector, where $\widehat{a}_i$ is the sum of the matrix normalization values and is divided by the number of criterion (n)

The largest eigenvalue is the number of times multiplying the number of columns with the main eigenvector (see Table 4). So it can be obtained by the equation

$$\begin{aligned} \lambda maks = &\left(\sum GM_{11-n1} \times \overline{X}1\right) + \ldots \\ &+ \left(\sum GM_{1n-ni} \times \overline{Xn}\right) \end{aligned} \tag{5}$$

Table 4: Eigenvector on criteria.

Criteria	*eigen*vector
Specific Gravity	0,3665
Color	0,2443
Hardness	0,1933
Cutting	0,1236
Clarity	0,0720

$$\begin{aligned} \lambda maks = &(0,3665 \text{ X } 2,5) + (0,2443 \text{ X } 5,667) \\ &+ (0,1933 \text{ X } 6,6667) \\ &+ (0,1236 \text{ X } 9,333) + (0,0720 \text{ X } 13) \\ \lambda maks = &\ 5,474 \end{aligned} \tag{6}$$

After obtaining maximum lambda value, the value of CI can be determined.

$$CI = \frac{\lambda maks - n}{n - 1} \tag{7}$$

where CI is the consistency index and maximum lambda is the largest eigenvalue of the n-order matrix.

$$\begin{aligned} CI &= \frac{5,474 - 5}{5 - 1} \\ CI &= 0,1185 \end{aligned} \tag{8}$$

If the value of CI is zero (0), this means the matrix is consistent. If the value of CI obtained is greater than 0 (CI> 0), then the limit of inconsistency applied by Saaty is tested. Testing is measured using Consistency Ratio (CR), i.e., index value (Table 3), or comparison between CI and RI.

$$CR = \frac{CI}{RI} \tag{9}$$

The RI value used is in accordance with the order n matrix. If the CR of a smaller matrix is 10% (0,1), this means that the inconsistency of each opinion is considered acceptable.

$$\begin{aligned} CR &= \frac{0,1185}{1,12} \\ CR &= 0,1058 \end{aligned} \tag{10}$$

Table 5: TFN scale.

TFN Scale	L	M	U
1	1	1	1
2	0,5	1	1,5
3	1	1,5	2
4	1,5	2	2,5
5	2	2,5	3
6	2,5	3	3,5
7	3	3,5	4
8	3,5	4	4,5
9	4	4,5	4,5
0,5	0,666667	1	2
0,333333	0,5	0,666667	1
0,25	0,4	0,5	0,666667
0,2	0,333333	0,4	0,5
0,166667	0,285714	0,333333	0,4
0,142857	0,25	0,285714	0,333333
0,125	0,222222	0,25	0,285714
0,111111	0,222222	0,222222	0,25

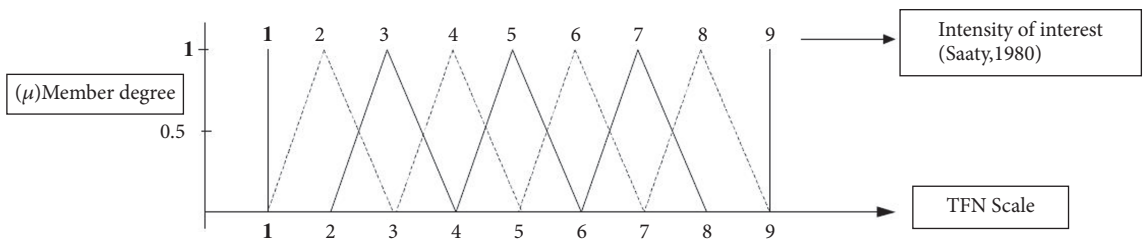

Figure 2: Graph of Fuzzy Triangle Set.

The consistency value of 0.1058 is equivalent to 10% inconsistency; this value can still be tolerated because the consistency value index must be less than 0.1.

Step 4 (set up Triangular Fuzzy Number (TFN) (see Figure 1)). The F-AHP scale has three values, namely, the lowest value (lower, L), middle value (median, M), and highest value (upper, U). So each fuzzy set will be divided into 2 (see Figure 2), except for the same comparison set, or can be seen on the TFN scale (see Table 5).

Based on the index (see Table 5), the comparison value in Table 2 will be made into a TFN set (see Table 6).

Step 5 (calculate the weight value of the fuzzy vector (see Figure 1)). After the AHP comparison value is transformed to F-AHP scale value, fuzzy synthesis value is calculated. The process to get fuzzy synthesis value is shown using equation of the following formula:

$$Si = \sum_{j=1}^{m} M_{gi}^{j} X \frac{1}{\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]} \tag{11}$$

Information:

Si = fuzzy synthesis value

$\sum_{j=1}^{m} \boldsymbol{M}_{gi}^{j}$ = summing the cell value in that column starting from column 1 in each row matrix

i = row

j = column

After the comparison of fuzzy synthesis values (see Table 7), we will get the defuzzification ordinate value (d′). From the above calculation, we can calculate the values of v and d′. To calculate V′ we use the equation of the following formula.

$$V\,(M2 \geq M1) = \begin{cases} 1, & ,if\ m2 \geq m1 \\ 0, & ,if\ l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)'} & ,etc \end{cases} \tag{12}$$

Calculating the value of the fuzzy vector weight (W′), calculation of the fuzzy weight value is shown using the equation of the following formula

$$d'^{(Ai)} = \min V\,(Si > Sk) \tag{13}$$

Table 6: TFN set of criteria; each value in the criteria comparison (see Table 2) is changed to TFN referring to the TFN scale.

	Specific Gravity			Color			Hardness			Cutting			Clarity		
	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U
Specific Gravity	1	1	1	1	1,5	2	0,5	1	1,5	1	1,5	2	1	1,5	2
Color	0,5	0,666667	1	1	1	1	1	1,5	2	0,5	1	1,5	1	1,5	2
Hardness	0,666667	1	2	0,5	0,666667	1	1	1	1	1	1,5	2	1	1,5	2
Cutting	0,5	0,666667	1	0,666667	1	2	0,5	0,666667	1	1	1	1	1	1,5	2
Clarity	0,5	0,666667	1	0,5	0,666667	1	0,5	0,666667	1	0,5	0,666667	1	1	1	1

Table 7: Synthesis value.

Synthesis Value		
L	M	U
0,125	0,246	0,439
0,111	0,215	0,387
0,115	0,215	0,413
0,101	0,183	0,362
0,083	0,139	0,258

Table 8: Criteria weight value, the result of calculation which contains the weight value of each criterion.

criteria	Weight
Specific Gravity	0,279088
Color	0,249106
Hardness	0,251526
Cutting	0,220279
Clarity	0,1546

collecting ordinate values that have been previously obtained, as below.

$$\Sigma W' = (vsk1, vsk2, \ldots, vskn) \tag{14}$$

Normalization of vector weight values is obtained by the equation of the following formula,

$$W' = \left(d'(A1), d'(A2), \ldots, d'(An)\right) \mathrm{T} \tag{15}$$

Step 6 (ranking and selection of decisions (see Figure 1)). Next is to do an alternative value calculation where the alternative settlement measures are the same as the completion steps on the criteria. Each alternative element's weight value (see Table 8) will be calculated by the weight of the criteria element and will be directed to get the decision result.

4. Result and Discussion

The built system consists of several menus that are the stages in running the decision support system. The first thing to do is login first. To be able to use this system we need to login. After login, we will enter into the main menu. On the main page the F-AHP algorithm and any data needed to start the system process are explained. After that alternative data and criteria are entered into the system. The gemstone data we have need to be input into the alternate data input page according to the criteria along with the criteria data we input into the input data page criteria. The next thing to do is to provide a comparison of the criteria and the value of alternative comparison to each criterion. After all has been done, next we can do the following process. In the process page we can see the value of criteria comparison and TFN set of criteria. When the process is completed, this will result in the ranking of each alternative; the decision-maker can determine which gemstones are qualified from the gemstones being compared. From the ranking results in Figure 3 and Table 9, it can be concluded that alternative 1 has the most optimum weight value compared with other alternatives. Therefore, a decision can be made that Rubi 1 is the highest-quality gemstone of all stones compared.

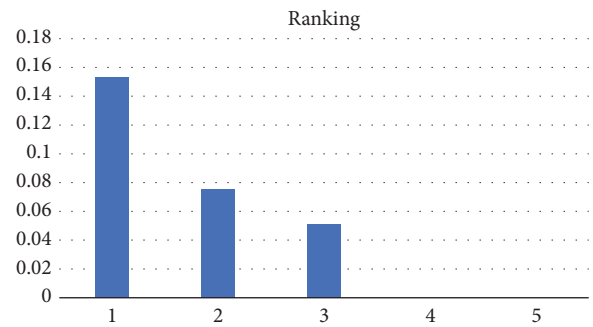

Figure 3: Ranking graph: ranking is derived from the result of alternate weight matrix by weight of criterion.

5. Conclusion

The conclusion of this research is as follows: we created a system that can assist decision-making in assessing and choosing quality gemstones accurately and effectively by using F-AHP algorithm.

The focus on the decision of the system is more on the decision of stones based on the same type of stone name; this is because, for the decision system to be more appropriate and relevant for use as a consideration in decision-making, it is impossible to compare one stone with stones of different types, not in the same class quality, so the end result of the system is based on the classification of the type of stone name.

As shown in Figure 3 we obtained the result by using the F-AHP model in the selection of quality gemstones Rubi 1 with a weight value of 0.152942, Rubi 2 of 0.075731, Ruby 3 of 0.050075, and Ruby 4 and Rubi 5 of 0. This weighting value

Table 9: Value of alternative calculation result on criteria.

	Specific Gravity	Color	Hardness	Cutting	Clarity	Total
Rubi 1	0,548005	0,389588	0,25	0,42711	0,427683	0,152942
Rubi 2	0,270062	0,531613	0,25	0,57289	0,491956	0,075371
Rubi 3	0,181933	0,028674	0,25	0	0,080361	0,050775
Rubi 4	0	0,050125	0,25	0	0	0
Rubi 5	0	0	0,25	0	0	0

indicates that a gemstone of the highest quality is Rubi 1 with a weight value of 0.152942 of all stones compared.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Distribution Network Risk Assessment Using Multicriteria Fuzzy Influence Diagram

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Risk assessment of distribution assets is one of the most important factors in the process of network development or maintenance planning decision-making. The process of decision-making is faced with uncertainties, involving technical, financial, safety, environmental, and other operational issues that make standard risk assessment techniques insufficient. Probabilistic uncertainties require appropriate mathematical modeling and quantification when predicting future state of the nature or the value of certain parameters. The paper is proposing a new methodology for the multicriteria risk assessment of the distribution network assets, based on influence diagrams and fuzzy probabilities. Influence diagram has been used to determine all relevant factors concerning risks and their interdependencies are depicted. Fuzzy probabilities are represented by triangular fuzzy numbers with constraints on feasibility of elicited probabilities. This methodology enables the decision process in uncertain environment, with the impact evaluation of each particular distribution asset, or the asset component. The methodology is illustrated on the example of a distribution substation circuit breaker maintenance strategy selection.

1. Introduction

Maintenance planning, development, and reconstruction of distribution networks are playing the crucial role in the asset management of distribution networks [1, 2]. One of the main problems of asset management in distribution companies is to find the best maintenance strategy out of following actions: do nothing and repair only after the breakdown, overhaul, or do the complete replacement of asset. Some activities, like minor or major maintenance, can be performed in a regular time interval, or depending on condition of an asset, but the problem is becoming more complex as alternatives must be evaluated on the basis of several criteria [3]. Some of them are easy to measure (costs and profit), while others can be very difficult to evaluate (public opinion, consequences of outages).

Risk and uncertainties are also present in the process of decision-making, whether it is in presupposed data (consumption increase rate, prices, and preferences) or in decision factors of business environment that affect the process of decision-making. One of the latest approaches is the risk management based maintenance, which evaluates the risk of equipment failure and consequences such failure can produce on the system [4–6]. With the quantification of risk, the most efficient strategy and the optimal risk level for distribution networks assets management can be obtained [6]. In all these approaches, risk is defined as a combination of probability indices and the consequences of failure in the network.

Decision about the optimal level of maintenance depends on several criteria of different nature:

(i) technical criteria
(ii) economic criteria
(iii) health and safety criteria
(iv) environmental impact
(v) public opinion and customer satisfaction
(vi) regulatory requirements

The number and structure of these categories is changing, depending on particular conditions (legislative, regulatory requirements, etc.) but these are basic attributes out of which the others can be derived. Furthermore, the asset management problem is facing the probabilistic uncertainty

and imprecision when modeling problem structural parameters, including the required goals, constraints, and external influences.

Various theories of imprecise probability include the Dempster-Shafer evidence theory [7, 8], the coherent lower prevision theory [9], probability bound analysis [10], and the fuzzy probability [11]. Stochastic nature of parameters and subjective probabilities are often described with interval probabilities or fuzzy sets. Interval and fuzzy probabilities are used when it is hard to model uncertainty by point value probabilities: when little or no information to evaluate them is available, or when several information sources (sensors, individual experts in group decision-making) are combined [12]. Fuzzy modeling can be understood as an extension to interval modeling, and fuzzy probabilities can be characterized by a possibility distribution of probability, representing degree of confidence in that probability expressed by an individual [13, 14].

Bayesian networks and Influence diagrams are used as a convenient tool for the large class of engineering problems, while the inherent uncertainty has been modeled by the fuzzification of random variables, and/or prior and conditional probabilities. A comprehensive review of development dealing with imprecise probabilities for the solution of various engineering problems is given in [15]. Fuzzy probabilities are treated as an extension of interval probabilities, emphasizing the correspondence between different α–levels and probability boxes. Various engineering analyses are then enabled using min–max operator and extension principle as the basis for the processing of fuzzy information.

In Bayesian networks, uncertainty embodies both sources: aleatoric (random events or uncontrollable variation) and epistemic (as the absence of complete knowledge). Furthermore, fuzzy probabilities, grouped in several fuzzy sets, can be denoted with linguistic terms: "extremely low", "very low", "medium", etc. [16–19]. These terms represent the information granules that are in great extent influenced by the psychological profile of the decision-maker.

In the deterministic case, alternatives and consequences are directly related in terms of criteria. In the presence of uncertainties, there may exist many possible outcomes that can be described quantitatively or qualitatively (through verbal descriptions).

Approaches like Bayesian networks, fault, and events trees are often used to understand and model random events and outcomes, but issues like interdependencies of different criteria in the decision-making process require further attention. New form of description, the influence diagram, that is both a formal description of the problem that can be treated by computers and a simple, easily understood representation is presented in this paper. The formal theory of Influence diagram is given in [20, 21], with the evaluation, or solving of influence diagram based on Bayesian networks.

This work introduces a new methodology for the risk assessment in distribution network based on the extension of Influence diagrams with the fuzzy probabilities and different consequence evaluation. Risk assessment is performed in two steps. In the first step, influence diagram has been used to determine all relevant factors influencing risks with the depiction of their interdependencies, together with all possible alternative decisions. In the second step, the set of each particular risk values is calculated as the combination of risk factor occurrence and their consequences. Subjective probabilities are represented as information granules described by linguistic terms and modeled as triangular fuzzy numbers.

In the next section of this paper, both steps of a risk assessment methodology using Bayesian networks and Multicriteria Influence diagram are presented. Building of an influence diagram and the way of solving it are presented. Using joint probability rule, the risk of particular event, for different risk categories, is calculated. In Section 3, the notion of fuzzy probability has been explained and in Section 4 the methodology is illustrated on the case study of the choice of circuit breakers maintenance strategy in one transformer substation.

2. Risk Assessment Using Influence Diagrams

2.1. Risk Assessment. Risk assessment, as the first step in the risk management process, attempts to identify possible failure events, evaluate their consequences, determine the probability of their future occurrence, and reduce the detrimental consequences. The usual definition of risk associated with an event E is defined as the product of event probability $p(E)$ and its consequence $Cons(E)$ [22, 23]:

$$Risk\,(E) = p\,(E) \cdot Cons\,(E) \tag{1}$$

More complex relationships between values introducing empirical scaling parameters x, y, and w are presented in the following [24]:

$$Risk\,(E) = p\,(E)^{y} \cdot w \cdot Cons\,(E)^{x} \tag{2}$$

Calculated value of risk became a crucial factor when deciding about the actions to be performed on distribution asset. However, decisions have to be made in a very uncertain environment. In this paper, a new graphical tool based on Bayesian networks—influence diagrams for risk assessment and decision-making under uncertainty—is proposed. The definition of Bayesian networks is given in the sequel, before proceeding to the risk assessment methodology.

2.2. Bayesian Networks. Bayesian network (BN) is a directed acyclic graph represented with pairs $N = \{(V, E), P\}$. Node V represents random variables (events) and links E between nodes represent a causal dependency. A link from variable X to variable Y indicates that X can cause Y, or, in BN terminology, X is a parent of Y, and Y is a child of X. P is a probability distribution over V. Discrete random variables $V = \{X_1, X_2, \ldots, X_n\}$ are assigned to the nodes variables representing a finite set of mutually exclusive states and annotated with a Conditional Probability Table (CPT) that represents the conditional probability of the variable given the values of its parents in the graph.

The simple Bayes net is presented in Figure 1 with two independent variables, X_1 and X_2, and dependent variable Y with appropriate CPT representing probabilities for each

Table 1: Consequences grading scale.

	Safety consequences
Grade	Description
1	No harmful consequences
2	Minor: failure results in minor system damage but does not cause injury to personnel or allow any kind of exposure to operational or service personnel
3	Major: failure results in a low level of exposure to Personnel, or activates facility alarm system
4	Critical: failure results in minor injury to personnel
5	Catastrophic: failure results in major injury or death of personnel

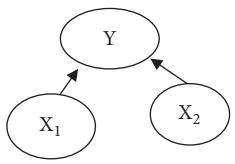

Figure 1: Bayes net with two independent variables.

possible state of the nature of variable Y, or event, in the risk assessment terminology.

The solving of BN is based on four rules, including conditional independence, joint probability, marginalization, and Bayesian rule, presented respectively in the following expressions [21, 22].

Conditional Independence

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i/Parents(X_i)) \quad (3)$$

Joint Probability

$$P(Y = y_i, \mathrm{X} = x_i) = P(X = x_i) \cdot P(Y = y_i/\mathrm{X} = \mathrm{x}_i) \quad (4)$$

Marginalization Rule

$$P(Y = y_i) = \sum_i P(X = x_i) \cdot P(Y = y_i/\mathrm{X} = \mathrm{x}_i) \quad (5)$$

Bayesian Rule

$$P(X = x_i/\mathrm{Y} = \mathrm{y}_j) = \frac{P(X = x_i) \cdot P(\mathrm{Y} = \mathrm{y}_j/X = x_i)}{P(Y = y_j)} \quad (6)$$

Using expressions (3)–(5), the probability of each possible state j out of n possible states of variable Y can be determined. After the calculation of probabilities, the following step in the methodology is to calculate the risk, using expressions (1) and (2), or more generally:

$$R_i = f(C(Y_i), P(Y_i)) \quad (7)$$

In order to incorporate the risk, BN is extended by two more nodes: consequence node *C(Y)* and risk value node *R* (Figure 2).

For instance, consequences grades for personal safety can be expressed by numerical grades, described in Table 1.

Risk value node is represented by the n-dimensional array, with elements calculated from (7).

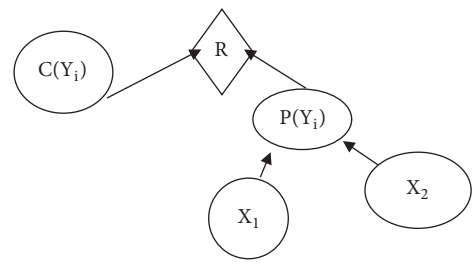

Figure 2: Extension of the Bayes net for the risk assessment.

2.3. Influence Diagrams. A generalization of a BN is the Influence diagram (ID), proposed by Howard and Matheson [21], as a tool to simplify modeling and analysis of decision trees, allowing not only probabilistic inference but also the graphical representation of decision-making problems. Like in BN, the input and output values of a node in an ID are based on the Bayesian theorem, allowing a user to make inferences with limited available information. Besides the chance nodes of BN, ID also contains decision nodes and utility nodes, depicting available information at the time of making a decision, and the degree of influence of each variable on other variables and decisions. Unlike a decision tree that shows more details of possible paths, ID shows dependencies among variables more clearly. IDs are particularly useful in creating computer-based models that describe a system or as descriptions of decision maker's mental models to assess the impact of their actions.

ID tries to capture system representation in a form that can be communicated to others, through several graphical symbols. A circle depicts an exogenous variable (an external influence) whose values are not affected by previous decisions. A rectangle depicts a decision, while intermediate variables depict an endogenous variable whose values are computed as functions of decision and other variables. Chance node (an ellipse) represents a random variable defined by discrete probability distribution. Arrow shows the influence between variables, and dotted arrow shows information being communicated between elements. Finally, value node (a diamond) is a quantitative criterion representing the subject of optimization. The simple example of an ID is presented in Figure 3.

Methods for evaluating and solving IDs are based on Bayes theorem and can be grouped in several categories. They can be (i) converted to decision trees and solved, (ii) solved by

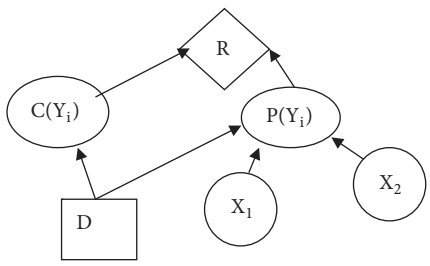

Figure 3: Influence diagram for the risk assessment.

the variable elimination algorithms, or (iii) solved by efficient algorithms using graphical structures, like the junction trees [25].

When nodes in the diagram are represented by appropriate fuzzy sets, ID can be solved using fuzzy reasoning [26–28]. A commonly used technique for combining fuzzy sets is fuzzy inference system, like the Mamdani type inference. The final step for building an ID model for the risk assessment is to aggregate different risk factors into one diagram. An illustration for the risk assessment ID with two criteria: safety risk (S) and economic risk (E), is presented in Figure 4.

3. Fuzzy Probability

Uncertain and subjective probabilities can be granulated in different terms like: improbable or doubtful, but we will draw our attention to special form of probability granulation, focusing on point value with inherent uncertainty: around 30%, around 75%, etc. These probabilities are defined starting from previous works on linguistic probability [29–32] defining similar probability measure for fuzzy probabilities.

Klir [31, 32] introduced a notion of a fuzzy interval defined on $[0,1]$ as a probability granule, that is, a normal fuzzy set on $[0,1]$ with α cuts for all as closed subintervals on $[0,1]$. These fuzzy probabilities will be denoted as $P_1, P_2, \ldots, P_n$ and they may be expressed by the canonical form:

$$P_i(x) = \begin{cases} f_i(x), & \mathrm{x} \in [0, \mathrm{b}) \\ 1, & x \in [b, c] \\ g_i(x), & x \in (c, d] \\ 0, & otherwise \end{cases} \tag{8}$$

where $a, b, c, d \in [0,1]$, $a \le b \le c \le d$, and f_i and g_i are strictly increasing right continuous and strictly decreasing left continuous real valued function, respectively. The α–cuts of P_i are expressed for all $a \in [0,1]$:

$$P_i^{\alpha} = \begin{cases} \left[f_i^{-1}(\alpha), \mathrm{g}_i^{-1}(\alpha)\right], & \alpha \in (0,1) \\ [b, \mathrm{c}], & \alpha = 1 \end{cases} \tag{9}$$

In this paper, we will investigate the elicitation of triangular fuzzy set support—left and right bounds of triangular fuzzy numbers. The support of fuzzy set A is the set of all points x in X such that $\mu_{A(x)} > 0$.

Consider a discrete random variable X with values in the set $X = \{x_i, i \in N_n\}$. We will assume that the probabilities of this random variables $P(x_i)$ are assessed approximately, by a triangular fuzzy number:

$$\mu_{P_i}(\mathrm{x}) = \begin{cases} 0, & x < a_i \\ \dfrac{x - a_i}{b_i - c_i}, & a_i < x < b_i \\ \dfrac{c_i - x}{c_i - b_i}, & b_i < x < c_i \\ 0, & x > c_i \end{cases} \tag{10}$$

We can interpret these fuzzy numbers as fuzzy probabilities as follows.

