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Optimizing Fuzzy Logic Control-Based Weather Forecasting through Optimal Antecedent Selection Using the Fuzzy Analytical Hierarchy Process Model

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The numerical weather forecasts rely largely on the amount of precipitation available, and the use of statistical and empirical methods, but fall short of higher accuracy and relatively short-time required. Recently, the fuzzy AHP (that combined AHP with fuzzy logic) for the purpose of arriving at better outcomes from fuzzy logic control (FLC) rules-list. While evolutionary computing and fuzzy logic techniques are known to guarantee better accuracy and reliability of the outcomes when applied to weather uncertainty problems. Though, the fuzzy logic approach has low accuracy, which needs to be improved with rules-list refinement. This paper pulls on these approaches to develop a weather forecasting model for cities. First of all, the outcomes of the FAHP model revealed that, Wind Direction (WND) and Relative Humidity (HUM) as contributing 30.01% and 19.97% influence to the decision-making process against air temperature, windspeed, WND, HUM, and air pressure identified earlier. Secondly, the select FAHP parameters served as antecedents for the FLC model, in which five fuzzy rules were included in rule-base. Upon validation with the standard and local datasets, the proposed model achieved lower error rates of 0.0010, 0.0317 and 0.0319 for MSE, RMSE and MAPE respectively when treated with the Kaggle standard dataset. By comparing the proposed FLC model outcomes to the unoptimized FLC model in term of error rates, MSE of 0.0010, RMSE of 0.0317, and MAPE of 0.0355 were achieved attained by former indicative of its superiority.

Povzetek: Predstavljena je optimizacija napovedovanja vremena z uporabo mehke logike in izbire optimalnih predhodnikov s pomočjo analitične hierarhije.

1 Introduction

Weather depicts the state of air over earth at given place and period. It is an unceasing, data-intensive, disorganized and dynamic technique. Forecasting is the procedure of evaluation in indefinite circumstances from past data. When "weather" and "forecasting" are put together, "Weather forecasting", is systematically and technically demanding issues across the globe in the past century. Weather forecasting is one field of traction for many scholars and researchers, which seek to ascertain the present state of atmosphere gets varied. Though, the tasks of predicting forecasts are daunting due to their unpredictable and muddled nature. These have been applied to diverse scenarios including severe weather alerts and advisories for transportation, agricultural production and development and forest fire minimizations[1] .

Also, weather nowcasting is a short-leaved approach to forecasting of weather, which involves analysis and estimation of weather on 6-hourly basis. Presently, the nowcasting hold special place during risk deterrence and crisis administration, even as severe weather happenings are imminent. Several stacks of meteorological dataset gather from satellite, radar, and other weather observatory sites, are used for diverse of analyses by meteorological research organizations globally. Weather and Radars facilities consistently curating live data whereas cloud patterns, temperature, and winds focus data are main concern of special satellites. Consequently, there is the endless stockpiles of meteorological data required for investigations using AI approaches (machine learning (ML) algorithms), which could enhance the accuracy of the forecasting especially at short-term weather estimation [2].

Weather-station process cloud data using high-performance approaches and algorithms in order to mine salient features to raise precision of the classification on the basis of the inputs supplied. This is made possible in recent times with a computationally proven deep learning approaches [3]. Aside this, many weathers forecasting models have been combined to improve the accuracy of outcomes [4]. AI algorithms have been deployed for dealing with real-life tasks in the same way as natural schemes. Though, human intelligence is capable of differentiating and adapting to fresh environments, AI follows a procedural algorithm when conforming to the certain situations. Fuzzy logic is an AI approach which utilizes an approximate-reasoning instead of actual-reasoning style by incorporating some levels of ambiguity as a form of reasoning procedure.

The numerical weather estimations have been used in enterprises, civil protection institutions, lifestyles of peoples globally; while reducing social and economic indemnities. However, there is the need to evolve better and more accurate parametrization of physical processes to raise the outcomes of estimates generated. There is the still the problem inability of existing weather forecasting techniques to produce location precise, time efficient and intensity of weather-related events [5].

Previously, the main procedure for forecasting weather, that is the state of atmosphere over a particular place, involves the use of statistical and empirical methods by means of the principle of physics, but fall short of higher accuracy and relatively short-time required [1] . Subsequently, the renew calls for machine learning and ensemble methods, which utilizes complex computerized mathematical models for desirable outcomes.

The birth of AI, big data analytics and machine learning techniques offered the opportunities for planners and policymakers to understand the implications of diverse weather conditions as well as allocating resources in the case of extreme weather-related systems disruptions. Nonetheless, researchers and scholars are making efforts to increase the accuracy and reliability of the modelling systems [6]. But, the accuracy of automated daily weather classification relies on both the applied classifiers and the training data [7].

The concept of the multi-criteria decision-making (MCDM) schemes undertake multichoice and multi-objective problems. In particular, there are three kinds of solutions derivable using MCDM especially when it concerns making choice from pool options having the best alternatives. Also, it is possible to rank the order of several alternatives in order of importance or preferences. More so, sorting and classifying decision alternatives within acceptable order of groupings [8], fuzzy TOPSIS, VIKOR, and TODIM and [9] are common methods when undertaking selection of alternative like bank websites and electronic banking application’s quality.

FAHP is held in high esteem as valuable for complex decision-making tasks, which empowers the analysts to minimize uncertainty and vulnerability connected to the process of preparing chiefs’ judgment not applicable in AHP approaches. The AHP proposed by Saaty was fine-turned or fuzzified in order to control and spot the vulnerability [10]. The key concept of the FAHP streamlines composite decision-making tasks across tiered structure made of criteria and sub-criteria in manner as a pairwise comparison to the criteria [11].

