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Augmented Reality-Supported Fuzzy Multi-Criteria Decision Making for Photovoltaic System Optimization

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Abstract: This paper models and evaluates the use of Augmented Reality technology, supported by the decision-making process, for modeling Photovoltaic system generation. Specifically, for the optimization of very short-term solar irradiance forecasting one hour ahead, with the recommended combination modeling design based on meteorological data, as well as the main data, namely the optimization of power generation operations of photovoltaic (PV) generation systems. This paper proposes an Augmented Reality (AR)-supported Multi-Criteria Decision-Making (MCDM) approach to simplify and improve the fuzzy decision-making process. The hybrid method is the first in theory of Fuzzy-Multi-Criteria Decision-Making, which combines Augmented Reality with Fuzzy-Multi-Criteria Decision-Making-Neural Networks (AR-F-MCDM-NN), using the main support for virtual environment decision-making. Specifically, the Augmented Reality model provides better visual information than other visual models, turning complex decision methods into easy-to-use tools, especially for modeling photovoltaic (PV) generation systems. A mathematical model is used to design a PV generation system to optimize Global Horizontal Irradiance (GHI) forecasting one hour ahead. In calculating the error value in the hybrid method, a Mean Absolute Percentage Error (MAPE) value of approximately 5.6% was obtained. The results of the combination model simulation were then compared with real data, and the training test results showed that the combination model proposed in this study could calculate SI with high validity and results consistent with the actual data.

Keywords: Photovoltaic system, augmented reality, decision making, solar irradiance, forecasting, asynchronous collaborative.

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1. Introduction

Augmented Reality and Fuzzy Multicriteria Decision Making (AR-F-MCDM) is a modern technology developed specifically for the design or modeling of photovoltaic generation systems to optimize Solar Irradiance (SI) forecasting. It can maximize the production of electrical energy by photovoltaic plants in the next hour. Researchers and practitioners have become even more involved in new hybrid models and highly effective, efficient applications, such as design using Augmented Reality (AR) models and multi-criteria decision-making, in the last decade. Of the several main input variables critical to the decision-making (DM) implementation for the design of photovoltaic (PV) system generation models that benefit from such an AR-MCDC hybrid model, the maximization of simulation capabilities for this aim and scope remains to be developed. There are several mathematical models, one of which uses augmented reality to support the decision-making process, related to several previous studies on augmented reality, namely Meister et al. (2022). of the dimensional augmented reality weather using general aviation weather and analysis video in live use augmented reality, as this has been described in reference (Chen et al., 2021). Modeling using decision support for analysis data is explained by Pan et al. (2021), who studied targeted decision-making using support through Asymmetric. Augmented reality has been studied for decision support in visualizing data, multisensory proximity and neural networks for perception (Zheng et al., 2022; Trepkowski et al., 2022; Liu et al., 2022). Another study on forecasting Solar Irradiance (SI) using multi-criteria decision-making is referenced in Behera et al. (2023), who studied a distributed fuzzy optimal decision-making strategy. Solar Irradiance forecasting integrating Geographic Information System (GIS), fuzzy and hybrid models has been studied using a model decision-making method based on fuzzy sets (Lyu et al., 2023; Nemaa et al., 2022; Jahani et al., 2022; Liu et al., 2021; Chuanbin et al., 2020). In their study, a hybrid analysis for forecasting using a model decision-making method based on fuzzy sets. Energy-repowering PV systems and adaptive global sliding can be explained with reference to Yundi et al. (2020), who studied a double-hidden-layer recurrent neural network for adaptive global sliding mode control. Modeling photovoltaic microgrids in Ecuador was performed by Rodriguez et al. (2022). The authors Su et al. (2022), Pan et al. (2023), Kumar et al. (2024), Jang et al. (2021), Marques et al. (2022), and Gu et al. (2023) have presented a collaborative augmented reality method for design and simulation. The authors Kim et al. (2024), Lupo et al. (2024), Geng et al. (2024), Kim et al. (2024), Hassan et al. (2024), Zhang et al. (2024), Kim et al. (2022), Tajjour et al. (2023), and Valentino et al. (2020) have presented short-term SI forecasting using deep learning.

Previous research has described the model and design of the AR combination model, but the forecast for SI in PV station systems using the hybrid method AR-F-MCDM-NN remains unavailable. This proposed study aims to design and evaluate a PV system user interface for asynchronous collaborative forecasting of SI in augmented reality to support decision-making.