Definition 1. Fuzzy numbers $P_i = [a_i, b_i, c_i]$, $i = 1, \ldots, n$ are called fuzzy probabilities of X if there are $x_1 \in [a_1, c_1], \ldots, x_i \in [a_i, c_i], \ldots, x_n \in [a_n, c_n]$ such that:

$$\begin{gathered} \sum_{i=1}^{n} x_i = 1, \\ \sum_{i=1}^{n} b_i = 1 \end{gathered} \tag{11}$$

The set of fuzzy numbers P satisfies (11) if and only if the following conditions hold [33]:

$$\begin{gathered} c_i + a_1 + \ldots + a_{i-1} + a_{i+1} + \ldots + a_n \ge 1, \quad \forall i \\ a_i + c_1 + \ldots + c_{i-1} + c_{i+1} + \ldots + c_n \ge 1, \quad \forall i \end{gathered} \tag{12}$$

If there are only two fuzzy probabilities $[a_1, b_1, c_1]$ and $[a_2, b_2, c_2]$, then $a_1 + c_2 = 1$, $a_2 + c_1 = 1$ and $b_1 + b_2 = 1$.Let us consider a set of fuzzy numbers $FP = \{FP_i = [a_i, b_i, c_i], i = 1, \ldots, n\}$. The interval of probability values for every α–cut will be denoted as $[a_{\alpha,i}, c_{\alpha,i}]$. We can interpret these fuzzy numbers as fuzzy probabilities as follows.

Definition 2. Fuzzy numbers $FP_i = [a_i, b_i, c_i]$ are called fuzzy probabilities of X if for $\forall \alpha \in [0,1]$ and $\forall x_i \in [a_{\alpha,i}, c_{\alpha,i}]$ there are $x_1 \in [a_{\alpha,1}, c_{\alpha,1}], \ldots, x_{i-1} \in [a_{\alpha,i-1}, c_{\alpha,i}], x_{i+1} \in [a_{\alpha,i+1}, c_{\alpha,i+1}], \ldots, x_n \in [a_{\alpha,n}, c_{\alpha,n}]$ such that:

$$\sum_{i=1}^{n} x_i = 1 \tag{13}$$

Lemma 3. *The set of fuzzy numbers FP satisfies (13) if and only if the following conditions hold:*

$$\begin{gathered} c_{\alpha,i} + a_{\alpha,1} + \ldots + a_{\alpha,i-1} + a_{\alpha,i+1} + \ldots + a_{\alpha,n} \le 1, \\ \forall \alpha, \forall i \\ a_{\alpha,i} + c_{\alpha,1} + \ldots + c_{\alpha,i-1} + c_{\alpha,i+1} + \ldots + c_{\alpha,n} \ge 1, \\ \forall \alpha, \forall i. \end{gathered} \tag{14}$$

Proof.

Sufficient Conditions. If the first part of Lemma 3 holds, then:

$$\begin{gathered} \forall \alpha, \forall i \\ x_i + a_{\alpha,1} + \ldots + a_{\alpha,\mathrm{i}-1} + a_{\alpha,\mathrm{i}+1} + \ldots + a_{\alpha,\mathrm{n}} \le c_{\alpha,i} + a_{\alpha,1} \\ + \ldots + a_{\alpha,\mathrm{i}-1} + a_{\alpha,\mathrm{i}+1} + \ldots + a_{\alpha,\mathrm{n}} \le 1 \end{gathered}$$

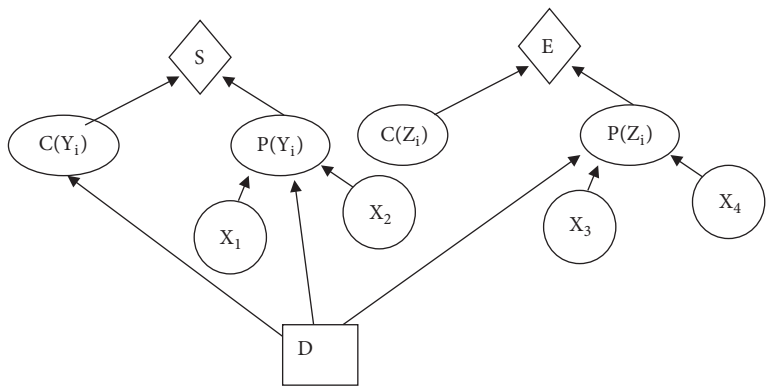

Figure 4: Complete influence diagram with different risk factors.

$$\forall\alpha, \forall i$$
$$x_i + c_{\alpha,1} + \ldots + c_{\alpha,\mathrm{i}-1} + c_{\alpha,\mathrm{i}+1} + \ldots + c_{\alpha,\mathrm{n}} \geq a_{\alpha,i} + c_{\alpha,1} + \ldots + c_{\alpha,\mathrm{i}-1} + c_{\alpha,\mathrm{i}+1} + \ldots + c_{\alpha,\mathrm{n}} \geq 1. \tag{15}$$

Then, the following expression holds:

$$x_i + a_{\alpha,1} + \ldots + a_{\alpha,\mathrm{i}-1} + a_{\alpha,\mathrm{i}+1} + \ldots + a_{\alpha,\mathrm{n}} \leq 1 \leq x_i + c_{\alpha,1} + \ldots + c_{\alpha,\mathrm{i}-1} + c_{\alpha,\mathrm{i}+1} + \ldots + c_{\alpha,\mathrm{n}}. \tag{16}$$

The expression shows that there exist $a_{\alpha,j} \leq x_j \leq c_{\alpha,j}$, $j \in \{1, \ldots n\}$, $j \neq i$ that satisfies (13).

Necessary Conditions. If the first part of Lemma 3 does not hold, then:

$$\forall\alpha, \exists i$$
$$c_{\alpha,i} + a_{\alpha,1} + \ldots + a_{\alpha,i-1} + a_{\alpha,i+1} + \ldots + a_{\alpha,n} > 1$$
$$\forall\alpha, \exists i$$
$$a_{\alpha,i} + c_{\alpha,1} + \ldots + c_{\alpha,i-1} + c_{\alpha,i+1} + \ldots + c_{\alpha,n} < 1. \tag{17}$$

Then, taking x_i as $a_{\alpha,i}$ or $c_{\alpha,i}$ (13) cannot hold.

An alternative definition of fuzzy probabilities can be formulated from two extreme cases of $\alpha = 0$ and $\alpha = 1$. □

Definition 4. Fuzzy numbers $FP_i = [a_i, b_i, c_i]$ are called fuzzy probabilities of X if for and $\forall x_i \in [a_i, c_i]$ there are $x_1 \in [a_1, c_1], \ldots, x_{i-1} \in [a_{i-1}, c_i], x_{i+1} \in [a_{i+1}, c_{i+1}], \ldots, x_n \in [a_n, c_n]$ such that:

$$\sum_{i=1}^{n} x_i = 1, \qquad \sum_{i=1}^{n} b_i = 1 \tag{18}$$

Bayesian networks with fuzzy numbers replacing point value probabilities are proposed [30] defining "Bayesian fuzzy probability" as convex, normal fuzzy set of $[0, 1]$. Complementation law has been relaxed in order to extend a partially defined linguistic probability measure, and this method has been successfully used in forensic statistics [29] and risk analysis [18]. More possible scenarios for fuzzifying the Bayesian approach are presented in [15] using nonfuzzy algorithmically efficient reformulation of the Bayesian formula. Although time-consuming, we will implement the corresponding fuzzy version of Bayesian formulas.

The fuzzy counterparts to the standard arithmetic operators are defined using the extension principle. It is possible to derive these operators by examining the effects of interval based calculations at each α–cut. The extended operators are defined by (19), using a circled arithmetic operator symbol for the extension of a real arithmetic operator.

Definition 5. For all $a, b \in R^F$a, the extended operators are defined by

$$\begin{aligned}
\mu_{A\oplus B}(z) &= \sup \min \left(\underset{x+y=z}{\mu_A(x), \mu_B(y)} \right) \\
\mu_{A\otimes B}(z) &= \sup \min \left(\underset{xy=z}{\mu_A(x), \mu_B(y)} \right) \\
\mu_{A-B}(z) &= \sup \min \left(\underset{x-y=z}{\mu_A(x), \mu_B(y)} \right) \\
\mu_{A\emptyset B}(z) &= \sup \min \left(\underset{x/y=z}{\mu_A(x), \mu_B(y)} \right)
\end{aligned} \tag{19}$$

From previous definition, two fuzzy Bayes rules analogue to classical crisp number relations are formulated. Operator "≅" stands for "=" operator.

Fuzzy Joint Probability

$$P\left(Y = y_j, X = x_i\right) \cong P\left(X = x_i\right) \otimes P\left(Y = y_j \setminus X = x_i\right) \tag{20}$$

Table 2: Fuzzy probabilities.

Triangular fuzzy probability number	Description	Notation
[5 10 15]	Extremely low probability	EL
[15 20 25]	Low probability	L
[25 30 35]	Low to medium	LM
[35 40 45]	Medium to low	ML
[45 50 55]	Medium probability	M
[55 60 65]	Medium to high	MH
[65 70 75]	High to medium	HM
[75 80 85]	High probability	H
[85 90 95]	Extremely high probability	EH

Table 3: Prior probability of weather states.

States	Description	Probability
Bad	Severe weather conditions	MM
Medium	No extreme temperatures below – 20 degree	LM
Good	Good weather conditions, no extreme temperatures below -10 degree	L

Fuzzy Bayes Rule

$$P\left(X = x_i \setminus Y = y_j\right) \cong \frac{P\left(X = x_i\right) \otimes P\left(Y = y_j \setminus X = x_i\right)}{P\left(Y = y_j\right)} \tag{21}$$

Based on the law of total probability another rule for the fuzzy marginalization can be added, represented by (22).

Fuzzy Marginalization Rule

$$P\left(Y = y_j\right) \cong \sum_i P\left(X = x_i\right) \otimes P\left(Y = y_j \setminus X = x_i\right) \tag{22}$$

Finally, risk can be calculated from

$$R = \sum_i^n P\left(C_i\right) \otimes C_i \tag{23}$$

It is possible to use any other form of additive, multiplicative, or tabular risk aggregation function. The influence diagram with fuzzy probabilities will be illustrated on a simple case study of maintenance strategy selection.

4. Case Study

Risk assessment methodology is illustrated on substation with low oil circuit breakers. The decision has to be made about three possible alternatives: do nothing, perform minor interventions, or do the overhaul and major repair of circuit breakers. The alternatives will be assessed by the risk assessment of two criteria: safety and environment. Both criteria will be evaluated by their risk and then aggregated in the one influence diagram value node.

Two failure modes and normal operating condition of a circuit breaker are taken into account: breaker is in operating conditions (OK), failure to close (Close), when breaker does not close the circuit to conduct current in one or more poles, and failure to open (FO), when breaker does not open the circuit to interrupt current. In the case of the bad weather conditions in the following year, the network condition will worsen due to the increased number of failure, the network loading will increase, and the breaker will be exposed to more severe operation conditions. Due to the uncertainty about the weather forecast, and consequently network technical condition, network maximal demand power (loading), and possible failure modes, probabilities elicited by experts are also uncertain. According to the definition of the fuzzy probabilities, possible probability grades are represented in Table 2.

Prior fuzzy probabilities of ambient conditions and global weather forecast for the next year are given in Table 3.

Conditional probability tables for network condition, circuit breaker failure modes, loading levels, and consequences are represented in Tables 4, 5, 6, and 7, respectively.

Safety and environment criteria evaluations are expressed in numerical grades (from 1 to 5) and represented in Table 8.

For $\alpha = 1$, the influence diagram becomes the deterministic influence diagram with crisp probability values. The solved diagram with calculated values for three different scenarios and two criteria is represented in Figure 5.

Risk is calculated using the following consequences grades: 1 for no consequences, 2 for minor, and 3 for major consequences, and aggregation of two risks is presented in Table 9.

It is visible that risk calculated values do not show great variance, and that decision about the future maintenance strategy cannot be easily determined. Therefore, the problem is solved again using fuzzy probabilities and expressions (19)–(22). Results are presented on Figures 6, 7, and 8.

Calculated values for risks for both alternatives with crisp values (Figure 5) and fuzzy probability values

Table 4: Conditional probabilities of network conditions.

Weather	States	
	Bad conditions on MV side—no tree trimming, no maintenance, increased number of failures	Good conditions on MV network, no increase in failure rate
B	MH	ML
M	MM	MM
G	ML	MH

Table 5: Conditional probabilities of failure modes.

Decision	NC	Ok	Close	FO
Minor		HM	L	EL
Minor	Good	H	EL	EL
Major	Bad	H	EL	EL
Major	Good	EH	EL	EL
Do nothing	Bad	MH	L	L
Do nothing	Good	MH	L	L

Table 6: Conditional probabilities of network loading levels.

Weather	Low Loading	Medium Loading	High Loading
Bad	EL	LM	MH
Medium	LM	MM	L
Good	MH	LM	EL

Table 7: Conditional probabilities of consequences.

Loading	Failure mode	Safety risk			Environmental risk		
Low loading	OK	EH	EL	Impossible	H	EL	EL
	Failure to close	H	EL	EL	H	EL	EL
	Failure to open	HM	L	EL	HM	L	EL
Medium loading	OK	H	EL	EL	H	EL	EL
	Failure to close	HM	L	EL	MM	LM	L
	Failure to open	MH	LM	EL	MH	LM	EL
High loading	OK	HM	L	EL	HM	L	EL
	Failure to close	MH	L	L	MH	L	L
	Failure to open	MM	LM	L	MM	LM	L

Table 8: Safety and environment criteria grades.

Grade	Safety risk	Environmental risk
1	No harmful consequences	No harmful consequences, Failure does not allow any release of chemicals into the environment
2	Minor: failure results in minor system damage but does not cause injury to personnel	Personnel exposure to harmful chemicals or radiation or fire
3	Critical: failure results in minor injury to personnel	A release of chemical to the environment

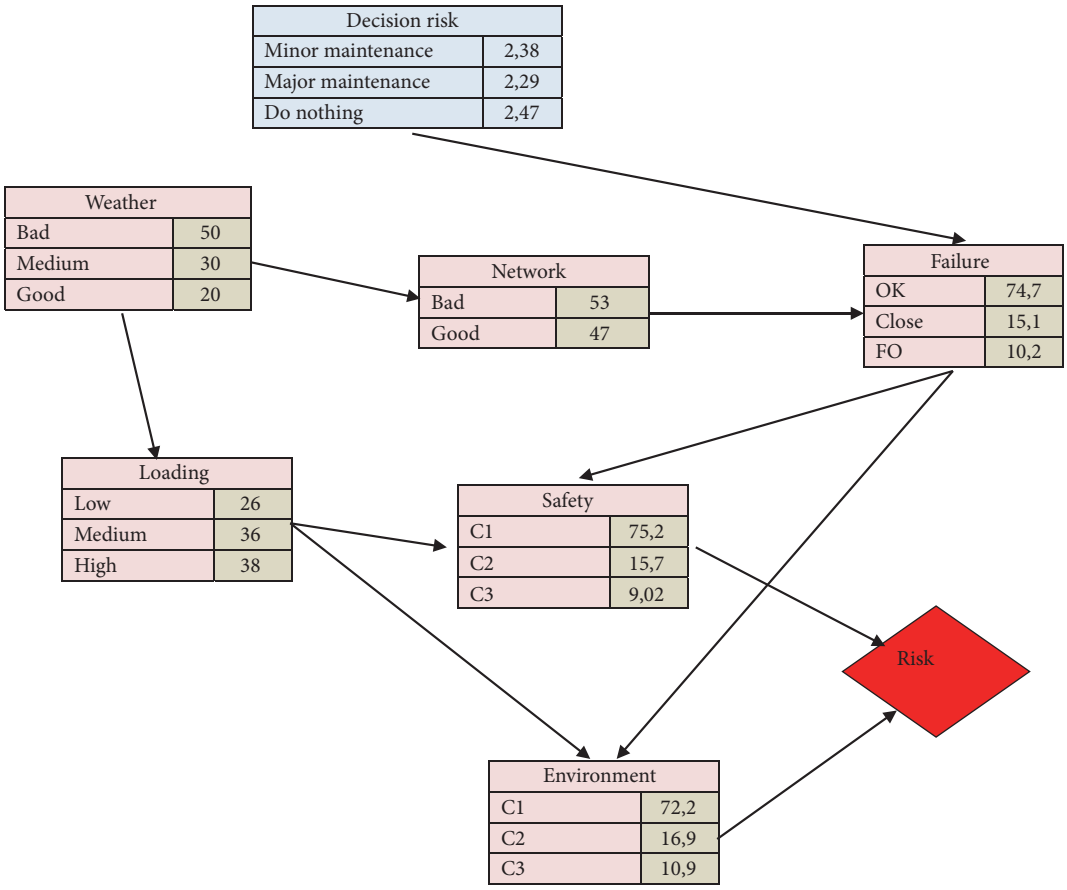

Figure 5: Influence diagram with crisp probabilities.

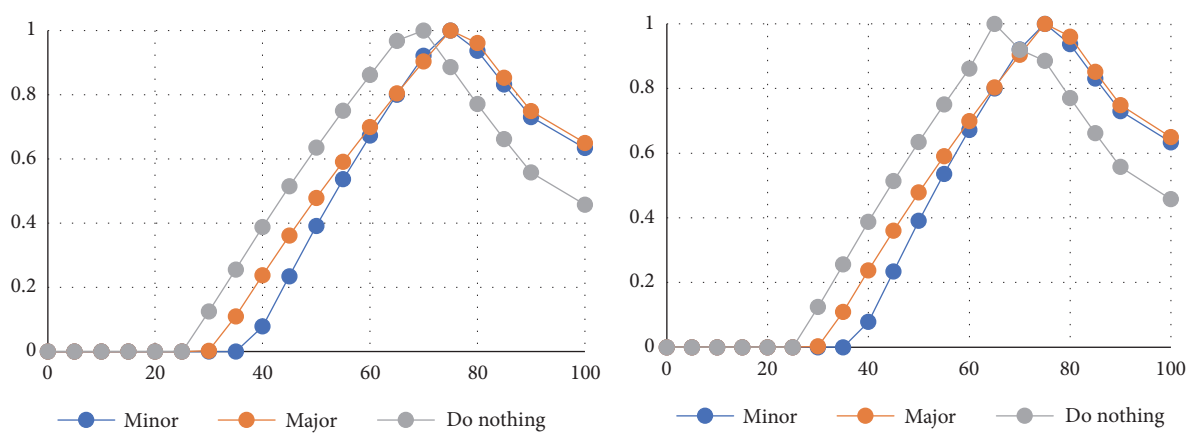

Figure 6: Fuzzy probabilities for no consequences state for (a) safety risk and (b) environmental risk.

defuzzified using the centroid method are given in Table 10.

Unlike the crisp calculated values for the risk node, the fuzzy probabilities of possible consequences are highlighting the whole range of future scenarios consequences, facilitating the decision-making process. From Figure 6 it is visible that the "doing nothing" strategy almost doubles the risk for minor and major consequences, while the minor and major maintenance practically do not make any difference.

5. Conclusions

Decision-making in maintenance planning is always confronted with several aspects: technical, financial, safety, environmental, and operational ones. Each of these factors can be modeled by the appropriate risk of possible harmful consequences. This paper introduces a new methodology for the optimization of maintenance activities in distribution network, based on the calculation of the risk of the particular

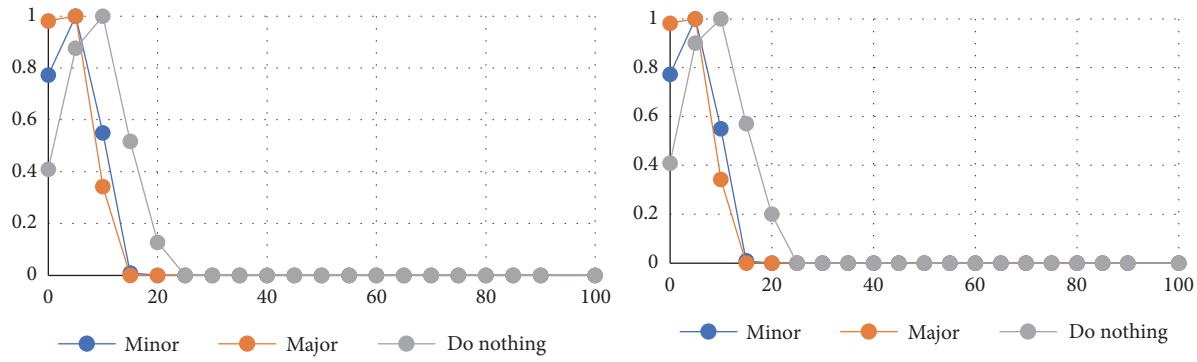

Figure 7: Fuzzy probabilities for minor consequences state for (a) safety risk and (b) environmental risk.

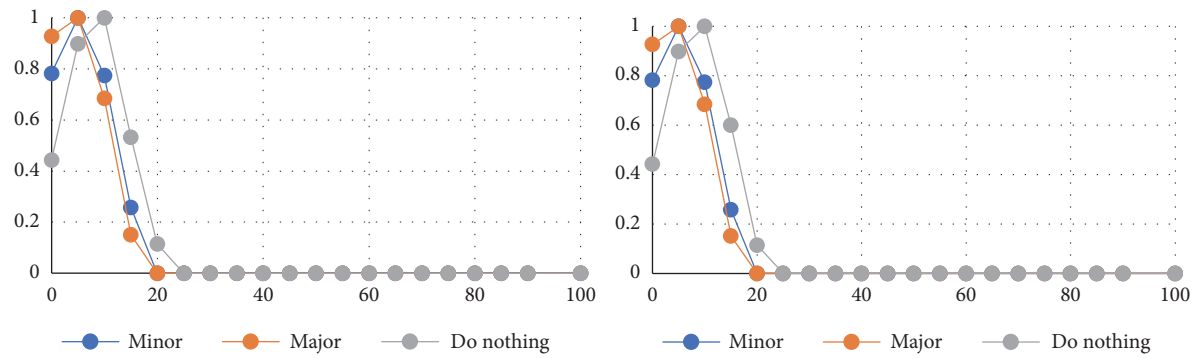

Figure 8: Fuzzy probabilities for critical consequences state for (a) safety risk and (b) environmental risk.

Table 9: Aggregated risks.

Safety	1	2	3	1	2	3	1	2	3
Environment	1	1	1	2	2	2	3	3	3
Aggregated risk	1	2	3	4	5	8	7	8	10

Table 10: Aggregated risk comparison.

	Crisp probability	Fuzzy probability
Minor	2,38	2,40
Major	2,29	2,65
Do nothing	2,48	4,12

component, or the overall risk of the distribution object. For this purpose, the Fuzzy Influence diagram has been used, in order to determine all relevant factors influencing risks, and depicting their interdependencies. Probabilistic uncertainties require appropriate mathematical modeling and quantification when predicting future state of the nature or the value of certain parameters and the proposed model enables evaluation of the impact of each particular component of maintenance decision process. Bayesian networks and Influence diagrams are used as a convenient tool for the large class of engineering problems, while the inherent uncertainty has been modeled by the fuzzification of random variables, and/or prior and conditional probabilities. The methodology is illustrated on the example of the choice of circuit breakers maintenance in one distribution transformer substation. This methodology is especially suited for systems with great number of unobservable components, in the presence of uncertainty and lack of operational data, like power distribution system is. The main challenges for the future research are the introduction of fuzzy multi-criteria decision analysis for the choice of activity minimizing the overall risk and more flexible representation of fuzzy subjective probabilities, as information granules described by linguistic terms and modeled as triangular fuzzy numbers.

Data Availability

Data used in the case study are used for simulation purposes. Any calculation result can be obtained from the author by request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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Research Article

Ultra-Short-Term Prediction of Wind Power Based on Fuzzy Clustering and RBF Neural Network

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High-precision wind power forecast can reduce the volatility and intermittency of wind power output, which is conducive to the stable operation of the power system and improves the system's effective capacity for large-scale wind power consumption. In the wind farm, the wind turbines are located in different space locations, and its output characteristics are also affected by wind direction, wake effect, and operation conditions. Based on this, two-step ultra-short-term forecast model was proposed. Firstly, fuzzy C-means clustering (FCM) theory was used to cluster the units according to the out characteristics of wind turbines. Secondly, a prediction model of RBF neural network is established for the classification clusters, respectively, and the ultra-short-term power forecast is performed for each unit. Finally, the above results are compared with the RBF single prediction model established by unclassified g wind turbines. A case study of a wind farm in northern China is carried out. The results show that the proposed method can effectively improve the prediction accuracy of wind power and prove the effectiveness of the method.

1. Introduction

In order to solve the challenges of current energy development, such as resources, environmental pollution, and climate change, the future electric power system adopts low-carbon, green, and clean development as the development direction, which will increase the installed capacity of renewable energy represented by wind energy. Due to the randomness and volatility of wind energy, grid-connected wind power generation results in fluctuations in grid voltage and frequency, which directly affect the stability of the power quality of the grid and the operation of the power system and also bring many uncertainties to the power grid dispatching [1]. Accurate wind power prediction is one of the effective ways to reduce the above factors.