This paper develops an effective FAHP model-based antecedents’ selection for fuzzy logic control weather forecasting system. The contributions include:

- To select the fuzzy logic antecedents through FAHP model.
- To develop enhanced fuzzy logic control model for weather forecasting.

The lasting parts of this paper explained the following: second section is the related works. Section three is the discussion about research methodology. Fourth section is results and discussion. The conclusion is obtainable in section 5.

2 Related works

This section demonstrates and discuss the literature in the field of forecasting weather. Selim Furkan Tekin et al. [12] proposed a deep learning approach to predict the high-resolution weather based on observations and input data. The prediction model works based on a spatio-temporal approach, where it is composed of a convolutional neural network with an encoder-decoder structure, and convolutional long-short term memory. The matcher mechanism is utilized to enhance the interpretability and performance of long-short term. The model is experimented on a real-life, high-scale numerical dataset that holds the temperature, and pressure levels. The results show that there is significant improvement when capturing temporal and spatial correlations. Matthew Chantry et al. in [13] proposed models of emulators based on machine learning that work as parameterization scheme accelerators for weather forecasting. The emulators are trained to produce accurate and stable results of forecasting timescales. The accuracy of emulators is correlated with the complexity of the networks, while it produces more accurate forecasts. With medium range forecasting, they found that the proposed emulators compared with the parameterization scheme are more accurate. With CPU hardware, the proposed emulators are similar to existing scheme in computational cost, while they performed 10 times faster based on GPU. K. Bala Maheswari et al. [14] proposed a model to make long-term weather forecasts using a historical dataset. The model is implemented based on support vector machine and decision tree algorithms to forecast different conditions such as rainfall, floods, storms, humidity, and temperature. While Mohammad Sadman Tahsin et al. in [15] proposed a daily weather forecasting model in an urban area. 12 data mining models are implemented over 20 years of climate data patterns in Chittagong city. The evaluation process of the model is implemented based on different metrics, such as precision, recall, accuracy, F-measure, receiver operating characteristics, and area under curve. The results show that J48 outperformed the other algorithms in accuracy.

The summary of related works according to author(s), objectives(s), methodologies, outcomes and limitations are presented in Table 1.

Table 1: The related works summary

S/N	References	Objective(s)	Methodology	Outcome(s)	Limitation(s)
1.	[16]	Wind power forecasting based on climatic conditions	Deterministic and probabilistic models.	It provides point predictions for day-to-day operations of power systems.	Accuracy to be improved.
2.	[17]	Solar Photovoltaic system forecasts under several weather factors	Machine learning techniques.	The weighted-KNN outperforms other ML approaches.	Energy efficiency and high error rates.
3.	[18]	Weather Nowcasting under Radar products' values.	Ensemble of deep learning techniques (NowDeepN).	The error is less than 4%.	No relationship between normal and adverse metrological products' values.
4.	[19]	Weather impact on COVID-19 outbreak based on users' twitter feeds.	Machine learning.	Correctly classified users' claims based on their tweets at 95% AUC-PR and AUC-ROC.	Classifier ineffectiveness on other languages.
5.	[20]	Cyclonic weather regimes impact on seasonal influenza.	Step by step linear regression model, clinical and laboratory tests.	Climate changes aggravates health risks of people using regression and root mean square difference.	Large inaccuracies from datasets.
6.	[21]	Weather-associated delays in transport sector.	ML modeling of weather events.	Determination of severe and disruptive weather events.	Accuracy could be improved.
7.	[22]	Weather radar reflectivity towards flood events.	Fraction Skill Score (FSS).	AUC of 91% for the predictive model.	Reliability of forecasts to be improved.
8.	[23]	Interpretability of satellite imagery.	CNN-based building damage image classification.	Accurate classification of building damages through images.	Pre-and-post-disaster images modelling.
9.	[24]	Smart weather reporting system.	Internet of Everything: sensors for measuring weather parameters.	Weather information are effectively disseminated.	Internet-enabled approach for farmers.
10.	[25]	Weather forecasting with gravity wave drag emulation.	Machine learning based on neural networks.	It has Increased speed and accuracy of models.	Neural network algorithms are less-effective.
11.	[26]	Spatio-temporal weather forecasting.	Convolutional LST Ms.	It offered superior MSE and performance.	Spatio-temporal dataset was utilized.
12.	[27]	Minimizing turbine clutter based on weather radar data.	Generalized Likelihood Ratio Test for identifying signal subspace and gates impacted by WTC.	It offers better prediction due to overlap of datasets.	To improve on local information about precipitation and filtered radar IQ.
13.	[28]	Nowcasting of extreme space weather events.	Magnetotelluric data of geomatic storms.	It used bivariate approach for polarization of	Short-leaved magnetic field of storm for spatial and temporal events.