This section discusses the estimation of Global SI for PV panel modules using a measured database for PV module systems using weather input variables. In this study, a new combination of two models that collaborate to AR with decision-making has been designed and evaluated for the user interface of the PV system. An AR-F-MCDM combination model predicts SI for PV generation via simulation, using AR-F-MCDM based on SI, weather data, the goal, and the division of pre-training input data. The virtue of very short-term SI prediction using asynchronous collaborative forecasting with the AR-F-MCDM method is that the collaboration model is widely used with actual data as input variables, which are highly suitable for making predictions. A hybrid model for prediction using AR-F-MCDM is based on mathematical formula calculations for very short-term SI prediction ahead and using a collaboration model at the AR-F-MCDM method analysis with meteorological data as a basis for a one-day-ahead forecast to get more meticulous and detailed results with accuracy, delivering outstanding precision performance and a very meticulous simulation step. The main principal model of this study is as follows.

1) The design and evaluation of a photovoltaic system user interface construction is suggested using the new formula. The proposed hybrid method, AR-F-MCDM.
2) A mathematical hybrid model is used for SI forecasting, which has output values that are highly adaptive to changes in input values. The input variables use meteorological data, which is well-suited for testing and training. Thus, an AR-F-MCDM hybrid model has been proposed.
3) The study utilizes a hybrid model with AR-F-MCDM, with a primary focus on subjective assessment to determine the weighting criteria for each decision-making component. Meanwhile, several input parameters, including weather data such as SI, wind speed, temperature, humidity, and wind direction, were used to predict global SI.
4) Simulating the value results of the research shows the high quality of the collaboration, the Augmented Reality method using the hybrid method, and the measurement data.
5) The application of this suggested study provides interesting knowledge insights for very short-term SI forecasting, one hour ahead.

This article will be described in the following order. Section II explains the variables required to predict SI based on the temperature, humidity, wind speed, and wind direction. Subsequently, a prediction model for the front and back outputs of PV modules was developed using estimated SI and hybrid AR-F-MCDM. Section III describes the results conducted to verify the forecast model's accuracy, wherein the output was measured while varying the position of the PV station, formula method details of the planning, and model design of the distance user interface. In section 4, explain the study analysis and evaluation data. And finally, section 5 presents the conclusion and the utility of this research.

2. Theory and Formula

2.1. Augmented Reality Photovoltaic System

Various techniques have been proposed to detect SI on PV station modules. In this section, we provide an overview of some of the existing hybrid models and focus on their main characteristics. This research proposes a hybrid AR-F-MCDM model for PV station prediction based on the position of each generator. This modeling addresses the ability to monitor the electrical power generated by the PV station and can detect SI for the next hour ahead. Collaborative hybrid AR-F-MCDM modeling detects SI and provides new datasets. This section explains the main modeling and design for analyzing the simulation data and subsequently visualizing data in a 3D augmented reality model. This study also discussed normality analysis, data testing, and training for simulation, preprocessing, and 3D area tracking using an AR-MCDM framework with a multicriteria decision-making function and 3D AR model visualization and position. Hybrid mathematical modeling techniques, combined with accurate analysis and data normalization, are essential for predicting SI, as detailed in the following subsection. Fig. 1 illustrates a block diagram of the analysis model and the visualization area for PV module components.

2.2. Data Collection

Before the visualization modeling processes, meteorological data collection is performed using the PV station generation database. This comprehensive dataset includes a wide implementation of test plan models illustrating various PV station positions, as shown in Fig. 1. The dataset covers a range of modeling plans of PV station positions based on weather data, incorporating diverse types of sample PV station generation panels.