At present, approaches for short-term wind power forecasting is mainly divided into two categories: statistical models based purely on historical data and physical numerical weather prediction (NWP) models. They are better for short-term forecasting 6–72 hours ahead. Though the former model is relatively concise and the calculation speed is fast, the prediction accuracy decreases sharply with the increase of prediction time. Models based on numerical weather prediction can obtain wind power prediction values for the next 1 to 3 days. The prediction accuracy is relatively stable, but the calculation volume is huge and often requires supercomputers to continuously operate for hours [2]. Statistical models with NWP data as additional exogenous inputs, considering spatial relationships is one of the main research methods for improving wind power prediction accuracy in the future. Considering the research of spatial correlation, most of the literature is based on the analysis of wind velocity and spatial correlation to establish wind speed prediction model [2–5]. In [4], based on the statistical data of wind speed in the history year, in order to study the temporal evolution and spatial extent of the statistics of the data, using a data-coupled clustering method (SODCC algorithm) to calculate the cluster size probabilities and the node to cluster size probabilities, a spatiotemporal model of wind speed is established. The method provides guidance for forecasting analysis of wind farm output. Assume that there exist low-dimensional structures governing the interactions among a

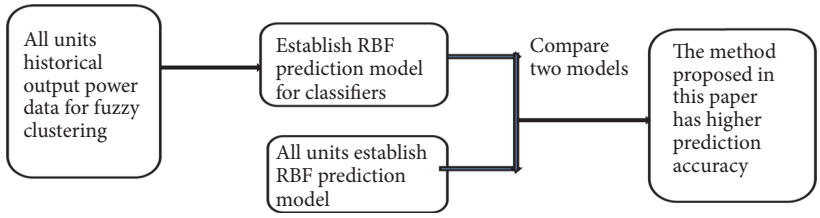

Figure 1: Fuzzy clustering and RBF network prediction model flow diagram.

set of historical data from meteorological stations, and we utilize Wavelet Transform (WT) for decomposition of the wind speed data into more stationary components. Based on Compressive Sensing (CS) and structured-sparse recovery algorithms, a spatiotemporal model of each subsequence is established to predict wind speed. Another study is about the spatial distribution of regional wind farms, analyzing the spatial-temporal correlation of the output of wind farms and establishing wind power forecasting models based on measured historical data. In [6], based on the geographic spatial distribution information of multiple wind farms and the historical time series of statistics, the power probability prediction of wind farms with parameters and nonparametric regression is carried out by using the correlation of wind power output in different locations. Using EFO decomposition to extract the characteristics of the regional wind farm, the representative unit of each wind farm is selected to predict the output of the wind farm. Finally, the statistical upscaling method is used to predict the total power value of the regional wind farm. At present, most of the research based on spatial correlation is mainly considering the changes of wind speed, caused by, for example, the geographical location of different wind farms, the terrain data of wind farms, wind direction, roughness, temperature, atmospheric pressure, and so on. The literature that directly analyzes the influence of spatial correlation on the output characteristics of a wind farm with different wind turbines is rarely seen.

Ultra-short-term (typically minutes to hours) forecasting is time series based models, which rely on historical wind speed or power measurements and take the predicted variable itself as explanatory variables. They can capture the hidden stochastic characteristics of wind speed or wind power [7]. Reference [8] applied a hybrid model to develop multipoint prediction and single-point prediction for ultra-short-term wind power prediction. Reference [9] proposed a novel hybrid wind power time series prediction model to improve accuracy of ultra-short-term wind power forecasting. There are also some literatures studying the impact of wind speed or wind direction on output power [10, 11]. For the same NWP data, in fact, the output power of wind turbines in different geographical locations is related to the above factors, but also to the geographical location and its own structural characteristics. In this paper, the spatial distribution information of the unit in the wind farm is considered. First, according to the historical data of the wind turbine output as the sample, the fuzzy mean clustering method is used to classify the units in the wind farm. Secondly, the RBF neural network prediction model is set up for the classified units, and the prediction results are added up to obtain the total wind power forecast power.

2. Fuzzy Clustering and RBF Network Forecasting Model

2.1. Flow Chart of Two-Step Forecasting Model. The proposed method considers the wind turbines at different space positions have different contributions to output power of wind farm. Fuzzy clustering is performed based on the measured historical power data of the wind turbines, and the classification of the unit is realized using the advantages of the nonlinear fitting of the RBF; a sample of historical data of 33 wind turbines in a wind farm is trained and tested. The specific flow chart is characterized in Figure 1.

2.2. Fuzzy C-Means Clustering (FCM). Fuzzy clustering is regarded as one of the commonly used approaches for data analysis. Fuzzy C-means clustering is adopted to classify the historical power data of wind turbines to discover the output characteristics of different turbines. Take a sample set of the n typhoon unit in the wind farm, the j-th sample has a set of eigenvectors, where m is the characterizing time series output characteristics of the j-th unit. All samples are classified into category c by fuzzy clustering algorithm [12, 13]. The sample set X can be expressed as follows:

$$\begin{gathered} X = X_1 \cup X_2 \cup \ldots X_c \\ X_i \cup X_j = \varnothing, \quad i \neq j \end{gathered} \tag{1}$$

where $X_i (i = 1, 2, \cdots, c)$ is the set of classification for the i-th crew and represents the i-th vector or cluster prototype vector, $X_i = (x_{i1}, x_{i2}, \cdots, x_{im})$.

The relationship between each sample and all clusters is represented by membership matrix. U_{ij} represents the degree of membership of the jth sample for the ith cluster center. In the clustering process, the distance weighted squared sum of each sample to all cluster centers is taken as the objective function, defined as follows:

$$J(U, X) = \sum_{j=1}^{n} \sum_{i=1}^{c} \left(u_{ij}\right)^m \left(d_{ij}\right)^2 \tag{2}$$

where m is the fuzzy coefficient, take 2 in this article; d_{ij} is the distance between the wind power history data and the cluster prototype in the i-th classification. $J(U, X)$ is the sum of squared errors of the sample data of each classifier and the prototype of the cluster.

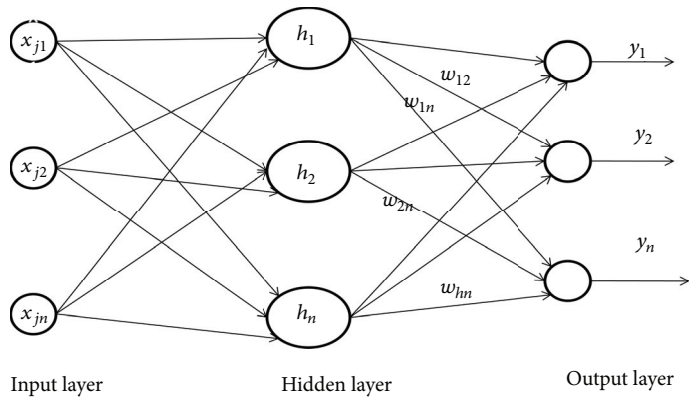

Figure 2: RBF neural network structure.

The specific steps of the FCM algorithm [14] are as follows:

Step 1. Update membership matrix $U^{(b)}$, and the matrix indicates the membership values of each cluster sample data belonging to the corresponding cluster prototype:

$\forall i, j$, if $\exists {d_{ij}}^{(b)} > 0$,

$$u^{(b)}{}_{ij} = \left\{ \sum_{k=1}^{c} \left(\frac{{d_{ij}}^{(b)}}{{d_{kj}}^{(b)}} \right)^{2/(m-1)} \right\}^{-1} \tag{3}$$

If $\exists i, r$, make ${d_{ir}}^{(b)} = 0$,

$$\begin{aligned} {u_{ir}}^{(b)} &= 1, \\ j &\neq r, \\ {u_{ij}}^{(b)} &= 0 \end{aligned} \tag{4}$$

Step 2. Update cluster prototype matrix $X^{(b+1)}$:

$$X_i^{(b+1)} = \frac{\sum_{j=1}^{n} \left({u_{ij}}^{(b+1)} \right)^m \cdot x_j}{\sum_{j=1}^{n} \left({u_{ij}}^{(b+1)} \right)^m}, \quad i = 1, 2 \cdots, c \tag{5}$$

Step 3. Repeated iteratively, if $\|X^{(b)} - X^{(b+1)}\| < \varepsilon$, the algorithm stops, and the membership degree matrix U and the cluster prototype matrix X are output. Otherwise, turn to the first step.

In order to evaluate the clustering results of wind turbines and determine the optimal number of clusters, two evaluation indexes, partition coefficient K_{PC} and classified entropy K_{CE}, were introduced [15].

$$\begin{aligned} K_{PC} &= \frac{1}{N} \sum_{i=1}^{c} \sum_{j=1}^{N} \left(u_{ij} \right)^2 \\ K_{CE} &= -\frac{1}{N} \sum_{i=1}^{c} \sum_{j=1}^{N} \left(u_{ij} \right) \log \left(u_{ij} \right) \end{aligned} \tag{6}$$

K_{PC} is used to evaluate the degree of separation between clusters of different units. The larger the value, the better. K_{CE} is used to evaluate the degree of fuzzy clustering among wind turbines. The smaller the value, the better.

2.3. RBF Neural Network Prediction Model. The RBF neural network is a highly efficient multilayer feed forward neural network. Using the multidimensional spatial interpolation technique, it can approximate any nonlinear function. Compared with other feed forward neural networks, the neural network has good optimal approximation performance and global optimal characteristics. The RBF neural network is composed of three layers of input layer, hidden layer, and output layer, as shown in Figure 1. $x_j = \{x_{j1}, x_{j2}, \ldots, x_{jm}\}$ is the jth input sample, $j = 1, 2 \cdots, n$, n is the total number of units. w is the connection weight between the output layer and the hidden layer; h is the number of hidden layer neurons [16, 17]. This is also demonstrated in Figure 2.

The determination of the RBF network structure requires three key parameters: the center of the basis function, the variance, and the connection weight from the hidden layer to the output layer. The parameters are solved as follows:

Step 1. The center of the basis function is obtained by the K-means clustering method. Firstly, the network is initialized, k training samples are randomly selected as the initial cluster center $c_i (i = 1, 2, \cdots, k)$, the Euclidean distance between x_j and the initial cluster center c_i is calculated, and clustering is performed according to the nearest neighbor rule. Secondly, the cluster center is readjusted and calculated. The average value of the samples in the clustering set thus obtains a new clustering center. If the new clustering center no longer changes, the calculation is stopped; otherwise, it returns to the previous step to continue to determine the center of the basis function.

Step 2. The function of RBF network is Gauss basis function, and the solution of its variance can be solved as follows.

$$\sigma_i = \frac{c_{\max}}{\sqrt{2k}} \tag{7}$$

where $i = 1, 2, \cdots, k$; $c_{\max}$ is the maximum distance from the selected basis function center.

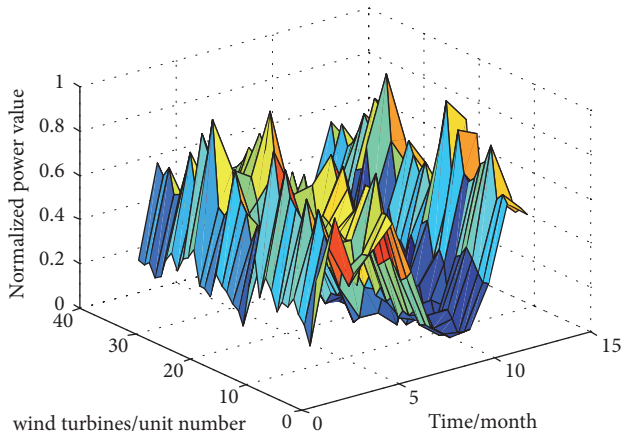

Figure 3: Wind turbine output power curve.

Step 3. The connection weights from the hidden layer to the output layer can be calculated directly using the least square method. The formula is described below.

$$w = \exp\left(\frac{k}{c^2_{\max}}\left\|x_j - c_i\right\|^2\right) \tag{8}$$

where $i = 1, 2, \cdots, k$; $j = 1, 2 \cdots, n$, n is the total number of samples.

The input layer to hidden layer mapping of the RBF network is nonlinear, and the hidden layer to output layer is a linear mapping. The parameter centers c_i and weights w are adjusted by the input and output errors, and then the internal layer coefficients of the network are adjusted accordingly, through repeated iteration calculations. When the output to network error of the network reaches the preset accuracy requirement, the network terminates the calculation and outputs the predicted value.

3. Case Study

The 12-month historical power data of 33 wind turbines measured at a northern wind farm was selected, and the single-unit capacity was 1.5 MW. The power curve is shown in Figure 3. It can be seen that the generating power of the 33 wind turbines horizontally related to the time sequence and has a certain correlation with the spatial distribution in the longitudinal direction.

Taking 12 months of historical power data as inputs of fuzzy clustering, clustering and grouping wind turbines are carried out. Figure 4 describes the membership matrix curve of the units divided into two clusters, and Figure 5 describes the membership matrix curve of the units divided into 3 clusters.

Select the number of different clusters c, and the membership matrix values are shown in Figures 3 and 4. Two index values are calculated by formula (6) and as shown in Table 1.

According to the membership matrix and Table 1, when the number of clusters is 2, the cluster evaluation index K_{PC} is large and K_{CE} is small. Therefore, it is better to divide the wind turbines into 2 clusters. The first group includes 14 units, and the second group includes 19 units.

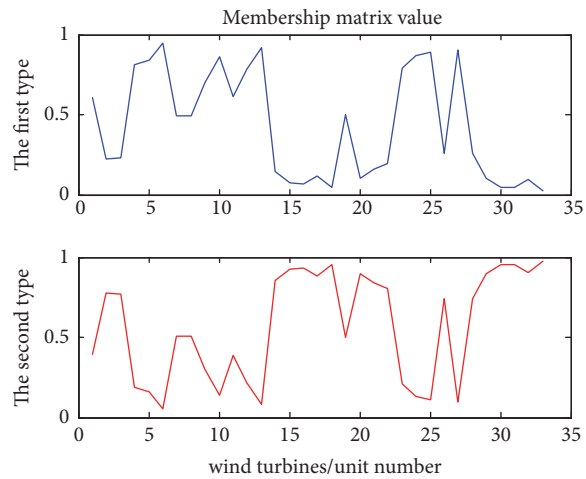

Figure 4: Membership matrix value curves of two types of units.

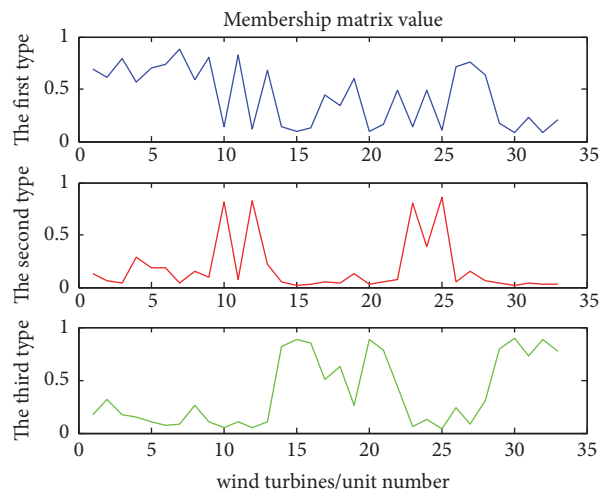

Figure 5: Membership matrix value curves of three types of units.

Table 1: Evaluation indicators of clustering results.

c	K_{PC}	K_{CE}
2	0.73	0.42
3	0.611	0.68

The 10-minute historical data of the wind farm in March 2017, 733 sampling points, are adopted to set the RBF neural network modeling and prediction. The objective function error is set to 0.001, and sc is 3, where the MN is 20, and the DF is 1. The prediction of the RBF neural network is carried out for the cluster group and the entire wind farm unit, respectively. The prediction curve is shown separately in the next following figures. Figure 6 is the RBF prediction curve for the first cluster, and Figure 7 is the RBF prediction curve for the second cluster. Figure 8 depicts the RBF prediction curve for all the wind turbines in the wind farm.

In the forecast of wind power generation, the commonly evaluation indexes are the root mean squared error (RMSE)

Table 2: Wind power forecast error comparison analysis.

Wind turbines	RMSE	MAE
The first group wind turbines	0.055	0.0096
The second group wind turbines	0.075	0.014
The combination model with two groups	0.085	0.013
A single model with all wind turbines	0.119	0.016

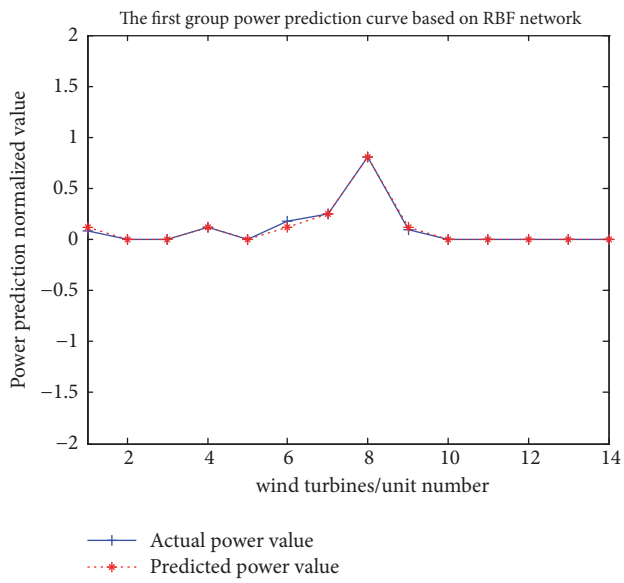

Figure 6: The first group power forecast curve.

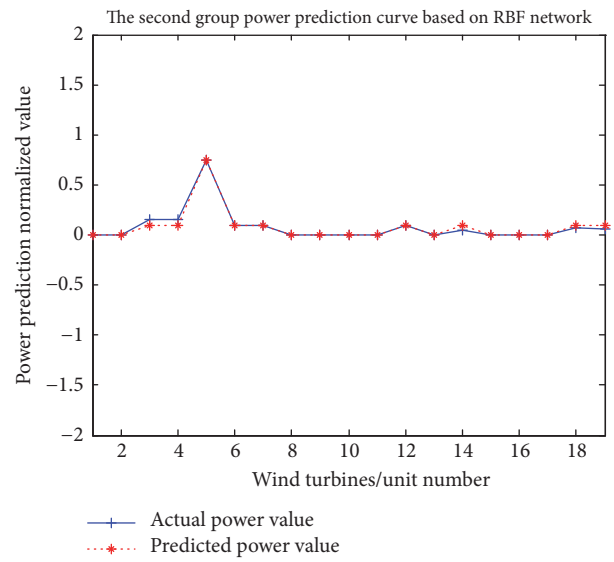

Figure 7: The second group power forecast curve.

and the absolute error (MAE). The specific definitions are as follows [18–20].

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{n} e^2{}_t} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t| \tag{10}$$

where $e_t = y_t - \hat{y}_t$, y_t and $\hat{y}_t$ are actual value and predicted value, respectively.

The RBF neural network prediction model is set up for different units, and the prediction error analysis is shown in Table 2. The predicted values of the two groups wind turbines are added by the equal weights to obtain the output of the combined model of the wind farm. From Table 2, the error based on combination model with two groups is lower than the single model.

Compared to RBF neural network prediction model, the ARIMA forecast model error curves are illustrated in Figure 9.

According to above comparison and analysis, the prediction error based on the ARIMA model is more than ultra-short time prediction model in this paper. The accuracy of wind power forecasting can be effectively improved by the two-step ultra-short-time prediction approach.

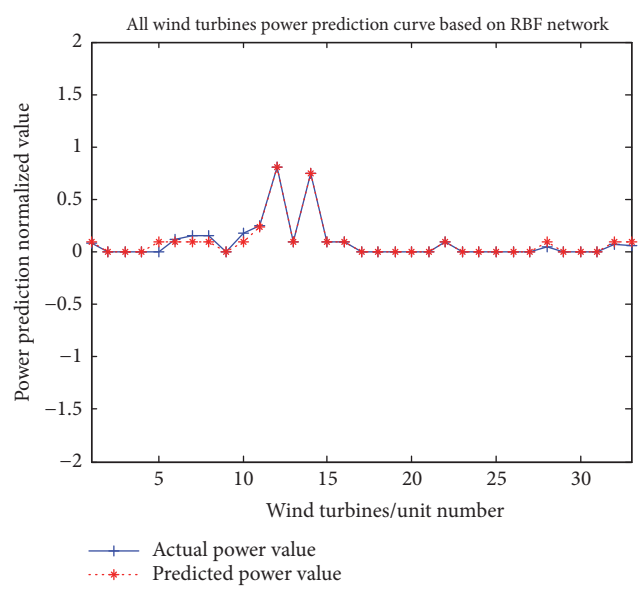

Figure 8: All wind turbines power forecast curve.

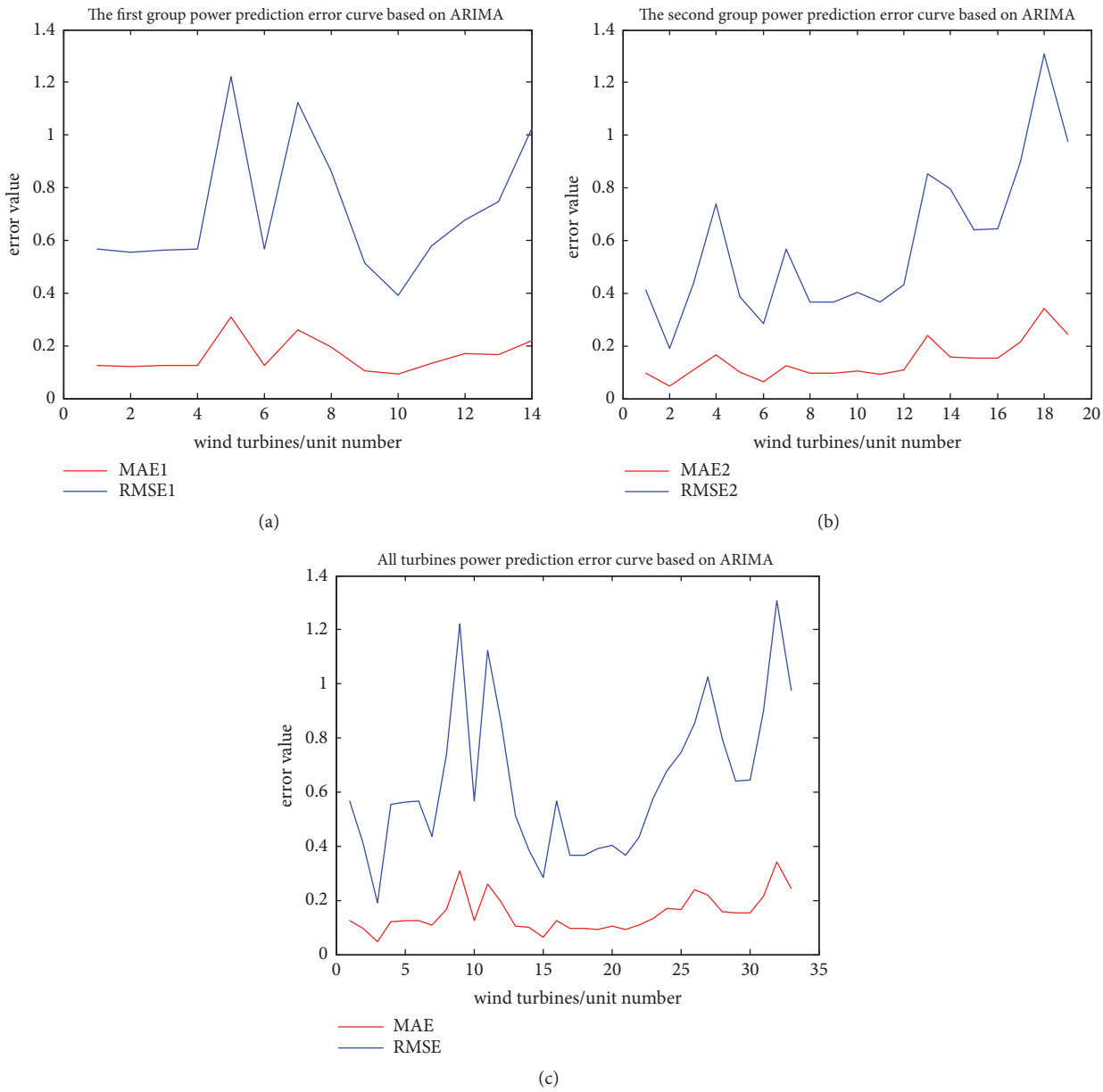

Figure 9: Wind power forecast error curves based on ARIMA model.