				storm time electric fields.	
14.	[29]	Classification of main synoptic meteorological patterns of atmosphere.	Particle formulation analysis of air quality.	It effectively determines weather scenarios.	Applicable to particle formulation and air quality prediction.
15.	[30]	Weather data knowledge mining.	Machine learning with rule base approach such as K-NN, ARIMA.	It improved the quality of concomitant factors prediction.	High errors during simulation of weather reports.
16.	[31]	NCDC weather data classification and predictive models.	Machine learning based models including CART, AdaBoost, Decision Tree, and XGBoost.	KNN, Random Forest and XGBoost had highest accuracy.	Overfitting and smaller datasets impart on performance.
17.	[32]	Photovotaic (PV) solar power forecasting based on climatic conditions	Particle swarm optimization and genetic algorithms.	CNN Deep learning model best for determining PV power.	Hyrid algorithms to be experimented.
18.	[33]	Weather files for building energy designs optimization.	Machine learning with regression and classification models.	It generated highly accurate subsequent weather files.	Location and climate change events and applications not considered.
19.	[34]	Weather forecasting	Numerical weather prediction.	It uses full-field weather system to perform anomaly weather forecasts.	Outcomes may be inaccurate and misleading without full-field data.
20.	[35]	Rainfall forecasts.	Hybrid ML model of PSO and Feed Forward Neural Network.	It improves outcomes of forecasts for rainfall.	To increase accuracy.
21.	[36]	Automated weather data processing.	LSTM based neural network model.	It predicts local weather events such as Tornado, flood, severe storm, etc.	To extend to more parameters of soils forecasts.
22.	[37]	Weather prediction.	Classification tree, KNN, Naïve Bayes.	Naïve Bayes had best accuracy of 77.1%.	More data consisting of weather observational data over stations.
23.	[38]	Weather conditions-based water quality prediction.	Bayesian Belief Networks.	Water surrogates are determinants for water quality prediction.	Higher accuracy required for safety of drinking water.
24.	[39]	Weather forecasts.	Naïve Bayes, C.45 and KNN.	KNN produced highest accuracy (71.59%) forecasts.	Input criteria and constraints are inconsistent.
25.	[40]	Multi-class classification of weather data.	Selection Based on Accuracy Intuition and Diversity (SAID) of ensemble scheme.	SAID outperformed other algorithms in classifying weather images.	To explore computer vision for weather classification.
26.	[41]	Solar irradiance forecast based on weather variables.	Naïve Bayes classifier.	It improved results and accuracy for real-time weather.	The smaller training dataset.

27.	[42]	Weather forecasting.	Machine learning and ensemble methods.	It increased the accuracy and speed of forecasting.	To utilize classification and clustering approaches.
28.	[43]	Weather-based major power outage forecasts.	A two-level hybrid risk determination model.	It identified risks to be associated with different factors.	To apply to resilience of power systems.
29.	[44]	Weather-based Solar PV power forecasting.	KNN, and SVM classifiers.	SVM produced the best accuracy of forecasts.	Expanding the models to K-Means, Random Forest, etc.
30.	[45]	Rainfall forecasts.	Data mining approaches.	Weather data extrapolation for determining rainfall patterns.	Optimization and integration of data-mining techniques for better accuracy.

From Table 1, majority of the weather forecasting considered different weather parameters using machine learning and numerical prediction schemes. However, there are no focus on selection of influential factors and their fuzziness as well as the effect of complexity of meteorological datasets during various forecasts tasks. To this end, the roles of the FAHP, AHP and Fuzzy Logic techniques in the weather forecasting tasks and others were analyzed as follows:

The concept of FLC identified for determining stock prices movements using the Nigeria Stock Exchange trading datasets for Dangote Cement PLC. Alfa et al. [46] proposed the rules-list's antecedent optimization with the genetic algorithms procedure to improve the forecasts effectiveness. Following from that, they further optimized the rule-list's consequent by means of the genetic algorithm method in which the error rates diminished substantially. However, the studies did not cover effects of the dataset complexity on the effectiveness of the fuzzy logic control schemes.

A grey fuzzy AHP-based flash flood vulnerability evaluation in watershed region of Himalayan, China was undertaken by [47]. Authors leveraged on geographical information system (GIS) and 12 natural and anthropogenic parameters. The low, moderate and high classes were assigned to the Flash Flood Vulnerability Index in which the sensitivity test revealed LULC was highly influential. However, there is the propensity of applying more effective methods like fuzzy logic control.

A GIS with multi-criteria decision making (MCDM) method were adopted in determining landslide-prone regions in highland of Southern Western Ghats by [48]. Nine landslide influencing factors were considered in ascertaining the thematic layers for the landslide susceptibility map. AUC scores of 79% and F1 scores of 85% were obtained from the standardized causative factor weights. More techniques can be applied to improve the performance of the FAHP.

Zhran et al. in [49] implemented the flood risk zonation in Egypt's Nile districts of Damietta using the IGS, remote sensing, and AHP. Twelve thematic layers of slope, elevation, vegetation index, topographic wetness index, water index, topographic positioning index, stream power index, modified Fournier index, drainage density, sediment transport index, distance to the river, and lithology. Also, six factors serve as flood vulnerability zonation including: total population, land cover/ land use, distance to hospital, density of population, road density, and distance to road. AUC score of 0.741 was obtained for AHP approach. Using the multicollinearity analysis revealed highly corrected independent variables. Though, specificity of the forecasts can be performed using other techniques.

Fanxiao Meng et al. in [50] deployed remote sensing, GIS datasets to determine the groundwater recharge zones (GWRZ) in Pakistan. The hydrology and geology factors influence on the GWRZ were investigated. In particular, thematic maps was composed of the slope, rainfall, geology, drainage density, land cover/ land use, lineament, and types of soil. Authors utilized multi-influencing factor and the AHP to assign weights to the factors. But, the use of advanced methods could improve the decision-making process and its accuracy.

Husam Musa Baalousha et al. in [51] evaluated the risk of flooding based on FAHP and Fuzzy Logic in the Arid places of Qatar using the land cover, precipitation, soil type, flow accumulation, and elevation. The outcomes from both the Fuzzy logic and the FAHP demonstrated resemblances in the low-risk and differences in the high-risk zones. While the FAHP accounted for higher variability and more accurate than Fuzzy Logic method.