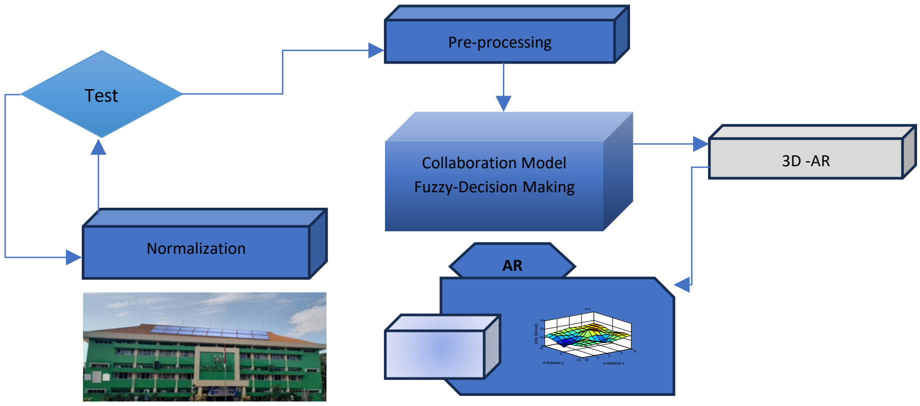

Fig. 1. The modeling and design used for predicting and analyzing the PV station

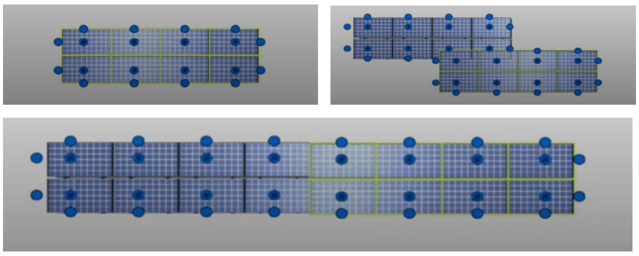

Fig. 2. Design thermal station PV system panels

Fig. 2 is a visual illustration of the differences in the position of the PV station and the visual appearance of normal conditions for identifying data simulation in this database, hence, to get better results by providing some visual reference. The images serve as the foundation for the research collaboration model. AR-F-MCDM visualization techniques allow for accurate modeling and design of normal data in the context of solar panels, one of the SI data, so that data can perform very short-term forecasting for SI, enabling power to be determined. The variable input data consists of 16 stations of solar panels. This dataset is for testing and training and is modeled for artificial intelligence vision projects related to PV panels for predicting SI. The images serve as the foundation for the research on AR-F-MCDM and visualization techniques, allowing for accurate modeling, design, and visualization of normalization data in a PV station system context. The input variable is the dataset of PV panels based on weather data for the prediction of solar irradiation. The variable input dataset consists of data on solar panels of irradiance solar, with an objectified detection format data model. The dataset is forecasted for application models related to solar panel components. Fig. 2 illustrates the design model of PV stations of the data, which provides an analysis visual representation of the main data.

2.3. Augmented Reality-Based MCDM

The proposed study is the first approach to hybrid decision-making using AR to develop an innovative design for estimating SI. In particular, the MCDM theory processes the decision-making until the final model with decision ranking is achieved. Moreover, the AR model provides various kinds of visual information using the F-MCDM method. In addition, F-MCDM is implemented to allow the evaluation of weights by comparing the criteria involved and the alternatives (Valentino et al., 2020).

2.3.1. Methods

The novelty of using a mathematical method, AR-MCDM based on weather data in the study, is illustrated. Fig. 3 presents the phases and collaboration procedure for AR-MCDM in a flowchart. To explain the AR-MCDM for forecasting using the process described above, several input variables need to be specified. The procedure following AR-MCDM for forecasting is as follows.

1) First Step: Choose the algorithm of the problem, AR-MCDM.
2) Second Step: Choose the concrete similarity measure and create a similarity AR- multi-criteria decision-making from the given training dataset, PV station system.
3) Third Step: The algorithm process of very short-term ahead SI forecasting alternatives, the dimension models, and the criterion models' local weights can be analyzed in the AR environment. For the calculation of each criterion's

weight, the BNP value for the very short-term hourly SI can be seen in the local weights for dimensions and criteria for forecasting SI.

4) Fourth Step: Calculation of AR-MCDM performance for the SI Forecasting. The value remaining for every element of average AR-decision-making performance of each criterion, and every alternative, to very short-term ahead SI, can be obtained by the same procedure.

2.3.2. The configuration of the problem

The first step in implementing the decision-making model is to define the problem and analyze each factor of the MCDM model to obtain more accurate parameter values. Next, the criteria, sub-criteria, and alternative values are used as input parameters.

2.3.3. Represent parameters with 3d modeling

In the second step, a process for creating the 3D design from meteorological data is explained to set up the AR model. The 3D design includes variable parameters and useful input data that can describe typological, functional, and characteristic aspects for very short-term SI forecasting.