4. Conclusions

In this study, the power of the generators in the wind farm is derived from wind energy. The power output of the wind farm is affected by, for example, wind speed, wind direction, the tail flow effect of unit, and so on. Each unit's output has a certain influence on each other. According to the output of the wind turbine and taking into account the uncertain relationship between these factors, fuzzy clustering and RBF neural network are combined to establish the two-step prediction model. Different contributions of the wind turbines at different space positions to the power of wind farm, and the correlation of wind power time series are also considered. Compared to the ARIMA forecast model and single RBF model, the case verified that the two-step forecasting method proposed in this paper can effectively improve the precision in the ultra-short-term power prediction and has obtained certain practical value in engineering.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Pythagorean Fuzzy (R, S)-Norm Information Measure for Multicriteria Decision-Making Problem

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In the present communication, a parametric (R, S)-norm information measure for the Pythagorean fuzzy set has been proposed with the proof of its validity. The monotonic behavior and maximality feature of the proposed information measure have been studied and presented. Further, an algorithm for solving the multicriteria decision-making problem with the help of the proposed information measure has been provided keeping in view of the different cases for weight criteria, when weights are unknown and other when weights are partially known. Numerical examples for each of the case have been successfully illustrated. Finally, the work has been concluded by providing the scope for future work.

1. Introduction

The concept of intuitionistic fuzzy set (IFS) (Atanassov) [1] has been widely studied and applied to deal with uncertainties and hesitancy inherent in practical circumstances. The prominent characteristic of an IFS is that it assigns a number from the unit interval $[0, 1]$ to every element in the domain of discourse, a degree of membership, and a degree of nonmembership along with the degree of indeterminacy whose total sum equals unity. In literature, intuitionistic fuzzy sets comprehensively span applications in the field of decision-making problems, pattern recognition, sales analysis financial services, medical diagnosis, etc.

Pythagorean fuzzy set (PFS), proposed by Yager [2], is an efficient generalization of intuitionistic fuzzy set, characterized by a membership value and a nonmembership value satisfying the inequality that the squared sum of these values is less than or equal to 1. Yager and Abbasov [3] well stated that, in some practical multiple-criteria decision-making problems, it is viable that sum of the degree of the membership and the degree of nonmembership value of a particular alternative provided by a decision-maker may be in such a way that their sum is bigger than 1, where it would not be feasible to use intuitionistic fuzzy set. Therefore, PFS proves to be proficiently more capable of representing and handling vagueness, impreciseness, and uncertainties than IFS in various decision-making processes. It may be noted that PFS is more generalized than IFS as the span of membership degree of PFS is more than span of membership degree of IFS which enables wider applicability.

Various researchers theoretically developed the concept of Yager's Pythagorean fuzzy sets [4] and applied it in the field of decision-making problems, medical diagnosis, and pattern recognition and in other real-world problem. In order to deal the decision-making problem with PFSs, Zhang and Xu [5] proposed a comparison method based on a score function to identify the Pythagorean fuzzy positive ideal solution (PIS) and the Pythagorean fuzzy negative ideal solution (NIS). Further they extended the TOPSIS method to compute the distances between each alternative with PIS and NIS, respectively. Peng and Yang [6] proposed some basic operations for PFSs and provided Pythagorean fuzzy aggregation operators along with their important properties. In continuation, they developed a Pythagorean superiority and inferiority ranking algorithm to solve group decision-making problems in view of uncertainty. Further, Peng et al. [7] established the relationship between the distance measure, similarity measure, entropy, and the inclusion measure and suggested the systematic transformation of information measures for PFSs. Yager [8] introduced some of the basic set operations for PFSs

and established the relationship between Pythagorean membership values and complex number. In addition to this, the solutions of multicriteria decision-making with satisfactions through Pythagorean membership values have been carried out. A new method for Pythagorean fuzzy MCDM problems with the help of aggregation operators and distance measures has been developed by Zeng et al. [9]. Further, they proposed the Pythagorean fuzzy ordered weighted averaging weighted average distance (PFOWAWAD) operator and developed a hybrid TOPSIS method.

Using PFSs, Ren et al. [10] had a simulation test to study the effect of the risk attitudes of the decision makers over the solutions of decision-making problems. Zhang [11] introduced a novel closeness index-based ranking method for Pythagorean fuzzy numbers and proposed interval valued Pythagorean fuzzy set with basic operations and important properties. In addition to this, the hierarchical multicriteria decision-making problems in Pythagorean fuzzy environment have been solved by developing a closeness index-based Pythagorean fuzzy QUALIFLEX method. Liu et al. [12] developed various types of Pythagorean fuzzy aggregation operators and used them to solve decision-making problems. Zeng [13] developed a Pythagorean fuzzy multiattribute group decision-making method on the basis of a new Pythagorean fuzzy probabilistic ordered weighted averaging (OWA) operator. Though various researchers have significantly contributed in the development of the theory of PFSs as deliberated above, a seldom study on the entropy of PFSs and its applications has been found in literature. Xue et al. [14] studied the linear programming technique for multidimensional analysis of preference (LINMAP) method under Pythagorean fuzzy environment to solve multiple attribute group decision-making problem by incorporating Pythagorean fuzzy entropy along with various other applications. Vital applications of entropy and information measures based on the IFS theory have been well known in the literature. In order to deal with real-world problems more efficiently and to cater the need of the hour, generalizations of the existing approaches play an important role as they contribute more flexibility in applications; e.g., parameters may characterize various factors such as time constraint, lack of knowledge, and environmental conditions, etc.

Bajaj et al. [15] proposed a new R-norm intuitionistic fuzzy entropy and a weighted R-norm Intuitionistic fuzzy divergence measure with their computational applications in pattern recognition and image thresholding. Gandotra et al. [16] studied multiple-criteria decision-making problem with the help of parametric entropy under α-cut and (α, β)-cut based distance measures for different possible values of parameters and provided the ranking method for the available alternatives.

In this communication, we have proposed a new (R, S)-norm information measure of Pythagorean fuzzy set and applied the information measure in an algorithm to solve multicriteria decision-making problem. In continuation, the implementation of the proposed algorithm by taking suitable examples has also been illustrated. The rest of this paper is organized as follows: in Section 2, we present some basic notions and preliminaries related to the proposed information measure. A new (R, S)-norm information measure of Pythagorean fuzzy set has been well proposed with the proof of its validity in Section 3. Further, in Section 4, the maximality and the monotonic behavior of the proposed information measure with respect to parameters R and S have been studied and validated empirically. In Section 5, a new multicriteria decision-making algorithm is provided on the basis of the proposed (R, S)-norm information measure of PFS in view of two cases of weights of criteria: one when weights are unknown and other when weights are partially known. In order to support and implement the proposed algorithm, an example for each case has been explicitly dealt in Section 6. The paper is finally concluded in Section 7.

2. Preliminaries

In this section, we recall and present some fundamental concepts in connection with Pythagorean fuzzy set, which are well known in literature.

Definition 1 (see [1]). An intuitionistic fuzzy set (IFS) I in X (universe of discourse) is given by

$$I = \{\langle x, \mu_I(x), \nu_I(x)\rangle \mid x \in X\} \tag{1}$$

where $\mu_I : X \longrightarrow [0,1]$ and $\nu_I : X \longrightarrow [0,1]$ denote the degree of membership and degree of nonmembership, respectively, and for every $x \in X$ satisfy the condition

$$0 \le \mu_I(x) + \nu_I(x) \le 1 \tag{2}$$

and the degree of indeterminacy for any IFS I and $x \in X$ is given by $\pi_I(x) = 1 - \mu_I(x) - \nu_I(x)$.

Definition 2 (see [2]). A Pythagorean fuzzy set (PFS) M in X (universe of discourse) is given by

$$M = \{\langle x, \mu_M(x), \nu_M(x)\rangle \mid x \in X\} \tag{3}$$

where $\mu_M : X \longrightarrow [0,1]$ and $\nu_M : X \longrightarrow [0,1]$ denote the degree of membership and degree of nonmembership, respectively, and for every $x \in X$ satisfy the condition

$$0 \le \mu_M^2(x) + \nu_M^2(x) \le 1 \tag{4}$$

and the degree of indeterminacy for any PFS M and $x \in X$ is given by

$$\pi_M(x) = \sqrt{1 - \mu_M^2(x) - \nu_M^2(x)}. \tag{5}$$

In case of PFS, the restriction corresponding to the degree of membership $\mu_M(x)$ and the degree of nonmembership $\nu_M(x)$ is

$$0 \le \mu_M^2(x) + \nu_M^2(x) \le 1, \tag{6}$$

whereas the condition in case of IFS is

$$0 \le \mu_I(x) + \nu_I(x) \le 1, \tag{7}$$

for $\mu_M(x), \nu_M(x) \in [0,1]$. This difference in constraint conditions gives a wider coverage for information span which can be geometrically shown in Figure 1.

Some of the important binary operations on PFSs are being presented below which are available in literature.

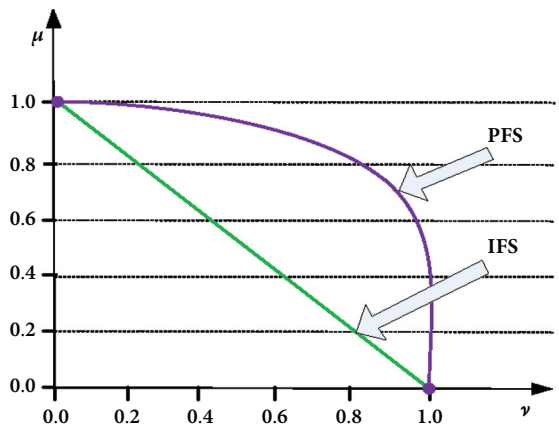

Figure 1: IFS versus PFS.

Definition 3 (see [7]). If M and N are two Pythagorean fuzzy sets in X, then the operations can be defined as follows:

(a) **Complement:** $M^c = \{\langle x, \nu_M(x), \mu_M(x)\rangle \mid x \in X\}$.

(b) **Containment:** $M \subset N$ iff $\forall x \in X$, $\mu_M(x) \leq \mu_N(x)$ and $\nu_M(x) \geq \nu_N(x)$.

(c) **Union:** $M \cup N = \{\langle x, \mu_M(x) \vee \mu_N(x), \nu_M(x) \wedge \nu_N(x)\rangle \mid x \in X\}$.

(d) **Intersection:** $M \cap N = \{\langle x, \mu_M(x) \wedge \mu_N(x), \nu_M(x) \vee \nu_N(x)\rangle \mid x \in X\}$.

Definition 4 (see [10]). Let M and N be two PFSs, then the Euclidean distance between M and N is defined as follows:

$$d(M,N) = \sqrt{\frac{1}{2}\left[\left(\left(\mu_M(x)\right)^2 - \left(\mu_N(x)\right)^2\right)^2 + \left(\left(\nu_M(x)\right)^2 - \left(\nu_N(x)\right)^2\right)^2 + \left(\left(\pi_M(x)\right)^2 - \left(\pi_N(x)\right)^2\right)^2\right]}. \tag{8}$$

Definition 5 (see [5]). Let M and N be two PFS, then the Hamming distance between M and N is defined as follows:

$$\begin{aligned} l(M,N) = \frac{1}{2}\Big(&\left|\left(\mu_M(x)\right)^2 - \left(\mu_N(x)\right)^2\right| \\ &+ \left|\left(\nu_M(x)\right)^2 - \left(\nu_N(x)\right)^2\right| \\ &+ \left|\left(\pi_M(x)\right)^2 - \left(\pi_N(x)\right)^2\right|\Big). \end{aligned} \tag{9}$$

3. New (R,S)-Norm Information Measure of PFS

Let $\triangle_n = \{P = (p_1, p_2, \ldots, p_n), p_i \geq 0, i = 1, 2, 3, \ldots, n$ and $\sum p_i = 1\}$ be the set of all probability distribution association with random variable X taking finite values $x_1, x_2, \ldots, x_n$. Joshi and Kumar [17] defined and studied a real valued function from $\triangle_n$ to $\mathbb{R}^+$ as (R,S)-norm information measure of the distribution P for R and $S \in \mathbb{R}^+$ and given by

$$H_R^S(P) = \frac{R \times S}{R - S}\left[\left(\sum_{i=1}^{n} p_i^S\right)^{1/S} - \left(\sum_{i=1}^{n} p_i^R\right)^{1/R}\right]; \tag{10}$$

where $0 < S < 1$ and $1 < R < \infty$. Or $0 < S < 1$ and $1 < R < \infty$.

The most important property of this measure is that when S=1 or R=1, then (10) becomes the R or S-norm entropy studied by Boekee and Lubbe [18] and if $R = 1$ and $S \longrightarrow 1$ or $S = 1$ and $R \longrightarrow 1$, then it gives Shannon's [19] entropy.

Based on the axiomatic definition of entropy for intuitionistic fuzzy set, proposed by Hung and Yang (2006) [20], we analogously define a real valued function $H : X \longrightarrow [0,1]$, called entropy of Pythagorean fuzzy set M if and only if the following four axioms are satisfied:

(i) **(PFS1) Sharpness:** $H(M) = 0$ iff M is a crisp set, i.e., $\mu_M(x_i) = 0$, $\nu_M(x_i) = 1$; or $\mu_M(x_i) = 1$, $\nu_M(x_i) = 0$; $\forall x_i \in X$.

(ii) **(PFS2) Maximality:** $H(M)$ is maximum iff

$$\mu_M(x_i) = \nu_M(x_i) = \pi_M(x_i) = \frac{1}{\sqrt{3}} \quad \forall x_i \in X. \tag{11}$$

(iii) **(PFS3) Symmetry:** $H(M) = H(M^c)$.

(iv) **(PFS4) Resolution:** $H(M) \leq H(N)$ iff $M \subseteq N$, i.e., $\mu_M(x_i) \leq \mu_N(x_i)$ and $\nu_M(x_i) \geq \nu_N(x_i)$ for $\mu_N(x_i) \leq \nu_N(x_i)$ or if $\mu_M(x_i) \geq \mu_N(x_i)$ and $\nu_M(x_i) \leq \nu_N(x_i)$ for $\mu_N(x_i) \geq \nu_N(x_i)$ $\forall$ $x_i \in X$.

In context with Pythagorean fuzzy information, we propose the following Pythagorean fuzzy entropy analogous to measure (10):

$$H_R^S(M) = \begin{cases} \dfrac{R \times S}{(R-S)}\displaystyle\sum_{i=1}^{n}\frac{1}{n}\left[\left(\mu_M(x_i)^{2S} + \nu_M(x_i)^{2S} + \pi_M(x_i)^{2S}\right)^{1/S} - \left(\mu_M(x_i)^{2R} + \nu_M(x_i)^{2R} + \pi_M(x_i)^{2R}\right)^{1/R}\right], & \text{where } R, S > 0;\ \text{either } 0 < S < 1 \text{ and } 1 < R < \infty \text{ or } 0 < S < 1 \text{ and } 1 < R < \infty, \\ \dfrac{R}{n(R-1)}\displaystyle\sum_{i=1}^{n}\left\{1 - \left(\mu_M(x_i)^{2R} + \nu_M(x_i)^{2R} + \pi_M(x_i)^{2R}\right)^{1/R}\right\}, & \text{where } S = 1,\ R > 0,\ R \neq 1, \\ -\dfrac{1}{n}\displaystyle\sum_{i=1}^{n}\left(\mu_M(x_i)^2 \log\left(\mu_M(x_i)^2\right) + \nu_M(x_i)^2 \log\left(\nu_M(x_i)^2\right) + \pi_M(x_i)^2 \log\left(\pi_M(x_i)^2\right)\right), & \text{where } R = 1 \text{ and } S \longrightarrow 1 \text{ or } S = 1 \text{ and } R \longrightarrow 1 \end{cases} \tag{12}$$

Theorem 6. *The proposed entropy measure $H_R^S(M)$ is a valid Pythagorean fuzzy information measure.*

Proof. To prove this, we shall show that it satisfies all the axioms PFS1 to PFS4.

(i) **(PFS1) (Sharpness):** If $H_R^S(M) = 0$, then

$$\left(\mu_M(x_i)^{2S} + \nu_M(x_i)^{2S} + \pi_M(x_i)^{2S}\right)^{1/S} - \left(\mu_M(x_i)^{2R} + \nu_M(x_i)^{2R} + \pi_M(x_i)^{2R}\right)^{1/R} = 0. \tag{13}$$

Since $R, S > 1$ $(R \neq 1 \neq S)$, it is possible only in the following cases:

(a) Either $\mu_M(x_i) = 1$, i.e., $\nu_M(x_i) = \pi_M(x_i) = 0$,
(b) $\nu_M(x_i) = 1$ i.e., $\mu_M(x_i) = \pi_M(x_i) = 0$,
(c) $\pi_M(x_i) = 1$ i.e., $\mu_M(x_i) = \nu_M(x_i) = 0$.

These three cases implies that M is a crisp set. Conversely, if M is a crisp set then $H_R^S(M) = 0$ which is obvious.

(ii) **(PFS2)(Maximality):**

In Section 4, we have empirically proved that $H_R^S(M)$ is maximum iff

$$\mu_M(x_i) = \nu_M(x_i) = \pi_M(x_i) = \frac{1}{\sqrt{3}}. \tag{14}$$

Analytically, we prove the concavity of the $H_R^S(M)$ by calculating its hessian at the critical point, i.e., $1/\sqrt{3}$ with particular values of R and S. The Hessian of $H_R^S(M)$ is as $[R > 1(= 3)$ and $S < 1(= 0.3)]$:

$$H_R^S(M) = \frac{2}{n}\begin{bmatrix} -10.4589 & 2.232816 & 2.232816 \\ 2.232816 & -10.4589 & 2.232816 \\ 2.232816 & 2.232816 & -10.4589 \end{bmatrix}. \tag{15}$$

It may be noted that $H_R^S(M)$ is a negative semidefinite matrix for different possible values of R and S which shows that it is a concave function. Hence, the concavity of the function establishes the maximality property.

(iii) **(PFS3)(Symmetry):** It is obvious from the definition that

$$H_R^S(M) = H_R^S(M^c). \tag{16}$$

(iv) **(PFS4)(Resolution):** We have

$$\begin{aligned} &\left|\left(\mu_M(x_i) - \frac{1}{\sqrt{3}}\right)\right| + \left|\left(\nu_M(x_i) - \frac{1}{\sqrt{3}}\right)\right| \\ &\quad + \left|\left(\pi_M(x_i) - \frac{1}{\sqrt{3}}\right)\right| \\ &\geq \left|\left(\mu_N(x_i) - \frac{1}{\sqrt{3}}\right)\right| + \left|\left(\nu_N(x_i) - \frac{1}{\sqrt{3}}\right)\right| \\ &\quad + \left|\left(\pi_N(x_i) - \frac{1}{\sqrt{3}}\right)\right|; \end{aligned} \tag{17}$$

and

$$\begin{aligned} &\left(\mu_M(x_i) - \frac{1}{\sqrt{3}}\right)^2 + \left(\nu_M(x_i) - \frac{1}{\sqrt{3}}\right)^2 \\ &\quad + \left(\pi_M(x_i) - \frac{1}{\sqrt{3}}\right)^2 \\ &\geq \left(\mu_N(x_i) - \frac{1}{\sqrt{3}}\right)^2 + \left(\nu_N(x_i) - \frac{1}{\sqrt{3}}\right)^2 \\ &\quad + \left(\pi_N(x_i) - \frac{1}{\sqrt{3}}\right)^2; \end{aligned} \tag{18}$$

because if $\mu_M(x_i) \leq \mu_N(x_i)$ and $\nu_M(x_i) \leq \nu_N(x_i)$ with $\max\{\mu_N(x_i), \nu_N(x_i)\} \leq 1/\sqrt{3}$, then $\mu_M(x_i) \leq \mu_N(x_i) \leq 1/\sqrt{3}$; $\nu_M(x_i) \leq \nu_N(x_i) \leq 1/\sqrt{3}$ and $\pi_M(x_i) \geq \pi_N(x_i) \geq 1/\sqrt{3}$ which implies that the above result holds. Similarly, if $\mu_M(x_i) \geq \mu_N(x_i)$ and $\nu_M(x_i) \geq \nu_N(x_i)$ with $\max\{\mu_M(x_i), \nu_M(x_i)\} \geq 1/\sqrt{3}$, then also the above result holds.

Now, since $H_R^S(M)$ is a concave function on the Pythagorean fuzzy set M, therefore, if $\max\{\mu_M(x_i), \nu_M(x_i)\} \leq 1/\sqrt{3}$ then $\mu_M(x_i) \leq \mu_N(x_i)$ and $\nu_M(x_i) \leq \nu_N(x_i)$ imply $\pi_M(x_i) \geq \pi_N(x_i) \geq 1/\sqrt{3}$.

Therefore, by the above explained result, we conclude that $H_R^S(M)$ satisfies condition of resolution PFS4.

Similarly, if $\min\{\mu_M(x_i), \nu_M(x_i)\} \geq 1/\sqrt{3}$, then $\mu_M(x_i) \leq \mu_N(x_i)$ and $\nu_M(x_i) \geq \nu_N(x_i)$. By using the above proved result, we conclude that $H_R^S(M)$ satisfies the condition PFS4.

Hence, $H_R^S(M)$ satisfies all the axioms of Pythagorean fuzzy entropy and, therefore, $H_R^S(M)$ is a valid measure of Pythagorean fuzzy information. □

Theorem 7. *Let M and N be two PFSs defined in $X = \{x_1, x_2, \ldots, x_n\}$ where $M = \{\langle x_i, \mu_M(x_i), \nu_M(x_i)\rangle \mid x_i \in X\}$ and $N = \{\langle x_i, \mu_N(x_i), \nu_N(x_i)\rangle \mid x_i \in X\}$ such that $\forall\, x_i \in X$ either $M \subseteq N$ or $N \subseteq M$. Then*

$$H_R^S(M \cup N) + H_R^S(M \cap N) = H_R^S(M) + H_R^S(N). \tag{19}$$

Proof. Divide X into two parts X_1 and X_2 such that $X_1 = \{x_i \in X \mid M \subseteq N\}$, i.e., $\mu_M(x_i) \leq \mu_N(x_i)$, $\nu_M(x_i) \geq \nu_N(x_i)$ $\forall\, x_i \in X_1$; $X_2 = \{x_i \in X \mid N \subseteq M\}$, i.e., $\mu_M(x_i) \geq \mu_N(x_i)$, $\nu_M(x_i) \leq \nu_N(x_i)$ $\forall\, x_i \in X_1$. Now

$$\begin{aligned} H_R^S(M \cup N) = \frac{R \times S}{(R - S)} \sum_{i=1}^{n} \frac{1}{n} \Big[&\left(\mu_{M\cup N}(x_i)^{2S} + \nu_{M\cup N}(x_i)^{2S} + \pi_{M\cup N}(x_i)^{2S}\right)^{1/S} - \left(\mu_{M\cup N}(x_i)^{2R} + \nu_{M\cup N}(x_i)^{2R} + \pi_{M\cup N}(x_i)^{2R}\right)^{1/R} \Big]; \end{aligned} \tag{20}$$

which implies

$$\begin{aligned} H_R^S(M \cup N) &= \frac{R \times S}{(R-S)} \\ &\cdot \sum_{X_1} \frac{1}{n} \left[\left(\mu_N(x_i)^{2S} + \nu_N(x_i)^{2S} + \pi_N(x_i)^{2S} \right)^{1/S} \right. \\ &\left. - \left(\mu_N(x_i)^{2R} + \nu_N(x_i)^{2R} + \pi_N(x_i)^{2R} \right)^{1/R} \right] \\ &+ \frac{R \times S}{(R-S)} \\ &\cdot \sum_{X_2} \frac{1}{n} \left[\left(\mu_M(x_i)^{2S} + \nu_M(x_i)^{2S} + \pi_M(x_i)^{2S} \right)^{1/S} \right. \\ &\left. - \left(\mu_M(x_i)^{2R} + \nu_M(x_i)^{2R} + \pi_M(x_i)^{2R} \right)^{1/R} \right]. \end{aligned} \tag{21}$$

Similarly,

$$\begin{aligned} H_R^S(M \cap N) &= \frac{R \times S}{(R-S)} \\ &\cdot \sum_{X_1} \frac{1}{n} \left[\left(\mu_M(x_i)^{2S} + \nu_M(x_i)^{2S} + \pi_M(x_i)^{2S} \right)^{1/S} \right. \\ &\left. - \left(\mu_M(x_i)^{2R} + \nu_M(x_i)^{2R} + \pi_M(x_i)^{2R} \right)^{1/R} \right] \\ &+ \frac{R \times S}{(R-S)} \\ &\cdot \sum_{X_2} \frac{1}{n} \left[\left(\mu_N(x_i)^{2S} + \nu_N(x_i)^{2S} + \pi_N(x_i)^{2S} \right)^{1/S} \right. \\ &\left. - \left(\mu_N(x_i)^{2R} + \nu_N(x_i)^{2R} + \pi_N(x_i)^{2R} \right)^{1/R} \right]. \end{aligned} \tag{22}$$

On adding the above two terms, we get

$$H_R^S(M \cup N) + H_R^S(M \cap N) = H_R^S(M) + H_R^S(N). \tag{23}$$

□

Theorem 8. *For any Pythagorean fuzzy set M, we have*

$$\begin{aligned} H_R^S(M) &= H_R^S(M^c) = H_R^S(M \cup M^c) \\ &= H_R^S(M \cap M^c). \end{aligned} \tag{24}$$

Proof. By definition, the proof is obvious. □

4. Monotonicity of (R, S)- Norm Information Measure of PFS

In this section, we carry an empirical study for investigating the maximality and monotonic nature of the proposed (R, S)-norm information measure of PFS. For this, we consider the following four Pythagorean fuzzy sets M_1, M_2, M_3, and M_4 over the universe of discourse $X = \{x_1, x_2, x_3\}$:

$$\begin{aligned} M_1 &= \left\{ \left(x_1, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}} \right), \left(x_2, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}} \right), \right. \\ &\left. \left(x_3, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}} \right) \right\}; \\ M_2 &= \{(x_1, 0.6, 0.6), (x_2, 0.7, 0.7), (x_3, 0.55, 0.55)\}; \\ M_3 &= \{(x_1, 0.5, 0.6), (x_2, 0.2, 0.9), (x_3, 0.9, 0.3)\}; \\ M_4 &= \{(x_1, 0.4, 0.8), (x_2, 0.9, 0.4), (x_3, 0.7, 0.6)\}. \end{aligned} \tag{25}$$

For various values of R and S and using equation (12), we compute and tabulate all the values of $H_R^S(M)$. On the basis of the tabulated data and the plots given in Table 1 and Figure 2, it is quite clear that $H_R^S(M)$ takes maximum value when $\mu_M(x_i) = \nu_M(x_i) = \pi_M(x_i) = 1/\sqrt{3}$; $\forall x_i \in X$ and is a monotonically decreasing function of R and S.