Sinan Keskin et al. in [52]developed a fuzzy spatial online analytical processing (FSOLAP) framework to provide predictive analytics of the complex data applications. The framework was validated with meteorological datasets from the Turkish Meteorological Office. When compared with traditional machine learning approaches, FSOLAP is a more scalable and accurate for big meteorological databases' fuzziness or uncertainty.

Susanta Mahato et al. in [53] combined FAHP and Fuzzy Logic techniques to determine the drought-based vulnerability factors in Odisha, India. Six criteria of water usage and demand, physical attributes, land use, groundwater, and development/population, and 22 sub-criteria were chosen. The FAHP weighted the parameters through pair-wise comparisons matrix. The Fuzzy logic provided five classes of vulnerability: very high, high, moderate, low, and very low. During validation, statistical evaluation parameters root means square error, accuracy, and mean absolute error were employed.

Waseem Alam et al. in [54] introduced the FAHP framework in assessing and ranking the criteria and weight factors of the behaviour of drivers in Peshawar, Pakistan. Three most important risky driving features include: errors, violations, and lapses. The driver attention and clear road signage were top influential factors in raising risk perception of the drivers. Also, the ensemble machine learning offered an accuracy of 0.84. Nonetheless, there are prospects of FLC in explaining the interconnection among various factors and driving behaviours.
The reviewed studies, in the second part, had drawn fascinating evidence about the weakness of the FLC and the complementary roles to be played by the FAHP in dealing with multi-criteria decision-making and highly complex meteorological datasets mining in computational weather mining and analysis as undertaken in this paper.

3 Research methodology

The paper utilizes the FAHP in filtering the most influencing factors for determining weather conditions of places whose datasets are traditionally composed of the complex meteorological parameters [52]. To improve the accuracy of FLC, the most impacting factors were utilized for the construction of the rules-base, which flaws decision-making processes and forecasting tasks because of redundancy of the rules-lists [51].

3.1 Fuzzy analytical hierarchical process criteria selection

The main steps for the FAHP model adoption in determining the most relevant criteria for building fuzzy logic control antecedents are analogous to the methods undertaken by [55], [56].

Algorithm: FAHP criteria selection for the FLC rule-base.

INPUT: Comparison matrix

Step 1 DEVELOP analytical hierarchy by utilizing a typical hierarchy plan based on distinct levels.

- ***a.*** The DETERMINATION of quantification for the prospective fuzzy logic control antecedents.
- ***b.*** ANALYZE prospective FLC antecedents.
- ***c***. GENERATE pairwise comparison matrix based on AHP scale
- ***d.*** TRANSFORM into a fuzzy triangular (FT) scale.

Step 2. DEVELOP a pairwise fuzzy comparison vector (PCV) with selected weather parameters or criteria. The crisp numeric values create PCV as the evaluation method being a single numeric value for categorizing FLC antecedents.

Step 3. COMPUTE fuzzy geometric mean from the lower, median, and upper fuzzy geometric means.

Step 4. COMPUTATE fuzzy AHP weight using the lower, median and upper fuzzy weights accordingly.

Step 5. GENERATE normalized weights of the parameters.

Step 6. SELECT top-two weighted parameters to serve as the antecedents for FLC-based weather forecasting system.

Step 7. CONSTRUCT the triangular fuzzy numbers.

- **e.** DEFINE the values and linguistic of the first antecedent and matching membership functions, that is, low, medium and high.
- **f.** DEFINE the values and linguistic of the second antecedent and matching membership functions, that is, low, medium and high.
- **g.** DEFINE the values and linguistic of the consequent and matching membership functions, that is, low, medium and high.

Step 8. BUILD the fuzzy rules from the membership functions for the Antecedents and Consequents for all the possible combinations.

Step 9. OPTIMIZE the fuzzy rules (the chromosomes) with genetic algorithm procedure to select the best rules for the FLC weather forecasting system.

Step 10. APPLY the weather datasets to evaluate the FLC system.

STOP.

End

OUTPUT: Normalized weights of criteria and FLC rule-base.

3.2 Data collection and preprocessing

This paper utilized both primary and secondary sources of datasets. Firstly, standard historical metrological data was collected from the Antarctic Automatic weather facilities (AntAWS)
Dataset: https://amrdcdata.ssec.wisc.edu/dataset/antaws-dataset) is 3-hourly, daily and monthly under strict quality control. Five parameters were measured by 267 AWSs from the period of 1980-2021 [57]. These include: air pressure, air temperature relative humidity, wind speed, and wind direction) by 267 AWSs collected between 1980 and 2021. The 25% and 75% thresholds were used to compute the products for daily and monthly quality-controlled readings.
Secondly, structured questionnaire was constructed to curate the required data for building effective antecedents for fuzzy logic control-based weather forecasting model. The lists of weather criteria including: TMP, PRS, WNS, WND, HUM, and VNS. The survey questionnaire was created using the identified weather criteria or parameters with associated nominal scale (1 – 9) of weather attributes as described in Table 2 [58], [59].

Table 2: The adopted membership function and linguistic scale.