5. MCDM Algorithm with (R,S)-Norm Entropy

Suppose that there is a set of m feasible alternatives, i.e., $Z = \{z_1, z_2, \ldots, z_m\}$ and a set of n criteria $O = \{o_1, o_2, \ldots, o_n\}$. The decision-making problem is to select the most suitable alternative out of these m alternatives. The appraisal values of an alternative z_i $(i = 1, 2, 3, \ldots, m)$ with respect to the criteria o_j $(j = 1, 2, 3, \ldots, n)$ are given by $z_{ij} = (p_{ij}, q_{ij})$, where p_{ij} is the degree to which the alternative z_i satisfies criteria o_j and q_{ij} is the degree to which the alternative z_i does not satisfy attribute o_j, satisfying $0 \le p_{ij} \le 1$, $0 \le q_{ij} \le 1$ and $0 \le p_{ij} + q_{ij} \le 1$ with $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$. This problem can be modeled by representing it through the following Pythagorean fuzzy decision matrix:

$$R = (p_{ij}, q_{ij})_{m \times n} = (z_{ij}) = \begin{array}{c|cccc} & o_1 & o_2 & \cdots & o_n \\ \hline z_1 & (p_{11}, q_{11}) & (p_{12}, q_{12}) & \cdots & (p_{1n}, q_{1n}) \\ z_2 & (p_{21}, q_{21}) & (p_{22}, q_{22}) & \cdots & (p_{2n}, q_{2n}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ z_m & (p_{m1}, q_{m1}) & (p_{m2}, q_{m2}) & \cdots & (p_{mn}, q_{mn}) \end{array} \tag{26}$$

Let $w = (w_1, w_2, \ldots, w_n)^T$ be the weight vector of all the criteria where $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j$ is the degree of importance of the jth criteria. Sometimes this criteria weight is completely unknown and sometimes it is partially known because of the lack of knowledge, time, data, and the limited expertise of the problem domain. In this section, we discuss and devise two methods to determine the weights of criteria by using the proposed entropy (12).

Table 1: Values of entropy for different values of R and S.

SI. No.	**R**	**S = 0.15**				**S = 0.25**				**S = 1**				**S = 4**				**S = 15**				**S = 60**			
		$H_R^S(M_1)$	$H_R^S(M_2)$	$H_R^S(M_3)$	$H_R^S(M_4)$	$H_R^S(M_1)$	$H_R^S(M_2)$	$H_R^S(M_3)$	$H_R^S(M_4)$	$H_R^S(M_1)$	$H_R^S(M_2)$	$H_R^S(M_3)$	$H_R^S(M_4)$	$H_R^S(M_1)$	$H_R^S(M_2)$	$H_R^S(M_3)$	$H_R^S(M_4)$	$H_R^S(M_1)$	$H_R^S(M_2)$	$H_R^S(M_3)$	$H_R^S(M_4)$	$H_R^S(M_1)$	$H_R^S(M_2)$	$H_R^S(M_3)$	$H_R^S(M_4)$
1	0.2	254.676	218.665	184.776	194.201	54.000	46.744	39.669	41.643	20.000	17.381	14.767	15.498	16.960	14.743	12.500	13.123	16.346	14.208	12.040	12.637	16.186	14.068	11.919	12.511
2	0.3	147.744	127.021	107.410	112.867	21.030	18.328	15.608	16.369	5.134	4.526	3.855	4.044	4.068	3.590	3.017	3.171	3.864	3.408	2.854	2.996	3.811	3.360	2.811	2.951
3	0.5	107.670	92.610	78.329	82.303	12.000	10.497	8.952	9.385	2.000	1.785	1.495	1.577	1.464	1.309	1.030	1.096	1.366	1.218	0.943	0.998	1.341	1.193	0.920	0.973
4	0.8	93.073	80.064	67.717	71.154	9.340	8.180	6.972	7.311	1.264	1.134	0.906	0.970	0.877	0.790	0.534	0.584	0.809	0.722	0.468	0.503	0.792	0.701	0.451	0.483
5	1.2	86.508	74.420	62.939	66.134	8.263	7.241	6.162	6.464	1.004	0.902	0.673	0.736	0.675	0.611	0.335	0.375	0.618	0.549	0.281	0.301	0.604	0.528	0.267	0.283
6	1.7	83.052	71.448	60.420	63.489	7.727	6.773	5.753	6.038	0.884	0.796	0.552	0.614	0.584	0.529	0.236	0.261	0.532	0.467	0.192	0.192	0.519	0.444	0.179	0.176
7	2.5	80.576	69.319	58.613	61.592	7.356	6.449	5.467	5.740	0.805	0.726	0.468	0.525	0.524	0.474	0.177	0.178	0.476	0.406	0.141	0.115	0.464	0.381	0.128	0.101
8	5	78.100	67.190	56.806	59.692	6.996	6.133	5.188	5.446	0.731	0.659	0.393	0.433	0.469	0.413	0.135	0.103	0.424	0.327	0.102	0.050	0.413	0.296	0.087	0.037
9	7	77.420	66.604	56.309	59.170	6.899	6.048	5.113	5.366	0.712	0.640	0.374	0.409	0.455	0.391	0.125	0.087	0.411	0.294	0.091	0.033	0.400	0.261	0.073	0.021
10	10	76.917	66.172	55.942	58.784	6.828	5.985	5.058	5.308	0.698	0.625	0.361	0.392	0.444	0.370	0.117	0.074	0.401	0.263	0.081	0.019	0.391	0.231	0.060	0.009
11	20	76.339	65.674	55.520	58.340	6.746	5.912	4.995	5.241	0.682	0.605	0.346	0.372	0.433	0.340	0.107	0.059	0.390	0.224	0.067	0.005	0.380	0.203	0.035	0.001
12	40	76.053	65.427	55.311	58.120	6.706	5.877	4.963	5.208	0.674	0.595	0.338	0.362	0.427	0.325	0.100	0.053	0.385	0.213	0.052	0.003	0.375	0.199	0.013	0.000
13	50	75.996	65.378	55.270	58.076	6.698	5.869	4.957	5.201	0.673	0.593	0.337	0.361	0.426	0.323	0.098	0.052	0.384	0.211	0.048	0.002	0.374	0.199	0.009	0.000
14	70	75.931	65.322	55.222	58.026	6.689	5.861	4.950	5.194	0.671	0.591	0.335	0.358	0.425	0.320	0.096	0.050	0.383	0.210	0.044	0.002	0.372	0.199	0.005	0.000
15	100	75.882	65.280	55.187	57.989	6.682	5.855	4.945	5.188	0.670	0.589	0.333	0.357	0.424	0.317	0.094	0.050	0.382	0.209	0.041	0.002	0.372	0.198	0.003	0.000
16	200	75.826	65.231	55.145	57.945	6.675	5.848	4.939	5.182	0.668	0.587	0.332	0.355	0.423	0.315	0.092	0.049	0.381	0.208	0.037	0.002	0.371	0.198	0.002	0.000
17	500	75.792	65.202	55.120	57.919	6.670	5.844	4.935	5.178	0.667	0.586	0.331	0.354	0.422	0.314	0.091	0.048	0.380	0.208	0.036	0.002	0.370	0.198	0.001	0.000

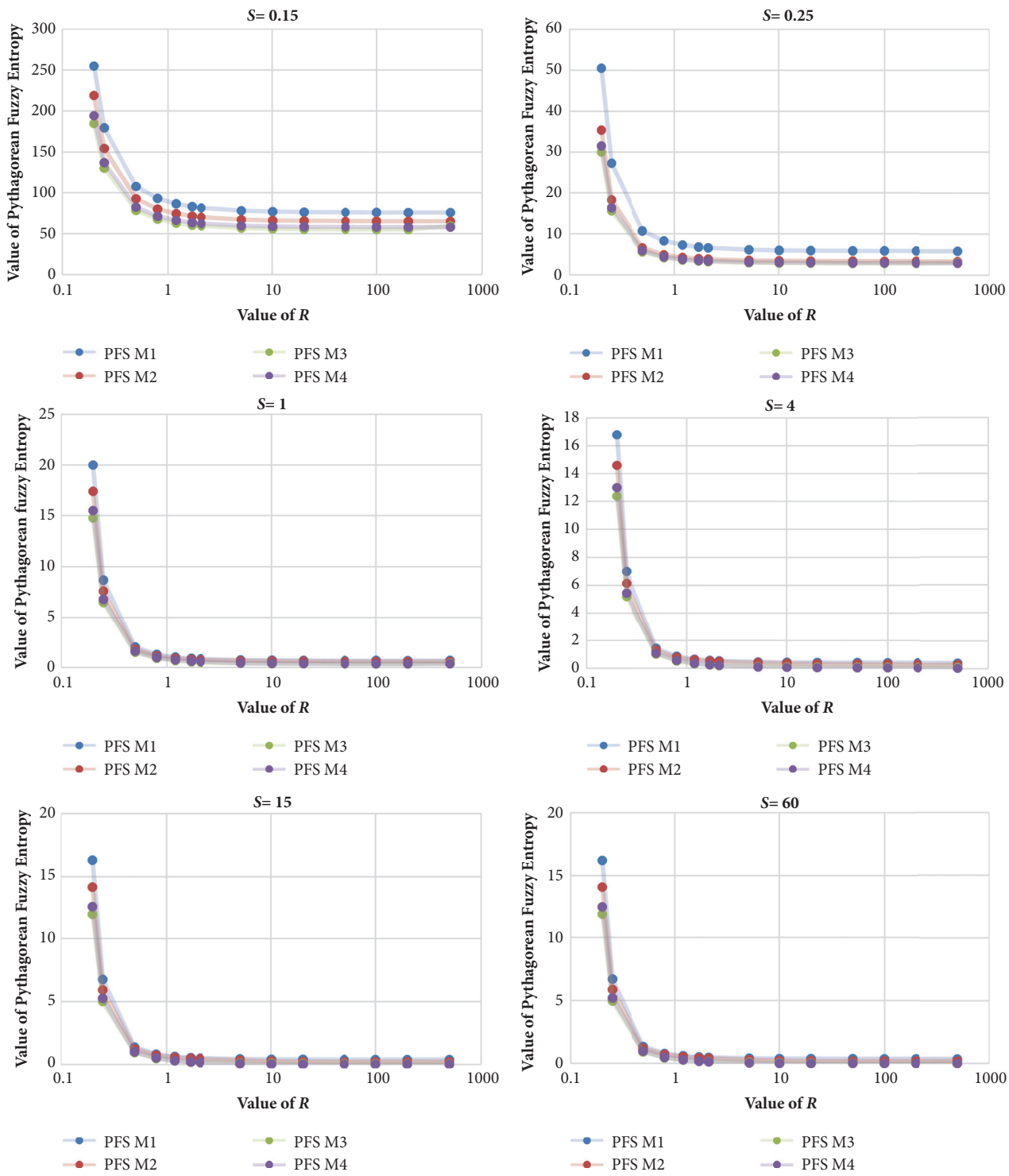

FIGURE 2: Monotonicity of the (R, S)-norm information measure.

Case 1 (unknown weights). When the criteria weights are completely unknown, then we calculate the weights by using the proposed PFS entropy as

$$w_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j}, \quad j = 1, 2, \ldots, n; \tag{27}$$

where $e_j = (1/m) \sum_{i=1}^{m} H_R^S(z_{ij})$, and

$$\begin{aligned} H_R^S(z_{ij}) = {} & \frac{R \times S}{(R - S)} \\ & \cdot \sum_{i=1}^{m} \frac{1}{m} \left[\left(\mu_M(x_i)^{2S} + \nu_M(x_i)^{2S} + \pi_M(x_i)^{2S} \right)^{1/S} \right. \\ & \left. - \left(\mu_M(x_i)^{2R} + \nu_M(x_i)^{2R} + \pi_M(x_i)^{2R} \right)^{1/R} \right] \end{aligned} \tag{28}$$

is the proposed Pythagorean fuzzy entropy for $z_{ij} = (p_{ij}, q_{ij})$.

Case 2 (partially known weights). In case the weights are partially known for a multiple-criteria decision-making problem, we use the minimum entropy principle (Wang and Wang [21]) to determine the weight vector of the criteria by constructing the programming model as follows.

The overall entropy of the alternative z_i is

$$\begin{aligned} E[z_i] &= \sum_{j=1}^{n} H_R^S(z_{ij}) \\ &= \frac{R\times S}{(R-S)}\sum_{j=1}^{n}\left\{\sum_{i=1}^{m}\frac{1}{m}\left[\left(\mu_M(x_i)^{2S}+\nu_M(x_i)^{2S}+\pi_M(x_i)^{2S}\right)^{1/S}-\left(\mu_M(x_i)^{2R}+\nu_M(x_i)^{2R}+\pi_M(x_i)^{2R}\right)^{1/R}\right]\right\}; \end{aligned} \tag{29}$$

where $R, S > 0$; $R > 1,\ S < 1$ or $R < 1,\ S > 1$.

Since there are fair competitive environments between each of the alternatives, the weight coefficient with respect to the same criteria should also be equal. Further, in order to get the ideal weight, we construct the following accompanying model:

$$\begin{aligned} \min E &= \sum_{i=1}^{m} w_j E(z_i) = \sum_{i=1}^{m} w_j\left\{\sum_{j=1}^{n} H_R^S(z_{ij})\right\} \\ &= \frac{R\times S}{(R-S)}\sum_{j=1}^{n} w_j \\ &\cdot \sum_{i=1}^{m}\frac{1}{m}\left\{\left(\mu_M(x_i)^{2S}+\nu_M(x_i)^{2S}+\pi_M(x_i)^{2S}\right)^{1/S}\right. \\ &\left.-\left(\mu_M(x_i)^{2R}+\nu_M(x_i)^{2R}+\pi_M(x_i)^{2R}\right)^{1/R}\right\} \end{aligned} \tag{30}$$

$R, S > 0$; $R > 1,\ S < 1$ or $R < 1,\ S > 1$, subject to $\sum_{j=1}^{n} w_j = 1$.

Finally, the procedure for implementing the proposed algorithm is being presented using Figure 3.

The steps of the proposed methodology are enumerated and detailed as follows.

Step 1. We construct the decision matrix $R = (p_{ij}, q_{ij})_{m\times n} = o_j(z_i)$, where the elements $o_j(z_i)$ $(i = 1, 2, ..., m;\ j = 1, 2, ..., n)$ are the appraisal of the alternative $z_i \in Z$ with respect to the criteria $o_j \in O$.

Step 2. Determine the criteria weights by using (27) and (30).

Step 3. Define the most preferred solution (z^+) and the least preferred solution (z^-) as

$$z^+ = \left((\alpha_1^+, \beta_1^+), (\alpha_2^+, \beta_2^+), \ldots, (\alpha_n^+, \beta_n^+)\right); \tag{31}$$

where $(\alpha_j^+, \beta_j^+) = (\sup \mu_M(z_i), \inf \nu_M(z_i))$, $z_i \in Z$; $(j = 1, 2, \ldots, n)$; and

$$z^- = \left((\alpha_1^-, \beta_1^-), (\alpha_2^-, \beta_2^-), \ldots, (\alpha_n^-, \beta_n^-)\right); \tag{32}$$

where $(\alpha_j^-, \beta_j^-) = (\inf \mu_M(z_i), \sup \nu_M(z_i))$, $z_i \in Z$; $(j = 1, 2, \ldots, n)$, respectively.

Step 4. By using Definition 5, the distance measures of $z_i's$ from z^+ and z^- will be evaluated as follows:

$$\begin{aligned} l(z_i, z^+) &= \frac{1}{2}\sum_{j=1}^{n} w_j\left(\left|(\alpha_{ij})^2-(\alpha_j^+)^2\right|\right. \\ &\left.+\left|(\beta_{ij})^2-(\beta_j^+)^2\right|+\left|(\pi_{ij})^2-(\pi_j^+)^2\right|\right); \end{aligned} \tag{33}$$

and

$$\begin{aligned} l(z_i, z^-) &= \frac{1}{2}\sum_{j=1}^{n} w_j\left(\left|(\alpha_{ij})^2-(\alpha_j^-)^2\right|\right. \\ &\left.+\left|(\beta_{ij})^2-(\beta_j^-)^2\right|+\left|(\pi_{ij})^2-(\pi_j^-)^2\right|\right). \end{aligned} \tag{34}$$

Step 5. Determine the relative degrees of closeness $l_i's$ as follows:

$$l_i = \frac{l(z_i, z^-)}{l(z_i, z^-)+l(z_i, z^+)}. \tag{35}$$

Step 6. On the basis of the relative degree of closeness obtained in Step 5, we determine the optimal ranking order of the alternatives. The alternative with the maximal degree of closeness $l(z_i)$ is supposed to be the best alternative.

6. Numerical Examples

Based on two different cases considered in the proposed algorithm, we present two different examples as follows.

Example 1 (unknown weights). Suppose an automobile company produces four different cars, say, z_1, z_2, z_3, and z_4. Suppose a customer wants to buy a car based on the four given criteria, say, comfort o_1, good mileage o_2, safety o_3, and interiors o_4. Assume the appraisal values of the alternatives with respect to each criterion provided by the expert are represented by PFS as

$$\begin{array}{cccccc} & o_1 & o_2 & o_3 & o_4 \\ z_1 & (0.9, 0.3) & (0.7, 0.6) & (0.5, 0.8) & 0.6, 0.3 \\ z_2 & (0.4, 0.7) & (0.9, 0.2) & (0.8, 0.1) & (0.5, 0.3) \\ z_3 & (0.8, 0.4) & (0.7, 0.5) & (0.6, 0.2) & (0.7, 0.4) \\ z_4 & (0.7, 0.2) & (0.8, 0.2) & (0.8, 0.4) & (0.6, 0.6) \end{array} \tag{36}$$

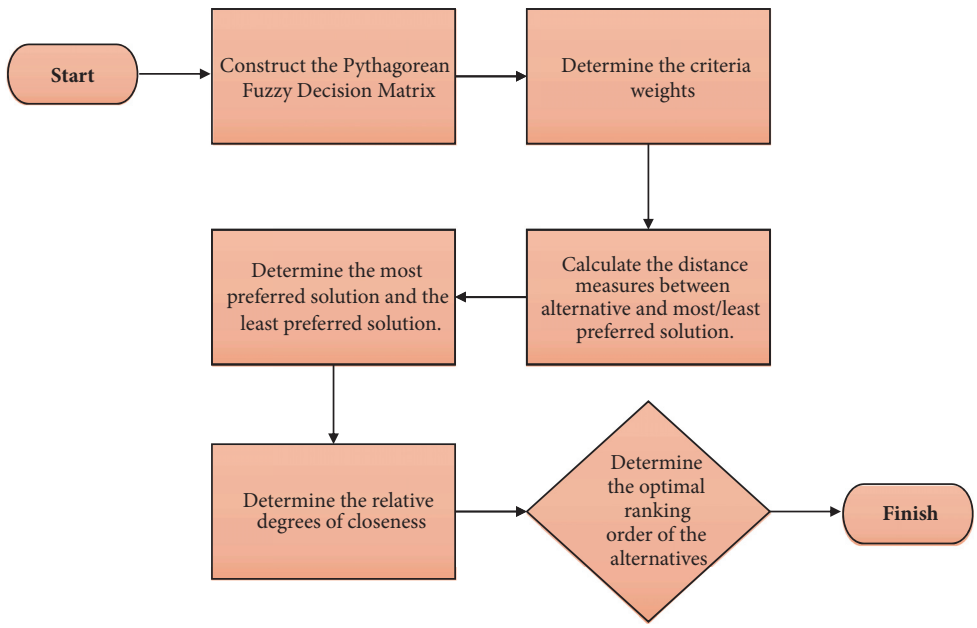

Figure 3: Flowchart of the proposed algorithm using PFS.

Then the calculations for the ranking procedure are as follows:

(1) Calculate the criteria weight vector using (27):

$$w = (w_1, w_2, w_3, w_4)^T = (0.272107, 0.263037, 0.34878, 0.116077)^T. \quad (37)$$

(2) The most preferred solution (z^+) and the least preferred solution (z^-) are given by

$$z^+ = \{(0.9, 0.3), (0.9, 0.2), (0.8, 0.1), (0.7, 0.4)\} \quad (38)$$

and

$$z^- = \{(0.4, 0.7), (0.7, 0.6), (0.5, 0.8), (0.6, 0.6)\} \quad (39)$$

respectively.

(3) The distances between each of $z_i's$ from z^+ and z^- are given by

$$\begin{aligned} l(z_1, z^+) &= 0.040622, \\ l(z_2, z^+) &= 0.186515, \\ l(z_3, z^+) &= 0.0.06623, \\ l(z_4, z^+) &= 0.048795, \\ l(z_1, z^-) &= 0.209804, \\ l(z_2, z^-) &= 0.13179, \\ l(z_3, z^-) &= 0.177491, \\ l(z_4, z^+) &= 0.116968. \end{aligned} \quad (40)$$

(4) The values of relative degree of closeness are as follows:

$$\begin{aligned} l_1 &= 0.837788, \\ l_2 &= 0.414036, \\ l_3 &= 0.728256, \\ l_4 &= 0.705633. \end{aligned} \quad (41)$$

(5) The ranking of the alternatives as per the relative degree of closeness is $z_1 \succ z_3 \succ z_4 \succ z_2$ and z_1 is the best available alternative. It may be noted that the above ranking is with respect to the specific values of $R = 3$ and $S = 0.3$.

The consistency of the ranking procedure for different values of parameters R and S may also be observed and studied by making a simulation study over the varying values of the parameters depending on the requirement.

Example 2 (partially known weights). Suppose there are 1000 students in a college. On the basis of three selected criteria, say, o_1 (personality), o_2 (intelligence), and o_3 (communication skills), the administration wants to select a college representative. Let there be three candidates, say, z_1, z_2, and z_3. The PFS decision matrix for the above problem is

$$\begin{array}{cccc} & o_1 & o_2 & o_3 \\ z_1 & (0.8, 0.5) & (0.6, 0.6) & (0.8, 0.2) \\ z_2 & (0.6, 0.5) & (0.7, 0.4) & (0.8, 0.4) \\ z_3 & (0.5, 0.7) & (0.7, 0.6) & (0.9, 0.3) \end{array} \quad (42)$$

Let the information about the criteria weight be partially given in the following form $\{0.10 \le w_1 \le 0.30, 0.35 \le w_2 \le 0.60, 0.25 \le w_3 \le 0.70\}$. The calculation for the ranking procedure for the above decision-making problem is presented as follows:

(1) Using (30), we determine the criteria weights by following linear programming model:

$$\begin{aligned} \min \quad & E \\ & = 0.609037w_1 + 0.641365w_2 \\ & \quad + 0.590874w_3 \\ \text{subject to} \quad & 0.10 \le w_1 \le 0.30, \\ & 0.35 \le w_2 \le 0.60, \\ & 0.25 \le w_3 \le 0.70, \\ & w_1 + w_2 + w_3 = 1. \end{aligned} \tag{43}$$

By solving this linear programming problem using MATLAB software, we obtained the criteria weight vector as follows:

$$w = (0.10, 0.35, 0.55)^T. \tag{44}$$

(2) The most preferred solution (z^+) and the least preferred solution (z^-) are given by $z^+ = \{(0.8, 0.5), (0.7, 0.4), (0.9, 0.2)\}$ and $z^- = \{(0.5, 0.7), (0.6, 0.6), (0.8, 0.4)\}$, respectively.

(3) The distances between each of $z_i's$ from z^+ and z^- are given by

$$\begin{aligned} l(z_1, z^+) &= 0.013843, \\ l(z_2, z^+) &= 0.015888, \\ l(z_3, z^+) &= 0.068163, \\ l(z_1, z^-) &= 0.052213, \\ l(z_2, z^-) &= 0.026855, \\ l(z_3, z^-) &= 0.049273 \end{aligned} \tag{45}$$

(4) The values of relative degree of closeness are

$$\begin{aligned} l_1 &= 0.79044, \\ l_2 &= 0.628297, \\ l_3 &= 0.419573. \end{aligned} \tag{46}$$

(5) The ranking of the alternatives as per the relative degree of closeness is $z_1 \succ z_2 \succ z_3$ and z_1 is the best available alternative. It may be noted that the above ranking is with respect to the specific values of $R = 3$ and $S = 0.3$.

The consistency of the ranking procedure for different values of the parameters R and S may also be observed and studied by making a simulation study over the varying values of the parameters.

7. Conclusions and Future Work

We have successfully proposed a new parametric (R, S)-norm information measure for Pythagorean fuzzy set along with the proof of its validity and discussed its maximality and the monotonic behavior with respect to parameters under consideration. Further, an algorithm for multicriteria decision-making problem has been well proposed and successfully implemented with the help of two different kind of numerical examples when weights are unknown and other when weights are partially known.

In the area of pattern recognition, the directed divergence measure/symmetric divergence measure explains dissimilarity between pairs of probability distribution which is generally utilized for the procedure of factual surmising. It might be noticed that these difference measures and similarity measures are dual ideas. The similarity measure might be characterized as a diminishing capacity of the difference measures, particularly when the scope of divergence measures is $[0, 1]$.

The proposed parametric (R, S)-norm information measure can further be extended to the concept of the parametric directed divergence measure/symmetric divergence measure for Pythagorean fuzzy sets. Various applications including total ambiguity and information improvement measures based on the proposed divergence measures may also be discussed in detail, e.g., taking a monotonic decreasing function into account, the upper bound of the symmetric divergence measure can be calculated and the similarity measure can be subsequently defined between two PFSs. The concept of similarity based clustering method (SCM) can also be investigated and the structure of the considered data set might be examined with the assistance of the similarity measure.

Data Availability

The data for the implementation of the proposed algorithm in the numerical example are hypothetical data and have no connection with any particular agency's data.

Disclosure

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Using Intuitionistic Fuzzy TOPSIS in Site Selection of Wind Power Plants in Turkey

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The reduction of energy resources and the increase in environmental consciousness have recently increased the interest in renewable energy sources. Wind energy is from renewable energy sources, which are used in many countries. Turkey has a lot alternative wind energy plants thanks to its favorable geographical location. Where the wind power plant is to be established is a complex and important decisive factor. It is very important to select the appropriate wind power plant site to take advantage of wind energy and reduce costs. In this study, we aimed to reach the solution of wind energy plant site selection. For this purpose 4 alternative wind power plant locations have been identified. To evaluate the alternatives, 10 criteria in four dimensions including wind potential, location, cost, and social benefits are selected. Since the Multicriterion Decision Making (MCDM) methods are often used in problem of location selection from past to present, TOPSIS method combined with intuitionistic fuzzy set (IFS) has been used to achieve this goal. The main purpose of the TOPSIS method is to rank the alternatives in the worst way. The IFS are used to reflect approval, rejection, and hesitation of decision makers by dealing with real life uncertainty, imprecision, vagueness, and linguistic human decisions. Finally, a numerical example is applied for wind power plant site selection. In order to demonstrate the effectiveness of IFS, the problem is solved by the Fuzzy TOPSIS method using the same data. Then, the obtained results are compared with the IFS method to show the effectiveness of the proposed method.

1. Introduction

Increased living standards have also increased the need for energy. The shortage of fossil fuels and the negative effects on the environment have created a need for clean energy [1]. Radioactive waste generated by nuclear power plants and security problems, especially the explosion of nuclear power plants in Japan Fukushima, triggered the tendency for renewable energy sources [2].

The use of renewable energy sources ensures sustainable development. Reducing the use of fossil fuels and energy imports, achieving national targets by increasing employment and competitiveness, and eliminating climate change and environmental problems are benefits of renewable energy sources [8].

Wind energy, which is the oldest energy source [3], is caused by the difference in pressure that occurs when the earth's surface is exposed to different solar rays [4]. Wind energy, which provides high usability, reliability, and clean energy, is one of the fastest growing renewable energy sources all over the world [9]. Wind energy is abundant, useful, and economical [1] compared to limited, expensive, and defective hydrocarbon based energy [5].

The increase of the urban population and the development of industry increased Turkey's energy needs [4]. Thanks to its geographical location, Turkey has an alternative renewable energy, especially wind energy [7]. It is important to establish where the power plant is to take advantage of this energy at the maximum level [5]. Political, social, environmental, cultural, and economic criteria should be considered in addition to the technical requirements for wind power plant site selection [10].

Multicriterion Decision Making (MCDM) methods are often used to solve wind power plant site selection problem

including complex criterion [9]. MCDM methods widely used in solution of this problem are Analytic Network Process (ANP), Analytic Hierarchy Process (AHP), Elimination and Choice Translating Reality (ELECTRE), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [6].

In this study, the Intuitionistic Fuzzy TOPSIS (IFT) approach is proposed for the solution of the problem of wind power plant site selection. The most commonly used method for ranking alternatives based on criterion is TOPSIS [11]. The alternative chosen from all alternatives is the closest to the positive ideal solution, in other words the farthest away from the negative ideal solution. Positive ideal solution maximizes the benefit criterion and minimizes the cost criterion. It is the inverse for the negative ideal solution [12]. The IFS is used to deal with real life uncertainty, imprecision, vagueness, and linguistic human decisions. Also, it provides reflection of approval, rejection, and hesitation of decision makers [13].

In numerical example, 3 alternatives were selected for the wind power plant and the results of the literature survey were sorted according to the 10 election decisions determined. These criteria are gathered in 4 dimensions. Wind potential includes wind speed and wind density criterion. Location consists of surface characteristics, proximity, power distribution network, and natural disaster occurrence. In dimension of cost, there are land purchase cost and initial and annual maintenance. Finally, social benefits cover cultural and environmental concerns and employment.

The rest of this article is organized as follows: In Section 2, a literature search of the wind power site selection is given. Then the IFTOPSIS method is given in Section 3. In Section 4 this approach is illustrated with a numerical example. The conclusion and comment of the problem are given in Section 5.

2. Literature Review

Increasing global warming and increased energy demand have led countries to use renewable energy sources. This study is about wind energy from renewable energy sources. Criterion and method for wind energy site selection have been determined by literature survey. Summaries of the literature study are given in Tables 1 and 2.

The work in [4] represents the importance of renewable energy sources and Turkey has a high potential for wind energy. The wind energy potential map has been examined and potential places in Amasra, Bandırma, Bozcaada, and Çanakkale have been selected. For site selection, surface characteristic, proximity, cost, and wind characteristic were chosen as the criteria for selection. Choquet integral method, which enables interaction between criteria and evaluates quantitative and qualitative data at the same time, is applied. Çanakkale was found as the most suitable alternative.

The authors of [3] have used an integrated hierarchical Data Envelopment Analysis (DEA) method for wind plant location optimization in their work and have implemented it in Iran. A total of 125 locations in 25 cities and 5 regions in each city were evaluated. In order to determine the best region at the first level of location optimization, land cost, population and human labor, and distances of power distribution networks indicators with social and technical structure were selected. At the second level in order to prioritize the cities used indicators, which have technical and geographical characteristics: intensity of natural disasters, quantity of proper topographical areas, quantity of proper geological areas, and average wind blow.

The authors of [6] have established a decision mechanism for SWHPS (solar-wind hybrid power station) site selection using AHP method. For the 49.5 MW SWHPS installation in China, the assessment committee chose business benefits, socioeconomic needs, and performances as subtargets and benefit, accessibility, environment, risk, and resource as evaluation features. Five alternative SWHPS sites are selected using the Geographic Information System (GIS) and grid map. As a result, alternative A site was chosen as the most suitable site.

The authors of [2] develop strategies for the selection of an offshore wind farm, in the coastal regions of South Korea's Jeju Island. The settlement criteria are divided into four categories: conservation areas and environmental protection, energy resources and economy, marine ecology and human activities, and marine environment. They have developed 4 scenarios for alternative site selection by utilizing GIS. In the scenario where 4 categories were taken into consideration, fewer suitable areas were found than other scenarios. But consideration of all categories will help to reduce the number of social conflicts among stakeholders and environmental issues by providing a sustainable and eco-friendly offshore wind farm.

The authors of [7] have done a study on site selection for wind energy plants. They choose Western Turkey as application area. The application consists of two stages: first stage is elimination of unfavorable stages and second stage is examination of existing ones. Alternative land areas are treated as grids of the same size, each large enough to build a wind turbine. GIS have been used to apply the elimination criterion and restrictions. Besides, Multiple Criterion Decision Analysis (MCDA) is then used to rank and sort the grids via the evaluation criterion specified. The problem has been assessed in 13 areas where several grids are assembled to evaluate larger areas of space to build wind farms instead of individual turbines. In all MCDA methods used, areas 3, 5, 8, and 12 are emphasized.

The authors of [5] used an integrated fuzzy-DEA approach in this study to decide on wind farm locations. They used the Basic Component Analysis (BCA) and Numerical Taxonomy (NT) methods to validate the results of the DEA model. The model was tested on 25 candidate cities in Iran with 5 regions in each city. In addition, 20 other cities are considered to be consumers of energy produced. The results show the importance of the proximity of consumers in the establishment of wind farms.

The authors of [1] evaluated the possibility of establishing wind farms in the province of Ardabil in northwestern Iran by combining ANP and Decision Making Experiment and Evaluation Laboratories (DEMATEL) methods in a GIS environment. Using the 13 layers of information according to three main criteria, environment, technical, and economical,

Table 1: Criterion from literature review.

Researchers	Methodology	Distance	Cost	Energy Resources	Wind Characteristics	Elevation	Slope	Proximity	Environmental Risks	Human Labor
Azadeh, Ghaderi, & Nasrollahi [3]	DEA	√	√						√	√
Cebi, S. & Kahraman [4]	AHP/Choquet Integral		√		√			√	√	
Ali Azadeh & ArminRahimi-Golkhanda & MohsenMoghaddam [5]	DEA	√	√						√	√
Ali Azizi & BahramMalekmohammadi & Hamid RezaJafari & Hossein Nasiri & VahidAmini Parsa, [1]	ANP/Dematel/GİS					√	√		√	√
Yunna Wu & ShuaiGeng [6]	AHP		√	√	√				√	
KazimBarisAtici& Ahmet BahadirSimsek& Aydin Ulucan & Mustafa UmurTosun, [7]	MCDA/GİS	√		√		√	√			
Taeyun Kim & Jeong-II Park & JunhoMaeng, [2]	AHP/GİS		√	√					√	√

Table 2: Literature review on renewable energy location selection.

Authors	Title of the Study	Article Name
Azadeh, Ghaderi, & Nasrollahi [3]	Location optimization of wind plants in Iran by an integrated hierarchical Data Envelopment Analysis.	Renewable Energy
Cebi, S. & Kahraman [4]	Using Multi Attribute Choquet Integral in Site Selection of Wind Energy Plants: The case of Turkey	Journal of Multiple-Valued Logic & Soft Computing
Ali Azadeh & ArminRahimi-Golkhanda & Mohsen Moghaddam (2013)	Location optimization of wind plants in Iran by an integrated hierarchical data envelopment analysis.	Renewable Energy
Ali Azizi & Bahram Malekmohammadi &Hamid Reza Jafari & Hossein Nasiri & Vahid Amini Parsa, [1]	Land suitability assessment for wind power plant site selection using ANP-DEMATEL in a GIS environment: case study of Ardabil province, Iran.	Environ Monit Assess
Yunna Wu & ShuaiGeng [6]	Multi-criterion decision making on selection of solar–wind hybrid power station location	A case of China Energy Conversion and Management
KazimBarisAtici & Ahmet BahadirSimsek & Aydin Ulucan & Mustafa UmurTosun, [7]	A GIS-based Multiple Criterion Decision Analysis approach for wind power plant site selection.	Utilities Policy
Taeyun Kim & Jeong-II Park & JunhoMaeng, [2]	Offshore wind farm site selection study around Jeju Island, South Korea.	Renewable Energy

a land suitability map was established. Then, it is reclassified according to the 5 equal-rate divisions from the most suitable areas that are least suitable. The results show that 6.68% of Ardabil province is most suitable for wind turbines.

3. Methodology

MCDM techniques are often used because mathematical and heuristic methods are inadequate in dealing with qualitative factors in the solution of the problem of location selection that has come up to date from the past and is still valid [4]. The MCDM methods are useful in reflecting the judgments of decision makers and in dealing with the complexity in the decision process [7].

The TOPSIS method of the MCDM techniques is proposed for solving the problem of wind power plant site selection. This section briefly reviews the intuitionistic fuzzy set and TOPSIS method.

3.1. Intuitionistic Fuzzy Set. Human decisions in real life problems involve uncertainty and ambiguity. In 1965, the fuzzy set theory was proposed by Zadeh to deal with this ambiguity and uncertainty [14]. The intuitionistic fuzzy set (A-IFS), which is generalized to the fuzzy set and characterized by a membership function and a nonmember function, was first introduced in 1986 by Atanassov. IFS has been applied to many different fields, including logic programming, medical diagnosis, decision making, evaluation function, and preference relation [15].

In this section a few definitions and operations of IFS are introduced.

Let X be fixed. IFS A in X can be defined as

$$X = \{s, \mu_x(s), v_x(s) \mid s \in S\}, \tag{1}$$

where

$$\mu_x(s) : \mu_x(s) \in [0,1], \quad S \longrightarrow [0,1] \tag{2}$$

$$v_x(s) : v_x(s) \in [0,1], \quad S \longrightarrow [0,1] \tag{3}$$

$\mu_x(s)$ and $v_x(s)$ are degrees of membership and nonmembership function, respectively, satisfying the following equation:

$$0 \le \mu_x(s) + v_x(s) \le 1 \quad \forall s \in S, \ R \longrightarrow [0,1] \tag{4}$$

For the IFS A in X, $\pi_x(s)$ is defined as the intuitionistic index. It is the measurement of the hesitation degree.

$$\pi_x(s) = 1 - \mu_x(s) - v_x(s). \tag{5}$$

Let A and B be IFS of the set S; then the multiplication operators are, correspondingly,

$$\begin{aligned} &X + Y \\ &= \{\mu_x(s) * \mu_y(s), v_x(s) + v_y(s) - v_x(s) * v_y(s) \mid \in S\} \end{aligned} \tag{6}$$

3.2. Intuitionistic Fuzzy TOPSIS. The TOPSIS, first introduced by Hwang and Yoon in 1981, is the most common method of ranking alternatives based on the selection criterion. The basic idea of the TOPSIS method is to rank the alternatives from best to worst. The best solution among the alternatives in the obtained order is the closest one to the positive ideal solution at the same time as the farthest negative solution [16].

Fuzzy numbers are used to deal with real life uncertainty, imprecision, vagueness, and linguistic human decisions. The intuitionistic fuzzy sets better reflect the decision makers' approval, rejection, and hesitation [17].

Table 3: Linguistic terms for rating DMs.

Linguistic terms	IFNs
Very Important	(0.80, 0.10)
Important	(0.50, 0.20)
Medium	(0.50, 0.50)
Bad	(0.30, 0.50)
Very Bad	(0.20, 0.70)

Table 4: Linguistic terms for rating criterion.

Linguistic terms	IFNs
Very Important	(0.90, 0.10)
Important	(0.75, 0.20)
Medium	(0.50, 0.45)
Unimportant	(0.35, 0.60)
Very Unimportant	(0.10, 0.90)

In this section, we present an Intuitionistic Fuzzy TOPSIS model introduced by [13] for the evaluation of the alternatives. The order of m alternatives is based on n criterion. A = {A1, A2, ..., Am} is set of alternatives, C = {C1, C2, ..., Cn} is set of criteria, and L = {l1, l2, ..., ll} represents set of decision makers.

Now we replace the algorithm with a seven-step procedure as follows.

Step 1 (calculate the weights of DMs). The importance of the DMs is represented as linguistic terms (Table 3).

Dl = $[\mu 1, \nu l, \pi l]$ is the intuitionistic fuzzy number for lth DM ranking. The weight of DM can be determined by the following formula:

$$\lambda l = \frac{[\mu l + \pi l\,(\mu l/(\mu l + \nu l))]}{\sum_{l=1}^{k}[\mu l + \pi l\,(\mu l/(\mu l + \nu l))]} \tag{7}$$

where

$$\lambda_1 \in [0,1] \text{ and } \sum_{l=1}^{k}\lambda l = 1 \tag{8}$$

Step 2 (calculate the weights of criterion). All criteria can not be regarded as having equal qualification. W represents a set of importance levels. In order to achieve W, all DM views on the importance of each criterion need to be integrated.

Let $w_j^k = (\mu_j^k, \nu_j^k, \pi_j^k)$ represent intuitionistic fuzzy number about the Xj criterion of the kth decision maker. The intuitionistic fuzzy weighted averaging (IFWA) operator is used to calculate the weights of the criterion. The IFWA operator is developed by Xu (2007).

$$\begin{aligned} w_j &= \mathrm{IFWAr}_\lambda\left(w_j^{(1)}, w_j^{(2)}, \ldots w_j^{(l)}\right) = \lambda_1 w_j^{(1)} \oplus \lambda_2 w_j^{(2)} \\ &\oplus, \ldots, \oplus \lambda_k w_j^{(l)} = \left[1 - \prod_{l=1}^{k}\left(1-\mu_{ij}^{(l)}\right)^{\lambda l},\right. \\ &\left.\prod_{l=1}^{k}\left(\nu_{ij}^{(l)}\right)^{\lambda l}, \prod_{l=1}^{k}\left(1-\mu_{ij}^{(l)}\right)^{\lambda l} - \prod_{l=1}^{k}\left(1-\nu_{ij}^{(l)}\right)^{\lambda l}\right] \end{aligned} \tag{9}$$

The importance of criterion is represented as linguistic terms (Table 4).

Step 3 (construct intuitionistic fuzzy decision matrix (IFDM)). To arrive at a precise conclusion, each view from a group of DMs must be combined into a single view to form the aggregated intuitionistic fuzzy decision matrix (AIFDM) model.

Let $R^{(l)} = (r_{ij}^{(1)})_{m*n}$ be the IFDM of each DM.
$\lambda = \{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_k\}$ is the weight of the DM.

$$R = \left(r_{ij}\right)_{m'*n'} \tag{10}$$

where

$$\begin{aligned} r_{ij} &= \mathrm{IFWAr}_\lambda\left(r_{ij}^{(1)}, r_{ij}^{(2)}, \ldots r_{ij}^{(k)}\right) = \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus, \ldots, \\ &\oplus \lambda_k r_{ij}^{(k)} = \left[1 - \prod_{l=1}^{k}\left(1-\mu_{ij}^{(l)}\right)^{\lambda l},\right. \\ &\left.\prod_{l=1}^{k}\left(\nu_{ij}^{(l)}\right)^{\lambda l}, \prod_{l=1}^{k}\left(1-\mu_{ij}^{(l)}\right)^{\lambda l} - \prod_{l=1}^{k}\left(1-\nu_{ij}^{(l)}\right)^{\lambda l}\right] \end{aligned} \tag{11}$$

Step 4 (the calculation of aggregated weighted intuitionistic fuzzy decision matrix (AWIFDM)). The aggregated weighted intuitionistic fuzzy decision matrix is calculated by combining W and R.

$$\begin{aligned} R \oplus W &= \left(\mu'_{ij}, \nu'_{ij}\right) \\ &= \left\{\left\langle x, \mu_{ij} * \mu_j, \nu_{ij} + \nu_j - \nu_{ij} * \nu_j\right\rangle\right\} \end{aligned} \tag{12}$$

$$\pi'_{ij} = 1 - \mu_{ij} * \mu_j - \nu_{ij} - \nu_j + \nu_{ij} * \nu_j \tag{13}$$

Step 5 (calculate intuitionistic fuzzy positive and negative ideal solution). Let J_1 be benefit criterion and J_2 be cost criterion. A^* represents intuitionistic fuzzy positive ideal solution and A^- represents intuitionistic fuzzy negative ideal solution. Then A^* and A^- are calculated as

$$\begin{aligned} A^* &= \left(r_1'^*, r_2'^*, \ldots, r_n'^*\right), \\ r_j'^* &= \left(\mu_j'^*, \nu_j'^*, \pi_j'^*\right), \quad j = 1, 2, \ldots, n \end{aligned} \tag{14}$$

$$\begin{aligned} A^- &= \left(r_1'^-, r_2'^-, \ldots, r_n'^-\right), \\ r_j'^- &= \left(\mu_j'^-, \nu_j'^-, \pi_j'^-\right), \quad j = 1, 2, \ldots, n \end{aligned} \tag{15}$$

where

$$\mu_j'^{*} = \left\{\left(\max_i \{\mu'_{ij}\}\ j \in J_1\right), \left(\min_i \{\mu'_{ij}\}\ j \in J_2\right)\right\}, \quad (16)$$

$$\mathrm{v}_j'^{*} = \left\{\left(\min_i \{v'_{ij}\}\ j \in J_1\right), \left(\max_i \{v'_{ij}\}\ j \in J_2\right)\right\}, \quad (17)$$

$$\pi_j'^{*} = \left\{\left(1 - \max_i \{\mu'_{ij}\} - \min_i \{v'_{ij}\}\ j \in J_1\right), \left(1 - \min_i \{\mu'_{ij}\} - \max_i \{v'_{ij}\}\ j \in J_2\right), \right\} \quad (18)$$

$$\mu_j'^{-} = \left\{\left(\min_i \{\mu'_{ij}\}\ j \in J_1\right), \left(\max_i \{\mu'_{ij}\}\ j \in J_2\right)\right\}, \quad (19)$$

$$\mathrm{v}_j'^{-} = \left\{\left(\max_i \{v'_{ij}\}\ j \in J_1\right),\ \min_i \{v'_{ij}\}\ j \in J_2\right\}, \quad (20)$$

$$\pi_j'^{-} = \left\{\left(1 - \min_i \{\mu'_{ij}\} - \max_i \{v'_{ij}\}\ j \in J_1\right), \left(1 - \max_i \{\mu'_{ij}\} - \min_i \{v'_{ij}\}\ j \in J_2\right), \right\} \quad (21)$$

Step 6 (obtain the separation measures between the alternatives). In this paper, the normalized Euclidean distance proposed by Szmidt and Kacprzyk (2000) is used for measure separation between alternatives on intuitionistic fuzzy set. Si^* and Si^-, the separation measures of each alternative, are calculated for intuitionistic fuzzy positive ideal and negative ideal solutions, respectively.

$$S_i^{*} = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[\left(\mu'_{ij} - \mu_j'^{*}\right)^2 + \left(v'_{ij} - \mathrm{v}_j'^{*}\right)^2 + \left(\pi'_{ij} - \pi_j'^{*}\right)^2\right]}, \quad (22)$$

$$S_i^{-} = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[\left(\mu'_{ij} - \mu_j'^{-}\right)^2 + \left(v'_{ij} - \mathrm{v}_j'^{-}\right)^2 + \left(\pi'_{ij} - \pi_j'^{-}\right)^2\right]}, \quad (23)$$

Step 7 (determine the final ranking). The relative closeness coefficient of an alternative A_i with respect to the intuitionistic fuzzy positive ideal solution A^* is defined as follows:

$$CC_i^{*} = \frac{S_i^{-}}{S_i^{*} + S_i^{-}}, \quad where\ 0 \geq C_i^{*} \leq 1. \quad (24)$$

After the relative closeness coefficient of each alternative is determined, alternatives are ranked according to descending order of CCi^*.