Fuzzy scale	Linguistic scale	Triangular fuzzy numbers	Triangular reciprocal fuzzy numbers
9	Extreme importance	9, 9, 9	1/9, 1/9, 1/9
8	Very, very strong	7, 8 ,9	1/9, 1/8, 1/7
7	Very strong or demonstrated importance	6, 7, 8	1/8, 1/7, 1/6
6	Strong plus	5, 6, 7	1/7, 1/6, 1/5
5	Strong importance	4, 5, 6	1/6, 1/5, 1/4
4	Moderate plus	3, 4, 5	1/5, 1/4, 1/3
3	Moderate importance	2, 3, 4	1/4, 1/3, 1/2
2	Weak or slight	1, 2, 3	1/3, 1/2, 1
1	Equal importance	1, 1, 1	1, 1, 1

3.3 Materials for experimentation

The weather forecasting model was validated on MATLAB R2019b discrete simulator on Laptop Personal Computer system. The minimum specifications of the computational resources include:
Hardware:
AMD E1-1200 APU Processor with RadeomTM Graphics 1.40 GHz, 4.00 GB RAM, 64-bit Operating System, x64-based processor.
Software:
Windows 10 Single Language 2012, 3.5 Windows Experience Index.
Genetic algorithm procedure parameters:
Crossover probability: 0.8, Population selection method: Elitism, Offspring Rank and Mutation, Original chromosomes: 18, Iteration: 5, Crossover type: Uniform crossover, Maximum population: 30, Mutation probability: 0.09.

3.4 Evaluation parameters

The effectiveness of the proposed weather forecasting model after applying the similar test and target datasets is computed by means of the mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE) metrics given by Equations 1, 2 and 3:

$$MSE = \frac{1}{x}\sum_{g=1}^{x}\left(A_g - \hat{A}_{ig}\right)^2 \qquad 1$$

$$RMSE = \sqrt{\frac{1}{x}\sum_{g=1}^{x}\left(A_g - \hat{A}_g\right)^2} \qquad 2$$

$$MAPE = \sqrt{\frac{1}{x}\sum_{g=1}^{x}\left|\frac{A_g - \hat{A}_g}{\hat{A}_g}\right|} \times 100\% \qquad 3$$

where,
A_i is the target of actual value of the output sample,
$\hat{A}_i$ is the predicted value of the output sample,
g is the index term starting at 1 to x of test dataset, and
x is the size of the test dataset.

4 Results and discussion

This section presents the weather forecasting outcomes after selecting antecedents with FAHP model. The conditions forecasts of cities were determined with optimized FLC model.

4.1 FAHP Model-based criteria selection from survey outcomes

The research question, what is are two topmost parameters influencing weather conditions? was posed to the three experts recruited for the survey. The three participants' responses in crisp numerical values and computed consistency index (CI) are shown in Tables 3, 4, and 5.

Table 3: The first respondent responses on two topmost weather parameters.

	TMP	PRS	WNS	WND	HUM	VMS	CR
TMP	1	1	1/3	1	1	1/3	0.0905
PRS	1	1	1/2	1/3	1/3	1/4	
WNS	3	2	1	1/4	1/5	1/4	
WND	1	3	4	1	4	5	
HUM	1	3	5	1/4	1	4	
VMS	3	4	4	1/5	1/4	1	

From Table 3, the responses offered by the showed preferences for the first item in the pair, which showed that highest score of 5 for HUM against WNS, and WNS against VMS. The lowest score of 1/5 was awarded to WNS against HUM, and WNS against VMS. The computed CR of 0.0905 < 0.1 threshold for acceptance of the responses of first respondent as reliable for further processing of the research questions.

Table 4: The second respondent responses on two topmost weather parameters.

	TM	PR	WN S	WN	HU	VM	CR
TMP	1	1/8	1/8	1/6	1/5	1/7	1.186 7
PRS	9	1	1/6	8	1/7	1/5	
WNS	8	6	1	6	5	7	
WN	6	1/8	1/6	1	3	8	
HU	5	7	1/5	1/3	1	8	
VMS	7	5	1/7	1/8	1/8	1	

In Table 4, the responses collected for the second respondent indicated the preferences for the both items in the pair. In case of the responses of first item against second item, highest score of 9 was awarded to PRS over TMP, and the lowest score of 1/8 was awarded to TMP against PRS, WND against PRS, VMS against WND, and VMS against HUM. In the case of the second item against first item, the highest score of 8 was preferred VMS against WND, and VMS against HUM. The lowest score of 1/8 was preferred to WNS against VMS, and HUM against VMS. The computed CR of 1.1867 > 0.1 threshold, the responses of second respondent were rejected as unreliable for further processing of the research question.

Table 5: The third respondent responses on two topmost weather parameters.

	TM	PR	WN S	WN	HU	VM	CR
TMP	1	1/7	1/7	1/8	1/9	1/6	1.343 2
PRS	7	1	1/7	6	1/7	1/8	
WNS	7	7	1	5	6	7	
WN	8	1/6	1/5	1	7	6	
HU	9	7	1/6	1/7	1	6	
VMS	6	8	1/7	1/6	1/6	1	

In Table 5, the responses collected for the third respondent point to the preferences in the both items in the pair. In case of the responses of first item against second item, highest score of 9 was preferred on HUM against TMP, and the lowest score of 1/7 was given to VMS against WNS, WND against PRS, VMS against WNS. In the case of the second item against first item, the highest score of 7 was preferred to HUM against WND, and VMS against WNS. The lowest score of 1/8 was given to VMS against PRS, and VNS against WNS. The calculated CR value of 1.3432 > 0.1 threshold, the responses of third respondent were rejected as unreliable and removed from further processing of the research question.

Considering the initial analysis of collected responses of respondents contained in Tables 3, 4, and 5, the computed CR values for first, second and third respondents are 0.0905, 1.1867, and 1.3432 respectively, which are greater than 0.1 threshold for the consistency and reliability of the participant's responses except for first respondent. This implies that, only the first respondent's responses were accepted on the basis of CR value for further investigation of the subject.