4. Case Study

In this section, the IFTOPSIS method for selection of appropriate wind power plant site is applied in a numerical example. It is shown in Figure 1. A decision maker group consisting of three experts was formed for this reason. Decision maker 1 is a geographer, decision maker 2 is a map engineer, and decision maker 3 is an energy engineer. Çanakkale, İzmir, Samsun, and Mersin are selected as the alternative for wind power plant location. Three decision makers evaluate these alternatives and for selection of an appropriate alternative we will use selection criterion given in Table 6. Ten criteria are considered as follows.

Wind speed (C1): this includes a high average wind speed and the ability to provide the maximum benefit from the wind.

Wind density (C2): it is the kinetic energy measure produced by wind, unit square meter and time.

Surface characteristic (C3): this includes geological conditions such as soil structure and infrastructure conditions and topographic conditions such as geographical direction, elevation of the plant, and slope which are properties to be taken into consideration in the site selection.

Proximity (C4): due to some factors such as noise pollution, healthcare, aesthetics, and safety, the wind power plant should be away from areas such as urban areas, water resource, main roads, protected areas, and airports.

Power distribution network (C5): to prevent energy losses, the plant must be installed in areas close to the consumers.

Natural disaster occurrence (C6): this criterion is aimed at establishing the plant in places where safe and natural disasters are less experienced.

Land purchase cost (C7): this criterion refers to the purchase cost of the place where the plant will be established.

Initial and annual maintenance cost (C8): installation and annual maintenance costs are the criteria that should not be ignored.

Cultural end environmental concerns (C9): the plant to be installed must not be allowed to harm the environment and the historical heritage.

Employment (C10): being close to the available human labor of the plant is important in terms of employee accommodation and salaries.

4.1. Application of Intuitionistic Fuzzy TOPSIS Method. In this section, Intuitionistic Fuzzy TOPSIS model is applied for the evaluation of the alternatives.

In Step 1, the linguistic terms in Table 3 and (7) are used to calculate the weight of the decision makers and the results in Table 7 were obtained.

In the second step, the opinions of the decision makers about the criterion weight are calculated as shown in Table 10 using Table 4 and (9).

Decision makers were asked to evaluate each alternative using linguistic terms in Table 5 for each criterion and Table 8 was generated. Using (11), Table 11 is calculated, so that the decisions of DMs are collected into a single decision.

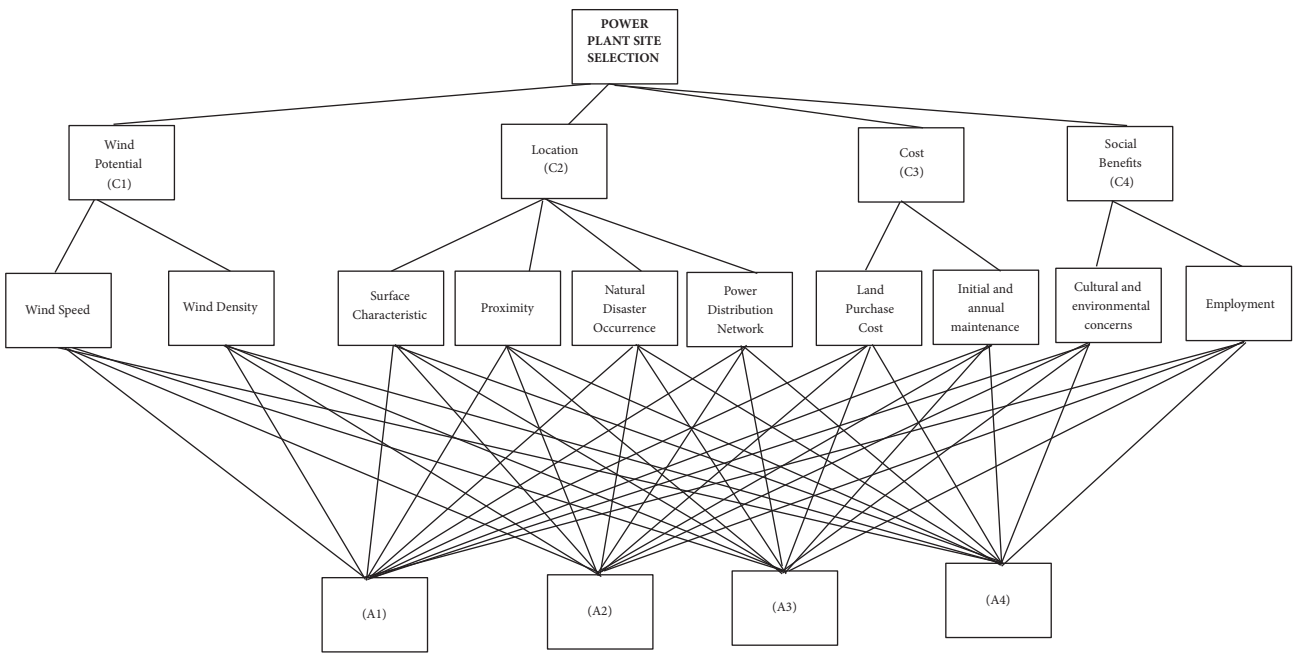

Figure 1: Alternative assessment based on criterion.

Table 5: Linguistic terms for rating the alternatives.

Linguistic terms	IFNs
Very Good (VG)	[1.00, 0.00, 0.00]
Good (G)	[0.85, 0.05, 0.10]
Moderately Good (MG)	[0.70, 0.20, 0.10]
Fair (F)	[0.50, 0.50, 0.00]
Moderately Poor (Mp)	[0.40, 0.50, 0.10]
Poor (P)	[0.25, 0.60, 0.15]
Very Poor (VP)	[0.00, 0.90, 0.10]

Table 6: The dimension and criterion of wind power plant site selection.

Target	Dimension	Criterion
Wind power plant site selection	Wind Potential	Wind speed
		Wind density
	Location	Surface characteristic
		Proximity
		Power distribution network
		Natural disaster occurrence
	Cost	Land purchase cost
		Initial and annual maintenance cost
	Social Benefits	Cultural end environmental concerns
		Employment

By combining the criterion weights and the aggregated intuitionistic fuzzy decision matrix with the help of (12) and (13), an aggregated weighted intuitionistic fuzzy decision matrix is obtained in Table 12.

Table 7: The importance and weights of decision makers' opinions.

	DM1	**DM2**	**DM3**
Linguistic terms	Very Important	Important	Medium
$\boldsymbol{\lambda}$	0,42	0,34	0,24

In Step 5 from AIFMD, A^+ is calculated by using (16), (17), and (18) and A^- is calculated by using (19), (20), and (21). A^+ and A^- are shown that in Table 13 and in Table 14, respectively.

To calculate S^* (22) is used, to calculate S^- (23) is used, and to calculate CC_i^* (24) is used. S^* and S^- represent separation measurement and CC_i^* shows ranking of alternatives. $S^*S^-$and CC_i^*values for the alternatives are determined and presented in Table 15.

4.2. Application of Fuzzy TOPSIS Method. In this section, the data used in the solution phase of the Intuitionistic Fuzzy TOPSIS model (decision makers opinions, importance weight of the criterion) were also used in Fuzzy TOPSIS application. As a result of this evaluation, the results obtained by the two different approaches under the same data will be compared and the effectiveness and solution results of the proposed Intuitionistic Fuzzy TOPSIS model will be evaluated.

After obtaining fuzzy ratings from Tables 9 and 10 normalized fuzzy decision matrix determined is shown in Table 16.

By combining the criterion weights and the aggregated Intuitionistic fuzzy decision matrix, aggregated weighted intuitionistic fuzzy decision matrix is obtained. After that, fuzzy positive ideal solution (A^+) and negative ideal solution (A^-) obtained according to the aggregated weighted intuitionistic fuzzy decision matrix are presented in Tables 17 and 18, respectively.

Table 8: Importance of alternative based on opinion of DMs.

Decision-Makers (DMs)	Alternative	Criterion									
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DM1	Mersin	MG	G	MP	MG	MG	MG	G	MP	F	P
	Çanakkale	VG	VG	G	VG	G	MP	MG	MG	MP	MP
	İzmir	VG	VG	F	G	VG	F	F	G	MG	MG
	Samsun	G	F	MG	MP	F	G	VG	F	P	F
DM2	Mersin	MG	G	F	F	F	G	VG	F	MP	P
	Çanakkale	VG	VG	MG	MG	VG	F	MG	G	G	MG
	İzmir	G	G	G	G	G	MP	F	MG	MG	F
	Samsun	MG	MG	MP	MP	MG	MG	G	MP	F	MP
DM3	Mersin	F	MG	MP	MP	F	F	G	F	MP	P
	Çanakkale	VG	VG	MG	G	G	MP	MG	G	MG	F
	İzmir	G	VG	G	MG	VG	P	MP	MG	F	G
	Samsun	MG	F	F	F	MG	MG	F	VG	P	MG

Table 9: The importance weight of the criterion.

Criterion	DM1	DM2	DM3
C1	I	VI	I
C2	VI	VI	VI
C3	I	M	M
C4	M	U	M
C5	M	I	M
C6	I	I	M
C7	VI	I	VI
C8	U	M	I
C9	VU	U	U
C10	M	U	U

Table 10: Weight of criterion.

C1	(0.82,0.16,0.03)
C2	(0.90,0.10,0.00)
C3	(0.63,0.32,0.05)
C4	(0.45,0.50,0.05)
C5	(0.60,0.34,0.05)
C6	(0.70,0.24,0.05)
C7	(0.86,0.13,0.01)
C8	(0.53,0.42,0.05)
C9	(0.25,0.71,0.03)
C10	(0.42,0.53,0.05)

The calculation of distance (S^* *and* S^-) of each alternative from A^+ and A^- is determined. Then, by using the (S^* *and* S^-) values closeness coefficient (CC_i^*) of each alternative is calculated and shown in Table 19. According to the obtained results, Çanakkale is the best alternative and Samsun is the worst alternative.

4.3. Comparison of Intuitionistic Fuzzy TOPSIS with Fuzzy TOPSIS Method. In this section, the results obtained by two different methods will be compared. As Table 20 and

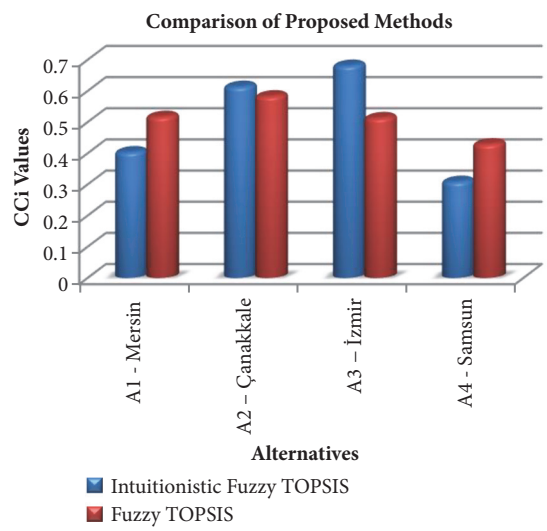

Figure 2: Comparison of two different methods results.

Figure 2 show the results obtained by Intuitionistic Fuzzy TOPSIS method and Fuzzy TOPSIS method, according to the Intuitionistic Fuzzy TOPSIS method the most important alternative is Izmir. Later, Çanakkale, Mersin, and Samsun are listed, respectively. According to the results obtained by Fuzzy TOPSIS method, Çanakkale is the most important alternative, followed by Mersin, İzmir, and Samsun, respectively.

Given the results obtained, it is clear how effective the weighting of decision makers' opinions is on the outcome, which demonstrates the effectiveness of the proposed method.

5. Conclusion

Many reasons, such as reduced resources, increased environmental problems, and energy need, have led the world to trend to renewable energy. The wind energy is from renewable energy that develops rapidly all around the world. To get the maximum benefit from wind energy, where the

Table 11: R matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.66,0.25,0.09)	(0.82,0.07,0.11)	(0.44,0.50,0.06)	(0.58,0.34,0.08)	(0.60,0.34,0.06)	(0.73,0.16,0.11)	(1.00,0.00,0.00)	(0.46,0.50,0.04)	(0.44,0.50,0.06)	(0.25,0.60,0.15)
A2	(1.00,0.00,0.00)	(1.00,0.00,0.00)	(0.78,0.11,0.11)	(1.00,0.00,0.00)	(1.00,0.00,0.00)	(0.44,0.50,0.06)	(0.70,0.20,0.10)	(0.80,0.09,0.11)	(0.68,0.18,0.13)	(0.55,0.37,0.09)
A3	(1.00,0.00,0.00)	(1.00,0.00,0.00)	(0.75,0.13,0.12)	(0.82,0.07,0.11)	(1.00,0.00,0.00)	(0.41,0.52,0.06)	(0.48,0.50,0.02)	(0.78,0.11,0.11)	(0.66,0.25,0.09)	(0.70,0.20,0.11)
A4	(0.78,0.11,0.11)	(0.58,0.37,0.05)	(0.57,0.34,0.09)	(0.43,0.50,0.07)	(0.63,0.29,0.08)	(0.78,0.11,0.11)	(1.00,0.00,0.00)	(1.00,0.00,0.00)	(0.35,0.56,0.09)	(0.53,0.40,0.07)

Table 12: Aggregated weighted intuitionistic fuzzy decision matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.540,0.368,0.092)	(0.741,0.163,0.097)	(0.273,0.660,0.067)	(0.262,0.668,0.070)	(0.361,0.566,0.073)	(0.516,0.361,0.123)	(0.863,0.127,0.010)	(0.243,0.709,0.048)	(0.113,0.856,0.031)	(0.104,0.813,0.083)
A2	(0.817,0.158,0.025)	(0.900,0.100,0.000)	(0.486,0.396,0.118)	(0.453,0.496,0.050)	(0.605,0.342,0.053)	(0.307,0.621,0.071)	(0.604,0.301,0.094)	(0.421,0.470,0.108)	(0.174,0.764,0.062)	(0.228,0.703,0.069)
A3	(0.817,0.158,0.025)	(0.900,0.100,0.000)	(0.471,0.410,0.120)	(0.373,0.531,0.096)	(0.605,0.342,0.053)	(0.292,0.638,0.070)	(0.412,0.563,0.024)	(0.409,0.483,0.108)	(0.168,0.783,0.048)	(0.292,0.623,0.085)
A4	(0.634,0.252,0.114)	(0.522,0.430,0.049)	(0.357,0.551,0.091)	(0.193,0.748,0.059)	(0.380,0.535,0.085)	(0.547,0.328,0.126)	(0.863,0.127,0.010)	(0.527,0.418,0.055)	(0.088,0.874,0.038)	(0.221,0.720,0.059)

Table 13: A^+.

C1	(0.817,0.158,0.025)
C2	(0.900,0.100,0.000)
C3	(0.486,0.396,0.118)
C4	(0.453,0.496,0.050)
C5	(0.605,0.342,0.053)
C6	(0.547,0.328,0.126)
C7	(0.412,0.563,0.024)
C8	(0.243,0.709,0.048)
C9	(0.174,0.764,0.062)
C10	(0.292,0.623,0.085)

Table 14: A^-.

C1	(0.540,0.368,0.092)
C2	(0.522,0.430,0.049)
C3	(0.273,0.660,0.067)
C4	(0.193,0.748,0.059)
C5	(0.361,0.566,0.073)
C6	(0.292,0.638,0.070)
C7	(0.863,0.127,0.010)
C8	(0.527,0.418,0.055)
C9	(0.088,0.874,0.038)
C10	(0.104,0.813,0.083)

Table 15: Separation measures and the relative closeness coefficient of each alternative.

Alternatives	S^*	S^-	CC_i^*
Mersin	0,2166	0,1466	0,4036
Çanakkale	0,1342	0,2131	0,6135
İzmir	0,1136	0,2425	0,6811
Samsun	0,2409	0,1075	0,3086

plant is installed is a very important decision that needs to be taken. In addition to cost, many factors such as sustainability and the environment must be considered. Therefore, the wind power station site selection problem should be considered as MCDM problem.

In this paper, to solve problem of wind power plant site selection, the TOPSIS method is used and combined with the intuitionistic fuzzy number which is reflecting the judgments of decision makers and dealing with the complexity in the decision process, so that more accurate results can be achieved. Wind potential, location, cost, and social benefits were defined as dimension of criterion and the ten selected criteria were collected under these dimensions. The weights of the criterion importance were decided in the establishment of the wind power plant and the selection was made in this direction. The alternatives evaluated based on these criteria are Mersin, Çanakkale, İzmir, and Samsun. The results have shown that İzmir is the best alternative for wind power site. Also Çanakkale, Mersin, and Samsun follow it, respectively. Thus which alternative is most appropriate is determined.

For the future research, the other MCDM methodologies like ELECTRE, PROMETHEE, etc. can be used for wind power site selection and the obtained results can be compared with ours. Furthermore, a comprehensive study can be carried out by identifying other main criteria and separating them with subcriterion.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Table 16: R matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(4.61, 2.18, 0.49)	(7.24, 0.90, 0.90)	(2.84, 3.27, 0.44)	(3.49, 2.62, 0.44)	(5.38, 3.79, 0.32)	(4.25, 1.56, 0.41)	(6.97, 0.26, 0.52)	(3.13, 3.35, 0.22)	(2.55, 2.94, 0.39)	(1.32, 3.17, 0.79)
A2	(7.28, 0.00, 0.00)	(9.05, 0.00, 0.00)	(4.91, 0.98, 0.65)	(5.56, 0.55, 0.44)	(8.54, 0.32, 0.63)	(2.70, 3.11, 0.41)	(5.42, 1.55, 0.77)	(5.37, 0.67, 0.67)	(3.82, 1.47, 0.59)	(2.82, 2.11, 0.35)
A3	(6.55, 0.24, 0.49)	(8.59, 0.15, 0.30)	(4.80, 1.31, 0.44)	(5.24, 0.65, 0.65)	(9.01, 0.16, 0.32)	(2.38, 3.32, 0.52)	(3.61, 3.87, 0.26)	(5.03, 1.01, 0.67)	(3.73, 1.77, 0.39)	(3.61, 1.32, 0.35)
A4	(5.46, 1.09, 0.73)	(5.13, 3.62, 0.30)	(3.49, 2.62, 0.44)	(2.84, 3.27, 0.44)	(6.01, 2.85, 0.63)	(4.67, 0.93, 0.62)	(6.07, 1.42, 0.26)	(4.25, 2.24, 0.22)	(1.96, 3.33, 0.59)	(2.82, 2.11, 0.35)

Table 17: A^+ positive distance of alternatives.

ALTERNATIVES	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0,726	0,550	0,433	0,331	0,733	0,173	0,153	0,393	0,143	0,319
A2	0,115	0,121	0,244	0,451	0,407	0,682	0,457	0,374	0,442	0,217
A3	0,223	0,178	0,211	0,436	0,414	0,570	0,966	0,332	0,372	0,328
A4	0,499	1,176	0,304	0,412	0,615	0,872	0,280	0,251	0,158	0,217

Table 18: A^- negative distance of alternatives.

ALTERNATIVES	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0,115	0,634	0,244	0,357	0,414	0,441	0,966	0,374	0,352	0,328
A2	0,726	1,176	0,433	0,412	0,638	0,191	0,523	0,393	0,158	0,251
A3	0,529	1,040	0,411	0,363	0,733	0,193	0,153	0,337	0,165	0,319
A4	0,238	0,121	0,222	0,451	0,332	0,536	0,708	0,294	0,442	0,251

Table 19: Separation measures and the relative closeness coefficient of each alternative.

Alternatives	S^*	S^-	CC_i^*	Ranking
A1 - Mersin	3,9545	4,2258	0,517	2
A2 – Çanakkale	3,5102	4,9020	0,583	1
A3 – İzmir	4,0305	4,2441	0,513	3
A4 - Samsun	4,7853	3,5938	0,429	4

Table 20: Comparison of the relative closeness coefficient of two methods.

Alternatives	*Intuitionistic Fuzzy TOPSIS* CC_i	*Ranking*	*Fuzzy TOPSIS* CC_i	Ranking
A1 - Mersin	0,4036	3	0,517	2
A2 – Çanakkale	0,6135	2	0,583	1
A3 – İzmir	0,6811	1	0,513	3
A4 - Samsun	0,3086	4	0,429	4

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Research Article

The Neural-Fuzzy Approach as a Way of Preventing a Maritime Vessel Accident in a Heavy Traffic Zone

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The paper dwells on the methodology of neural-fuzzy approach to solving the problem of ship collision prevention in a heavy traffic zone. The authors present the technique of using maneuvering board to form the elements of learning sample. The authors prove that it is rational to use a neural-fuzzy system, where generation is carried out by the lattice method without clustering. The authors investigate the effect of optimization on the quality differences. The researchers define optimal membership functions that are used to generate the input linguistic variables of a neural-fuzzy system.

1. Introduction

Despite all significant positive outcomes, the issue of ship collision avoidance in a heavy traffic zone [1] is still urgent. So, in the paper [2] the authors report on the concept of expected dangerous patterns (areas) projected on the automatic identification system data. The integration of the Geographic Information System, the International Regulations for Preventing Collisions at Sea (COLREGs), and a thorough investigation of various navigation vessel cases gives the system an opportunity to generate a safe ship collision prevention route and maritime features. The authors [3] suggest a similar task of making up a system for preventing vessel collisions on the ECDIS (electronic chart display and information system) and AIS (automatic identification system). The authors of the paper [4] introduce a method for automatic trajectory planning and collision avoidance using the APF (artificial potential field) search method and speed vector. Another approach providing ship collision avoidance is Bayesian networks declared in the paper [5]. Fuzzy logic is also successfully applied [6] for this kind of problem. In particular, the papers [7, 8] are devoted to support systems of decision making that are undertaken on board vessels. Thus, the authors specify an approach for decision making on sea vessels collision avoidance in the research [8]. The authors are encouraged to use Microsoft Visual Studio to build up a list rule according to the International Regulations for Preventing Collisions at Sea (COLREGs, 1972). That list is able to offer an appropriate collision avoidance algorithm to the boat master after the assessment of maritime traffic according to the vessel traffic service (VTS).

In the papers [9, 10] authors present a model based on the fuzzy sets theory to rank a risk of sea vessel collision in a heavy traffic zone to agree on the navigational decision support because of safe ship control needed. In this model, a maneuvering board was used to draft a fuzzy production rules system [11–13]. In addition, a well-known Mamdani Algorithm was used as an algorithm for fuzzy logic conclusion.

These days, neural network technologies are widely used in navigation issues [14, 15]. For example, the paper [16] focuses on the neural network classification of marine targets on noise images in bad weather conditions and in case of sea waves. In the paper [17] the neural network succeeds in detecting icebergs by typical textural features from the image of satellite-based Synthetic Aperture Radar. Moreover, the neural network has been used successfully in issues of improving an accurate position of a vessel from radar data [18] and designing laser metering systems [19].

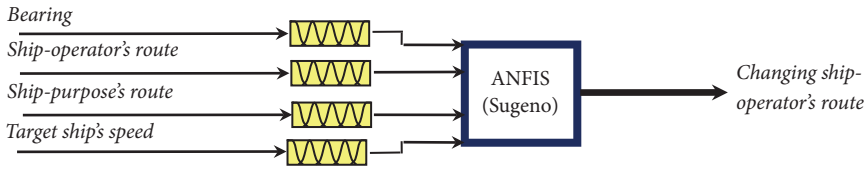

Figure 1: Neural-fuzzy ship collision prevention in a heavy traffic zone.

Neural networks are also proved to be successful in warning [20, 21]. A number of surveys are worth noting in the supplement to navigation practice. In particular, the methodology of a short-term forecast of the Caspian Sea level by means of a perceptron-type neural network [22] is developed in the paper [23]. The paper [24] deals with online forecast of the maneuvering vessel turn, a neural network model RBF having a mutating nature, and the ability to adjust network features by the sliding window method. The authors designed a predictive model which was marked by a leaner structure, fast processing, and a high degree of measurement accuracy.

As the use of neural nets has clear benefits [22], it is potentially capable of improving the projection of ship collision risks. In addition, significant headway had been made against it. For example, the paper [25] comments on the methodology and strategy of ship collision avoidance using artificial neural networks, optimal control theory methods [26, 27], and a game theory. The paper [28] also mentions an autonomous navigation system for a robotic submarine based on an adaptive neurocontroller.

Several papers [29–34] should also be noted in the connection with developing approaches to prevent ship collisions.

In order to improve the effects of a fuzzy system [35], the authors carried out hybridization involving the elements of artificial neural networks theory, which resulted in designing a neural-fuzzy network [36, 37]. In turn, a neural-fuzzy ship collision prevention system is based on it. This paper submits the results of simulating modelling.

2. Materials and Methods

The neural-fuzzy ship collision prevention system in a heavy traffic zone is an adaptive neural-fuzzy inference system (ANFIS) [22, 36, 37], consisting of 5 layers. This kind of system is defined as a multilayer feedforward neural network without any feedback. Its features are those of fuzzy logic inference. But an algorithm for making a decision of the neural network is a fuzzy logic inference algorithm. ANFIS model used for the neural-fuzzy ship collision prevention system in a heavy traffic zone development is based on Takagi–Sugeno fuzzy inference system, which is highly interpretable and efficient in connection with computing.

The first layer of ANFIS is a layer of membership functions. There is a fuzzification in the first layer; i.e., fuzzy sets are established corresponding to the terms of source (input) and target (output) linguistic variables.

The neural-fuzzy ship collision prevention system in a heavy traffic zone observed in the paper (Figure 1) includes four input linguistic variables:

(i) Electronic bearing on the target ship, i.e., on that one to which the operator vessel needs to prevent collision safely

(ii) The ship-operator course

(iii) The target-ship course, i.e., a vessel in a heavy traffic zone, to which, if necessary, it is required to prevent collision

(iv) The target-vessel speed [35], as well as the only output linguistic variable, which is the value of the operator-vessel course change calculated on the maneuvering board in advance with the output value corresponding to the interval [-60°; 360°], where the value of -60° corresponds to the term "much to the left," the value to -30° corresponds to the term "to the left," the value 0° corresponds to the term "keep it steady" (neither the course nor the speed of the operator-vessel changes); 60° stands for the term "much to the right," the value of 30° means the term "to the right," and the value of 360° implies the maneuver (AmE) or manoeuvre (BrE) of circulation (that is, the term "circulation")

The set of values for the inputs "bearing," "the ship-operator course," and "vessel-target course" is the set [0; 360]°. The range of values for the ship-target speed source is determined according to the information from the reviewing feedback of The Russian Maritime Register of Shipping (RS), [0; 34] knots.

The number of nodes performed in the first layer is equal to the sum of the term powers of the input linguistic variable sets. The output values focused in the first layer are the values of membership functions with specific values of the input variables. The features of membership functions in the first layer compose the first group of features that are to be set during the learning process.

The second layer of ANFIS is a layer of fuzzy production rules. The number of nodes is the same as the number of rules in the second layer. Moreover, each node is connected to those ones in the first layer that form the premises (antecedents) of the corresponding rule. In general, the distribution of the links between the first and second layers is performed in such a way that each input variable of the neural-fuzzy network is associated with each neuron of the rule layer.

The output values in the second layer correspond to the relative degrees (weights) of the rules, which are calculated as a logical product (intersection) of membership functions of the input variables.

The third layer of ANFIS is a layer of absolute value in which the output values of this layer are determined by adding the outputs of all nodes of the rule layer and dividing each of the output values in the second layer by this total value. This ensures scaling of the output values so that increases the neural-fuzzy network resilience.

The fourth layer of ANFIS is the output layer of the linear combination. Each node of the fourth layer is connected to

one node of the previous layer and, as a consequence, to all inputs of the neural-fuzzy network. In the fourth layer there is determination of coefficients of linear combinations, as a result, for example, of an algorithm for backpropagation (backpropa) or hybrid, which is a combination of the method of Ordinary Least Squares (OLS) and a backward propagation of errors (backpropa). Coefficients of linear combinations constitute the second group of features to be determined in the learning process.

Finally, the fifth layer of ANFIS is the output total layer. The fifth layer, corresponding to the adder of the legacy neural network, completes defuzzification.

Learning a neural-fuzzy network, which is a combination of two stages, is an iterative procedure that allows determining the features of membership functions that minimize the discrepancy between "real (or valid) and desired behavior of the model."

In the first stage, the learning sample goes to the inputs, and then the parameters of the fourth layer of the neural-fuzzy network are set up in such a way so as to minimize the discrepancy between the reference output values and the calculated output of the neural-fuzzy network.

In the second stage, residual discrepancy is transferred from the network output to the inputs, and backpropa modifies the parameters of the nodes in the first layer. Besides, the coefficients of the conclusion of the rules produced in the first stage do not change.

The iterative setup procedure continues until discrepancy exceeds a preestablished value.

Thus, the general methodology for constructing the neural-fuzzy network underlying the neural-fuzzy ship collision prevention system in a heavy traffic zone includes the following steps.

Step 1. Forming a sample for learning, which contains implicit knowledge, revealed as a result of learning the neural-fuzzy network.

Step 2. Selecting fuzzy inference parameters, i.e., selection of membership functions, fuzzy intersection, and defuzzification.

Step 3. Selecting an algorithm for learning and setting up the parameters of the neural-fuzzy network.

Step 4. Direct learning of the neural-fuzzy network to configure both groups of parameters.

Step 5. Optimizing and verifying learning outcomes of a neural-fuzzy network.

The implementation of the neural-fuzzy ship collision prevention system in a heavy traffic zone was carried out by the Fuzzy Logic Toolbox of MATLAB system [14, 15]. The model is shown in Figure 1.

Furthermore, a series of computer experiments was conducted to define the following.

(1) The best type of membership functions used to specify the terms of input linguistic variables

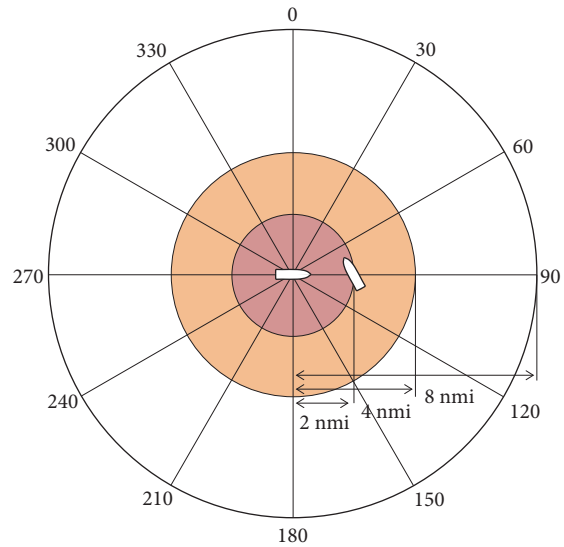

Figure 2: Resulting simulation model with ships in a heavy traffic zone.

(2) The best type of membership functions used to specify the terms of the output linguistic variable, i.e., a type of dependence that connects input and output linguistic variables (constant or linear coefficients)

(3) The best learning algorithm: the backpropagation algorithm (AOPO, backpropa) or the hybrid algorithm. They are a combination of AOPO and OLS [22]

(4) The optimal number of learning cycles for a neural-fuzzy network

A learning set is designed to carry out simulation modelling of the neural-fuzzy collision ship prevention system. At first, a list of different cases with ships in a heavy traffic zone was developed by means of a full search having stepped to broaden the input ranges. Then, the equation of each certain case and assessment of a changing value on the operator ship course were made on the maneuvering board. It should be noted that the equation on the maneuvering board was followed by the rules of the International Regulations for Preventing Collisions at Sea (COLREGS), commentaries to them, and recommendations on so-called "good seamanship." Finally, the values of the input vector and the value corresponding to that one made with the maneuvering board for changing the operator ship course were recorded in a learning sample.

The authors would like to present the way of designing one of the learning pairs. They also imagine the situation when ships are in a heavy traffic zone, as shown in Figure 2. The distance from the ship-operator to the target ship is 2 miles, the ship-operator course is 90 degrees, and the operator ship speed is 15 knots. The radar navigation determined that the target-ship course is 330 degrees, an object bearing is 90 degrees, and the target-ship speed is 8 knots.

In the circumstances described, the target ship is right ahead the ship-operator and at risk of colliding, since the ship-operator and the target ship are too close to each other.

As it is prescribed in Rule 16 of the International Regulations for Preventing Collisions of Ships at Sea, the ship-operator must give way not to run into the target ship. Having simulated this case on a maneuvering board and having calculated it, the scholars found out that the new ship-operator course was going to be 120 degrees. It requires turning a ship at 30 degrees to the right and the ship-operator will not collide with the ship-target at a safe distance behind the vessel stern. After considering this situation it was possible to set a learning pair number 91. The rest of the 525 training pairs were similarly set.

Simulation modelling of neural-fuzzy ship collision prevention system was carried out in two modes. First, neural-fuzzy networks were generated using the lattice method without clustering, and, second, it was performed by the subclustering method. 192 different neural-fuzzy networks were trained for the first mode. Each of them had five terms in each of the four input linguistic variables. Although the backpropagation and hybrid algorithms were used [22], backpropagation has been widely applied in solving various problems, but the algorithm has a number of drawbacks, in particular, "a long time learning," as well as determining local or relative instead of global or absolute minima. The authors used eight different membership functions (MF) to determine the input linguistic variables. They are trimf (triangular MF), trapmf (trapezoidal MF), gbellmf (generalized bell-shaped MF), gaussmf (Gauss's MF), gauss2mf (two-sided Gauss's MF), pimf (P- shaped MF), dsigmf (MF as a difference between two sigmoid functions), psigmf (the product of two sigmoid MF), and constant or linear coefficients for the output variable. The learning intervals numbered from 100 to 600.

3. Results and Discussion

As a result of the simulation modelling of the neural-fuzzy ship collision prevention system in the mode of grating generation without clustering, it was revealed that the best were the hybrid method as a learning algorithm, constant factors as a type of the output linguistic variable, the product of two sigmoid MF, the difference between two sigmoid functions, and the U-shaped membership function to derive input linguistic variables.

The authors chose six out of learned neural-fuzzy networks with the least learning errors. They gave a test for each one and had quality evaluation.

3.1. Mean Absolute Error. MAE is given by the formula [38]

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| CCOS_i - \overline{CCOS_i} \right|, \tag{1}$$

where N is number of model-based testing instances, $CCOS_i$ is a standard value of the change in the ship-operator course for the i-model test counted with a maneuvering board, and $\overline{CCOS_i}$ is the value of changing the ship-operator course for the i-model test, counted using a neural-fuzzy network.

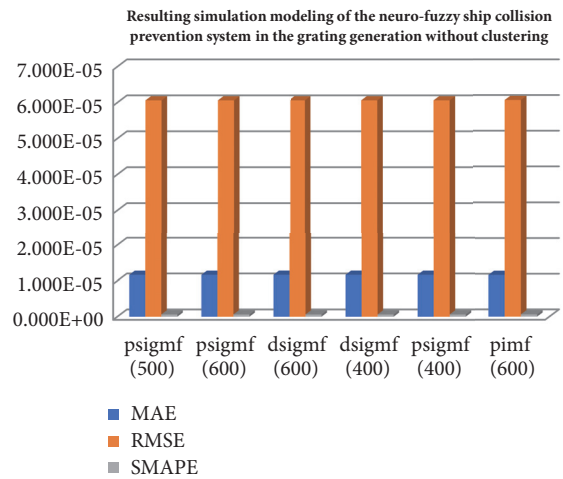

Figure 3: Resulting qualitative evaluation in the neural-fuzzy ship collision prevention system training in the generation by the lattice method without clustering.

3.2. Root Mean Square Error. RMSE is given by the formula [38]

$$RMSE = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(CCOS_i - \overline{CCOS_i} \right)^2}. \tag{2}$$

3.3. Symmetric Mean Absolute Percentage Error. SMAPE is given by the formula [38]

$$SMAPE = \frac{\sum_{i=1}^{N} \left(\left| CCOS_i - \overline{CCOS_i} \right| \right)}{\sum_{i=1}^{N} \left(\left| CCOS_i + \overline{CCOS_i} \right| \right)}. \tag{3}$$

The values of qualitative measures are summarized in Table 1, and a resulting diagram is in Figure 3.

For the second mode, 288 different neural-fuzzy networks were trained (144/144 by the backpropa and hybrid optimization method). Parameters of the subclustering method varied as follows: the parameter "Range of Influence" is from 0.2 to 0.5; step size is 0.1, the parameter 'Squash Factor' is from 1 to 1.375; step size is 0.125; the parameter "Accept Ratio" is from 0 to 0.4; step size is 0.2; and the parameter "Reject Ratio" is from 0 to 0.3; step size is 0.15. In all 288 neural-fuzzy nets 100 learning intervals were being selected.

The authors came to the following conclusion after simulating the neural-fuzzy ship collision prevention system in the subclustering generation mode. The best method is the hybrid optimization method for neural-fuzzy networks as a learning algorithm, as well as for the grid-free generation mode, while "Range of Influence" constantly equals 0.3, the best ratio for "Squash Factor" is the parameter that equaled 1, and the parameter that equaled 0.4 is for "Accept Ratio."

Six best neural-fuzzy networks were chosen for testing. Furthermore, the authors made qualitative evaluation for each of them. The resulting Table 2 is presented in Figures 4 and 5.

Let the authors compare the results presented in this paper with the results of the neural-fuzzy ship collision

Table 1: Resulting simulation modelling of the neural-fuzzy ship collision prevention system in the grating generation without clustering.

Type of MF for input LVs	Number of Training intervals	Learning error	MAE	RMSE	SMAPE
psigmf	500	$5.4532 \cdot 10^{-5}$	$1.165 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.2555 \cdot 10^{-7}$
psigmf	600	$5.4532 \cdot 10^{-5}$	$1.165 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.2555 \cdot 10^{-7}$
dsigmf	600	$5.4553 \cdot 10^{-5}$	$1.166 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.257 \cdot 10^{-7}$
dsigmf	400	$5.4556 \cdot 10^{-5}$	$1.166 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.257 \cdot 10^{-7}$
psigmf	400	$5.456 \cdot 10^{-5}$	$1.1656 \cdot 10^{-5}$	$6.063 \cdot 10^{-5}$	$6.257 \cdot 10^{-7}$
pimf	600	$5.5002 \cdot 10^{-5}$	$1.171 \cdot 10^{-5}$	$6.064 \cdot 10^{-5}$	$6.2836 \cdot 10^{-7}$

Table 2: Resulting simulation modelling of the neural-fuzzy ship collision prevention system through subclustering generation method.

Range of influence	Squash factor	Accept ratio	Reject Ratio	Optim. Methods	Learning error	RMSE	MAE	SMAPE
0.3	1	0	0	backpropa	$1.26 \cdot 10^{-1}$	$3.865 \cdot 10^{-1}$	$5.05 \cdot 10^{-2}$	$2.7 \cdot 10^{-3}$
0.3	1.125	0	0	backpropa	$1.26 \cdot 10^{-1}$	$1.365 \cdot 10^{-1}$	$3.54 \cdot 10^{-2}$	$1.9 \cdot 10^{-3}$
0.3	1	0	0.15	backpropa	$1.26 \cdot 10^{-1}$	$3.865 \cdot 10^{-1}$	$5.05 \cdot 10^{-2}$	$2.7 \cdot 10^{-3}$
0.3	1	0.4	0	hibrid	$1.363 \cdot 10^{-3}$	$1.36 \cdot 10^{-3}$	$5.5 \cdot 10^{-4}$	$2.94 \cdot 10^{-5}$
0.3	1	0.4	0.15	hibrid	$1.363 \cdot 10^{-3}$	$1.36 \cdot 10^{-3}$	$5.5 \cdot 10^{-4}$	$2.94 \cdot 10^{-5}$
0.3	1	0.4	0.3	hibrid	$1.363 \cdot 10^{-3}$	$1.36 \cdot 10^{-3}$	$5.5 \cdot 10^{-4}$	$2.94 \cdot 10^{-5}$

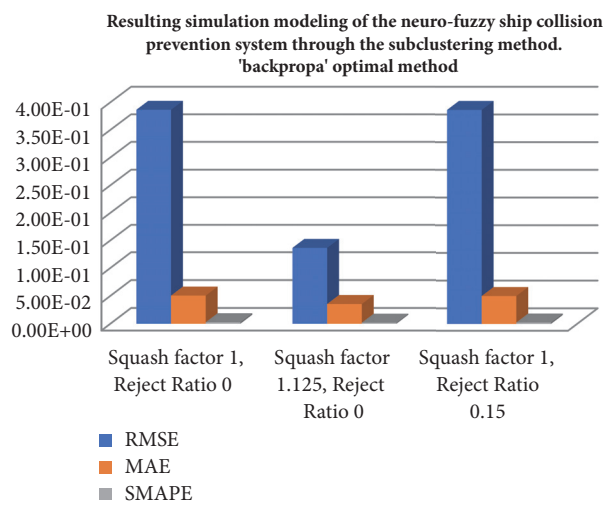

Figure 4: Resulting qualitative evaluation in the neural-fuzzy ship collision prevention system training when generating by the subclustering method through backpropagation error algorithm.

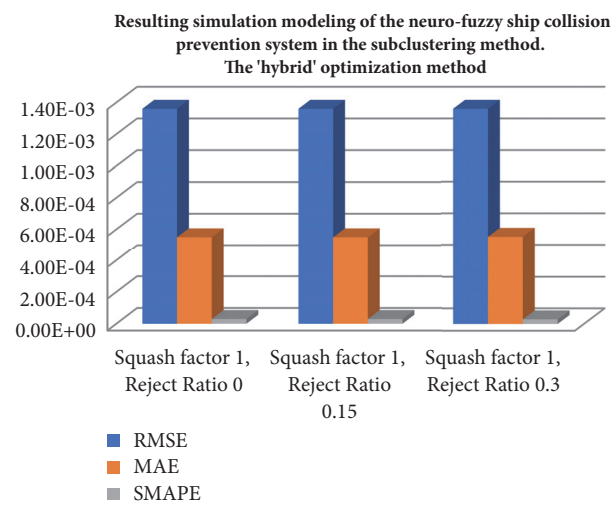

Figure 5: Resulting qualitative evaluation in the neural-fuzzy ship collision prevention system training in the generation of the hybrid algorithm through the subclustering method.

prevention system in a heavy traffic zone [35], in which only the fuzzy logic apparatus is used.

In the paper [35], a fuzzy system is offered. The first linguistic variable called *Peleng* included the following five terms of the basic term set: eastern bearing, western bearing, northern left bearing, northern right bearing, and southern bearing.

The second and third input linguistic variables *operator-vessel course* and *target-vessel course* had a basic term set consisting of the following elements [35]: the left course to the north, the right course to the north, easterly course, heading south, and westerly course.

The fourth input linguistic variable *ship-target speed* had the following terms of the basic term set [35]: fixed target, low speed, average speed, high speed, and a very high speed.

According to the point from Rule 8 in International Rules of Preventing Collision at Sea, COLREGS, "if there are enough waters, only a course change may be the most effective mode of action to prevent collisions." Boatmasters state that most of the ways to prevent collision at sea are due to the course maneuvers. So, the change of the operator-vessel course is chosen for the output linguistic variable.

In the description of terms for the output linguistic variable, the values of fuzzy set cores corresponding to the terms [35] are given in brackets: much to the left (-60°), to the left (-30°), keeping it steady (the course and speed do not change) (0°), to the right (30°), much to the right (60°), and circulation (360°).

In the paper [35] the author presents the results of fuzzification of the indicated input and output linguistic

Table 3: Results of imitating simulation of a fuzzy ship collision prevention system in a heavy traffic zone proposed in [35].

Defuzzification Method	MAE	RMSE	SMAPE
Centroid	$2.2460 \cdot 10^{-1}$	$2.3120 \cdot 10^{-1}$	$1.19 \cdot 10^{-2}$
Bisector	$1.2379 \cdot 10^{0}$	$1.2568 \cdot 10^{0}$	$7.12 \cdot 10^{-2}$
MOM	$1.2379 \cdot 10^{0}$	$1.2568 \cdot 10^{0}$	$7.12 \cdot 10^{-2}$
SOM	$1.2379 \cdot 10^{0}$	$1.2568 \cdot 10^{0}$	$7.12 \cdot 10^{-2}$

variables, as well as the characteristics of the fuzzy system product base with a description of the fuzzy logic inference algorithm designed by *Mamdani Algorithm*.

The author [35] did the testing for fuzzy ship collision prevention system in a heavy traffic zone. It should be noted that the same measures (MAE, RMSE, and SMAPE) were also used to evaluate the quality. Four defuzzification methods were used as a defuzzy: centroid, bisector, and the mean of maximums and the smallest of maximums. The results are summarized in Table 3.

As a result of testing the fuzzy ship collision prevention system in a heavy traffic zone offered in [35], it was found out that the best defuzzification method is centroid, but the discrepancy quality values are insufficient to decide on sea vessels collision prevention in a heavy traffic zone.

4. Conclusions

Having verified the results of simulating the neural-fuzzy ship collision prevention system for both modes (both for grid-generated without clustering and for subclustering generated) the authors draw the following conclusions.

First, it is advisable to use the neural-fuzzy ship collision prevention system to avoid ship collision in a heavy traffic zone, where generation is held through the lattice method without clustering. The comparison of the results of Tables 1 and 2 proves much better quality of discrepancies using the neural-fuzzy ship collision prevention system in a heavy traffic zone with generation by the lattice method without clustering than when generated by subclustering method, which produces the best MAE result comparable to 10^{-4}.

Second, the hybrid method of optimization gives much better results than the algorithm for backpropagation when using both the lattice method without clustering and the subclustering one. In particular, AOPO produces the best MAE result equal to $3.54 \bullet 10^{-2}$, while the hybrid algorithm produces MAE result equal to $5.5 \bullet 10^{-4}$ when generating by subclustering method.

Third, the authors believe that best results to develop input linguistic variables are given by such membership functions as the product of two sigmoid MF as a difference between two sigmoid functions and a U-shaped membership function. That is proved by the results in Table 1.

Fourth, it is necessary to refer to constant coefficients for the neural-fuzzy ship collision prevention system in the mode of grating generation without clustering, as a type of the output linguistic variable.

To sum up, 192 different simulating models of neural-fuzzy ship collision prevention systems were generated through the lattice-free clustering method, as well as 288 neural-fuzzy ship collision prevention systems, where the network was generated through the subclustering method. After finishing the simulation, the hybrid optimization method turned out to be the best (allows to get MAE value about 10^{-5}). The best neural-fuzzy ship collision prevention systems testing has proved that they can determine very accurately the value of changing the ship-operator course to avoid ship collision in a heavy traffic zone, which is dangerous for the ship-operator. The authors compared the results reflected in this paper, for example, with those of the fuzzy ship collision prevention system in a heavy traffic zone proposed in the paper [35]. They came to the conclusion that the defuzzification method *Centroid* with MAE and RMSE values about 10^{-1} and SMAPE about 10^{-2} produces the best result. Thus, it is correct to say that using neural network technologies in solving the problem significantly improves the quality of safe navigation of sea-going vessels in a heavy traffic zone. The neural-fuzzy collision avoidance system investigated in this research is one of the modules of the intelligent navigation safety system. The authors are definitely going to keep developing them in the future.

Data Availability

Data were obtained by the authors independently. The data used to support the findings of this study are included within the supplementary information files.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Supplementary Materials

Supplementary 1. Table 1_1.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 500 training intervals, using the membership function as a product of two sigmoid membership functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 2. Table 1_2.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 600 training intervals, using the membership function as a product of two sigmoid membership functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 3. Table 1_3.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 600 training intervals, using the membership function difference of functions (as a result of subtraction) between two sigmoid functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 4. Table 1_4.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 400 training intervals, using the membership function difference of functions (as a result of subtraction) between two sigmoid functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 5. Table 1_5.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 400 training intervals, using the membership function as a product between two sigmoid functions for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 6. Table 1_6.xlsx: data for testing the neural-fuzzy ship collision prevention system where generation is carried out by the lattice method without clustering, with 600 training intervals, using the U-shaped membership function for input linguistic variables, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 7. Table 2_1.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using backpropagation with parameters Range of Influence, Squash Factor, Accept Ratio, and Reject Ratio equal to 0.3, 1, 0, and 0, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 8. Table 2_2.xlsx: data for testing the neural-fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using backpropagation with parameters Range of Influence, Squash Factor, Accept Ratio, and Reject Ratio equal to 0.3, 1.125, 0, and 0 respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 9. Table 2_3.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using backpropagation with parameters Range of Influence, Squash Factor, Accept Ratio, and Reject Ratio equal to 0.3, 1, 0, and 0.15, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 10. Table 2_4.xlsx: data for testing the neural-fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using the hybrid optimization method with parameters Range of Influence, Squash Factor, Accept Ratio and Reject Ratio equal to 0.3, 1, 0.4, and 0, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 11. Table 2_5.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using the hybrid optimization method with parameters Range of Influence, Squash Factor, Accept Ratio and Reject Ratio equal to 0.3, 1, 0.4, and 0.15, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

Supplementary 12. Table 2_6.xlsx: data for testing the neural -fuzzy ship collision prevention system generated by subclustering, with 100 training intervals, using the hybrid optimization method with parameters Range of Influence, Squash Factor, Accept Ratio and Reject Ratio equal to 0.3, 1, 0.4, and 0.3, respectively, with the necessary quality assessment calculated (MAE, RMSE, and SMAPE).

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