Similarly, the fuzzy numbers format PCM corresponding to crisp numerical values of the first participant's responses (refer to Table 3) are shown in Table 6. Each crisp number for every response in the Table 3 is substituted with matching fuzzy numbers and inverse fuzzy numbers in Table 6.

Table 6: The Fuzzy numbers for first participant responses on two weather parameters.

	TMP	PRS	WNS	WND	HUM	VMS
TMP	(1,1,1)	(1,1,1)	(1/4, 1/3, 1/2)	(1,1,1)	(1,1,1)	(1/4, 1/3, 1/2)
PRS	(1,1,1)	(1,1,1)	(1/3, 1/2, 1)	(1/4, 1/3,1/2)	(1/4, 1/3, 1/2)	(1/5, 1/4, 1/3)
WNS	(2, 3,4)	(1,2, 3)	(1,1,1)	(1/5, 1/4, 1/3)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)
WND	(1,1,1)	(2, 3, 4)	(1/5, 1/4, 1/3)	(1,1,1)	(3, 4, 5)	(4, 5, 6)
HUM	(1,1,1)	(2, 3, 4)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1,1,1)	(3, 4, 5)
VMS	(2, 3, 4)	(3, 4,5)	(1/5, 1/4, 1/3)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1,1,1)

Table 6 contains the computed outcomes of the Chang' FAHP codes on MATLAB R2013b. The FAHP mode computes the weights, normalized weights, and rank based on independent responses. The FAHP model use the extended approach in determining the top tw parameters that are highly influencing weather forecast and related decision-making tasks as illustrated in Tabl 7.

Table 7: The weights and ranks of respondent's responses computed.

Parameter	Weight	Normalized Weight(%)	Rank	Remarks
TMP	0.0946	9.46	5	Moderate importance
PRS	0.0741	7.41	6	Weak or slight importance
WNS	0.1459	14.59	4	Strong plus
WND	0.3003	30.03	1	Extreme importance
HUM	0.1997	19.97	2	Very, very strong
VMS	0.1854	18.54	3	Very strong importance

In Table 7, the five weather parameters received various contributions to the subject of weather forecasts and decision-making process. As shown, TMP paid 9.46%, PRS contributed 7.41%, WNS donated 14.59%, WND gave 30.03%, HUM explained 19.97%, and 18.54% was accounted by VMS. Interestingly, the two topmost parameters having extreme importance, and very, very

strong importance when determining weather conditions of regions in the study area include: WND and HUM at 30.03% and 19.97% respectively.
More so, graphical comparisons of the select parameters preferred by the respondent using the FAHP computational weights are shown in Figure 1.

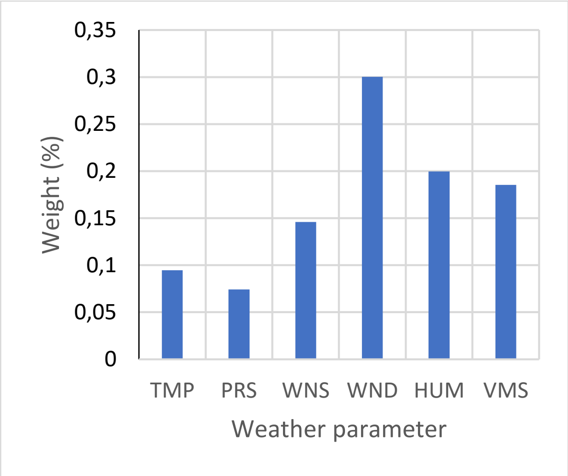

Figure 1: The contributions of the select parameters on weather conditions forecasts.

From Figure 1, the graphical display of the select weather parameters in forecasts and determination using FAHP model weights, which showed clearly the top leading parameters as WND and HUM at 0.3 and 0.2 weighting scale respectively. While the least contributing parameter to the weather forecasting tasks was PRS at 0.09 of the FAHP model's weighting scale. The FAHP model derived two weather parameters of WND and HUM as important to the subject of weather forecasting; thereby included as antecedents for FLC system as explained in the next subsection.

4.2 Outcomes of the fuzzy logic control model

The fuzzy rules are generated according to data items and type of datasets selected from the FAHP model's outcomes. The two top parameters, WIND and HUM, were to serve as the antecedents for the inference engine of the FLC. The FLC model developed to determine uncertainty problems and trends of weather in the city of Austin, United States at more effective and reliability style. The antecedents and consequents with their respective conditions are given in Table 8.

Table 8. Antecedents and consequent constraints for the fuzzy engine.

Antecedents	**Conditions Indices**	**Range of Values**
Wind direction (WND)	High (3) Medium (2) Low (1)	[93.37 – 226.53]
Humidity (HUM)	High (3) Medium (2) Low (1)	[70.24 – 84.10]
Consequents		
Weather condition (WEATHER)	High (3) Medium (2) Low (1)	[84.10 – 226.53]

From Table 8, the antecedents for the FLC include: wind direction (WND), and Humidity (HUM). The range of values are [93.37 – 226.53], and [70.24 – 84.10]. The consequent variable is weather condition (WEATHER) under investigation whose range of values are derived from minimum and maximum values of the antecedents, that is, [84.10 – 226.53]. The layout of the FLC-based weather forecasting model is composed of two inputs (FAHP select parameters/antecedents: HUM and WND), and an output (consequent: weather condition) as shown in Figure 2.

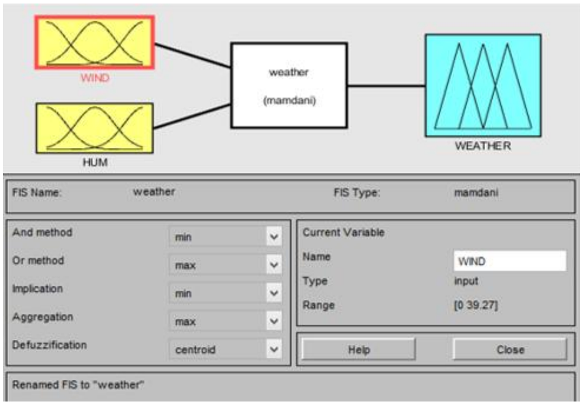

Figure 2: The FLC-based weather forecasting system layout.

The triangular membership function was adopted because of its popularity and effectiveness for modeling uncertainties and fuzziness during decision-making processes. Three membership conditions were developed for both antecedents and consequent namely: Low, Medium and High. While, the matching indices of membership functions include: 1, 2, and 3. The membership functions, variables, and range of values for all the input and output are specified in Table 8. These refined fuzzy rules-list is used in constructing the fuzzy inference engine by means of the logical AND, and IF-THEN statements as established by [60]. Therefore, the rule-list for the fuzzy inference engine of the proposed forecasting weather events is given in Table 9.

Table 9: The optimized FLC rules-list indices after genetic algorithm refinement.

Rule N	Input 1	Input 2	Output
1	3	1	2
2	1	1	2
3	3	3	3
4	3	1	2
5	2	2	3

From Table 9, the refined fuzzy rule-lists are utilized for generating different mapping of the antecedents' membership function indices to the membership functions of the consequent using the input and output weather parameters defined in Table 8. The rule-base generated for the FLC, from Table 9, is illustrated in Figure 3.

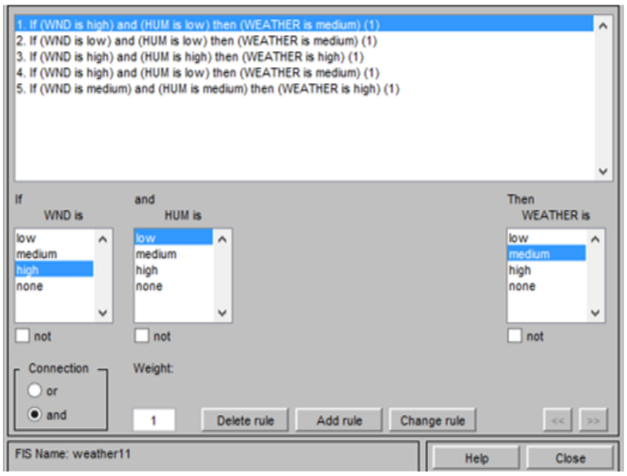

Figure 3: The optimized rules-list design of the FLC weather forecasting model.

Following from Figure 3, the antecedent variables are WND and HUM, which correspond to the inputs of the FLC weather system. Also, the consequent is the output of the FLC system. The logic function of "AND" are used to map the different membership functions of the inputs to those of the output. More importantly, the weight of the rules-list is 1, which denotes equal importance of all the inputs and output membership functions indices in order to remove biases in decision-making process about weather conditions of cities.

The performance of the proposed optimized FLC weather forecasting system in terms of error rates using optimized rules-list the fuzzy inference engine against conventional FLC weather forecasting system is given in Table 10.

Table 10: Proposed weather FLC forecasting model performances with different datasets.

Dataset	MSE	RMSE	MAPE	Remarks
NIMET	0.1563	0.3953	0.2104	Effective
Kaggle	0.0010	0.0317	0.0319	More Effective

From Table 9, the performance of the proposed optimized FLC with the standard dataset was better at MSE of 0.0010 against the local NIMET dataset of 0.1563. The same trend was observed for the RMSE error measure that put the proposed model performance with the standard dataset at 0.0317 over the NIMET dataset at 0.3953. When MAPE evaluation parameter was considered, the proposed weather model performed highly at 0.0319 for Kaggle dataset when compared to the NIMET dataset at 0.2104. This shows the proposed weather forecasting model performed best with less complex and refined factors against highly complex meteorological local weather datasets as depicted by Figure 3.

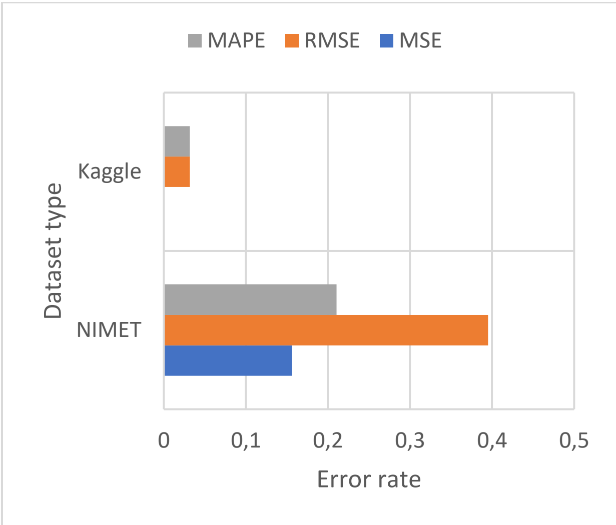

Figure 3: The performance of the FLC weather forecasting systems with diverse datasets.

Again, the outcomes of weather forecasting model with the optimized FLC were superior when compared to the ordinary FLC with refined rules-base as shown in Table 11.

Table 11: The comparisons of the proposed model to the FLC model.

Model	MSE	RMSE	MAPE	Remarks
FLC	0.0011	0.0332	0.0319	Effective
Optimized FLC	0.0010	0.0317	0.0355	More Effective

From Table 11, the weather forecasting model performed better with fewer rules-lists in the rule-base rather than unfiltered rules-list. These showed that the proposed weather forecasting model in terms of the evaluation metrics of MSE, RMSE, and MAPE at 0.0010, 0.0317 and 0.0355 were most preferred because of their capability to explain smaller variations in the outcomes against the target weather data in the area of study as illustrated in the Figure 4.

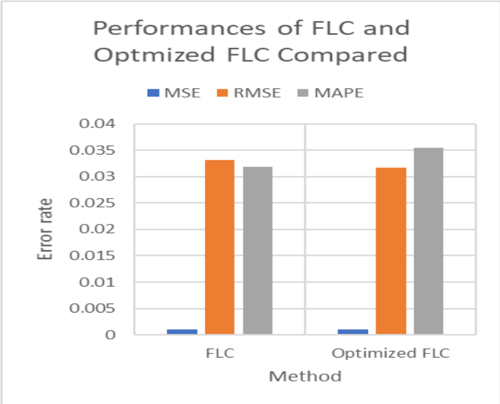

Figure 4: The performance of FLC and Optimized FLC methods for weather forecasts.

The reasons being that, FAHP model procedure improves the selection of the most influencing parameters required to building FLC rule bases. More so, the FLC model's rules-list redundancy was filtered with genetic algorithm procedure to realize 5 best rules out of 9 original rules. The outcomes of this paper increase the reliability of the weather information generation for diverse purposes as shown in Figure 5.

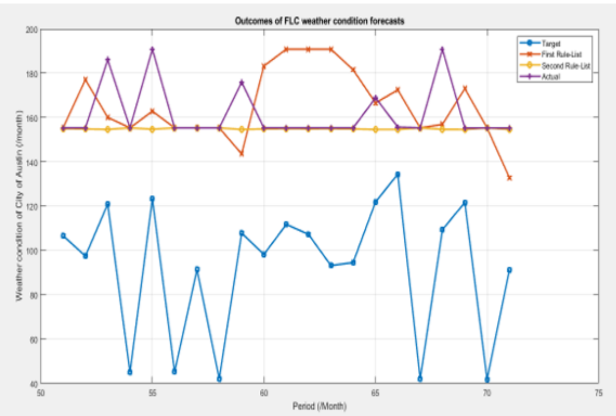

Figure 5: The Line graph of FLC weather forecasts model performances compared.

From Figure 5, the testing dataset is 30% of the entire weather dataset collected in which the target line depicts the original weather data for 25 days periods corresponding to after 51 months of observations. As shown, the weather forecast model was unsteady from the starting 110 points by 51st month, and changed sharply to attain its lowest value at 42 points. Then, it continues to gain at the highest point of 139 points by 64th month. However, by the end of 71 months testing period, the weather condition reached 86 points. In terms of the forecasts performance, the optimized FLC weather system outcomes (the Actual line in the graph) showed similar trends as the Target line through the comparable periods of observations, that is, 51st month, 54th month, 56th month, 58th month, 60th – 67th months, 70th month and 71th month accordingly.

These illustrate the capabilities of the proposed FLC system in accurately forecasting weather conditions of cities at minimal error rates. It can be attributed to the involvement of AI techniques like FAHP and FLC systems for the decision-making processes. Furthermore, the process of filtering weather parameters, and refining of the rules-list in rule-base increased the outcomes of FLC weather forecasting system. The FLC weather forecasting system has shown to perform better with the removal of redundancy in the rules-list as well as its input variables (or weather parameters). In this paper, the choice of the FAHP and FLC methods offer complementary roles which increase the variability and accuracy [51]. The uncertainty and fuzziness of meteorological datasets like Kaggle and NIMET, were best interpreted using both approaches [52]. The FAHP method refines the decision-making procedure and data analytics of the FLC [50]. The paper extended the prospects of the both FAHP and FLC to the weather forecasting and analytics, which falls into the MCDM research domain.

5 Conclusion and future works

This paper provides required tool for determining weather and state of the atmosphere in certain places and periods through the application of fuzzy logic technique. It will benefit individuals, government agencies, business sector, built and construction sector, researchers and scholars concerned with planning and policymaking depending on weather outlooks. This increases the understanding of the hidden relationships and patterns available for a more accurate and reliable local weather information dissemination.

The outcomes of the FAHP model when used to select the most important parameters affecting weather forecasts of cities identified Wind Direction (WND) and Relative Humidity as contributing 30.01% and 19.97% influence to the decision-making process.

Thereafter, the select parameters from the FAHP model procedure served as antecedents of the FLC model. The GA-optimized FLC model was adopted from the study by [46] which overcame the problem of redundancy of the fuzzy inference engine rule-list. Consequently, the refined rules-list serves the building block for the proposed FLC weather forecasting model. The outputs revealed that the FLC weather forecasting model in terms of the MSE, RMSE, and MAPE at 0.0010, 0.0317 and 0.0355 were most preferred against comparable models because of its capability to explain smaller variations of the datasets. It was superior due to the initial FAHP-based selection of weather parameters and rule-list reduction procedures. It equally attributable is the filtered rules-list used to construct the fuzzy inference engine of the FLC.

This paper found that, the subjectivity of expert judgements during FAHP modelling of the criteria and the over reliance of FLC model on its rule-base's optimization impact greatly on the outcomes of the weather forecasts generated. In future works, more dataset can be experimented to include long periods and extended site specificity.

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