2.3.4. The weights evaluation of dimensions and criteria

The third step concerns applying k-Nearest Neighbors (k-NN) to the virtual 3D models and is divided into three phases for evaluating the treatment combination model. Once all forms of 3D modeling are complete, DM can evaluate local weight values by analyzing decisions within the AR environment.
Stage 1-AR: Choose the 3D design from the simple model to the highly complex model to obtain better results according to the multi-criteria decision-making model. Where the focus is on conducting analysis and AR as the main support, in 3 stages: stage 1-AR, stage 2-AR, and stage 3-AR. In stage 1-AR, users have sorted the 3D models from least to most important according to Simos Roy-Figuera's (SRF) decision-making theory. Therefore, users have classified designs with 3D models that prioritize the right side of AR as a principal factor. Additionally, if the user assigns the same weight to all decisions, then stage AR-1 serves as the initial ranking of the parameters used. Fig. 3(a) and 3(b) illustrate the initial stage of the generic 3D model from the least important to the most important.

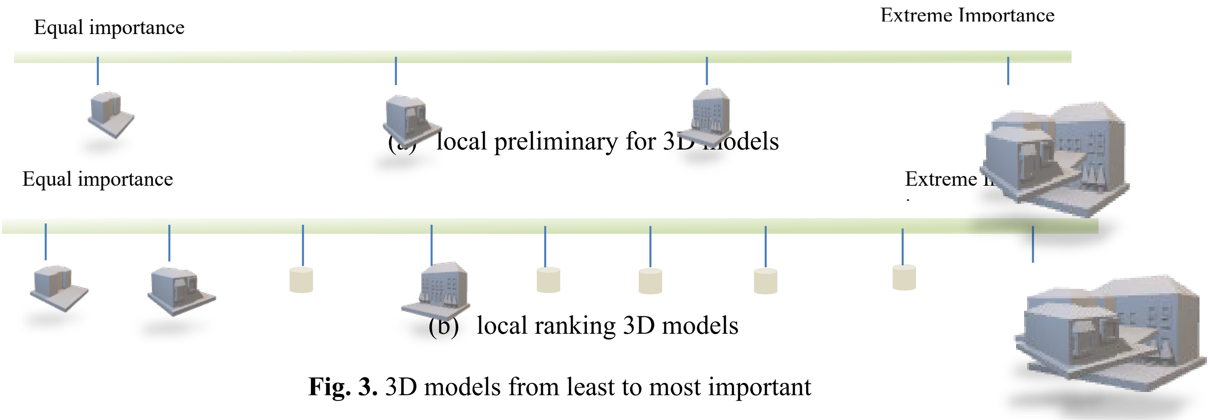

Fig. 3. 3D models from least to most important

Stage 2-AR: Performing a comparison of model Augmented Reality simulation designs to determine local rankings in pairs. In detail, users model 3D shapes or select small shape models from design AR to predict SI models.
Stage 3-AR: The local weights are evaluated during the AR-MCDM evaluation.
By using input data from process phase 2 and following the process hybrid model proposed in the combination modeling using the k-nearest neighbor method. In particular, the design-AR process calculated a set $P = \{x|x = 1,2,...,m\}$ of m input variables. To achieve the objectives of this research, $C = \{C_x | x = 1,...,p\}$ is the value series of the Augmented Reality model design C_x, connected with the x^{-kh} variable for x = 1, 2, ..., m. The set $Ct = \{ct_x | x = m+1,...,p\}$ (where p > m) is explained to calculate the value zero. So, the set $CY = C \cup Ct$ is a collection of several models, including those with unfilled or empty space. Every design modeling CY is assigned $s_x \in N$, (q = 1, ..., p) in the second process step (N according to the original set). In the design model, $c_x \in C$ (consequently to every variable p), an area weight $vt \in R+$ (actual positive value), analysis calculation can be denoted as Eq. (1).

$$v_t = r_t / \sum_{q=1}^{p} r'_y \qquad \text{for t = 1, ……, n} \tag{1}$$

Where $v_t \in [0,1]$ with $v_t = 1$
The third step is the iteration step, performed for total value criteria and alternatives with a weighted value.
Step 4-AR: Parameters are weighted, and priorities are assigned to obtain better weights. In accumulating load values, the main equation has been used, employing specific formulations of several equations to forecast SI intensity in photovoltaic station systems. Fig. 4. Illustrates about step AR-F-MCDM process.

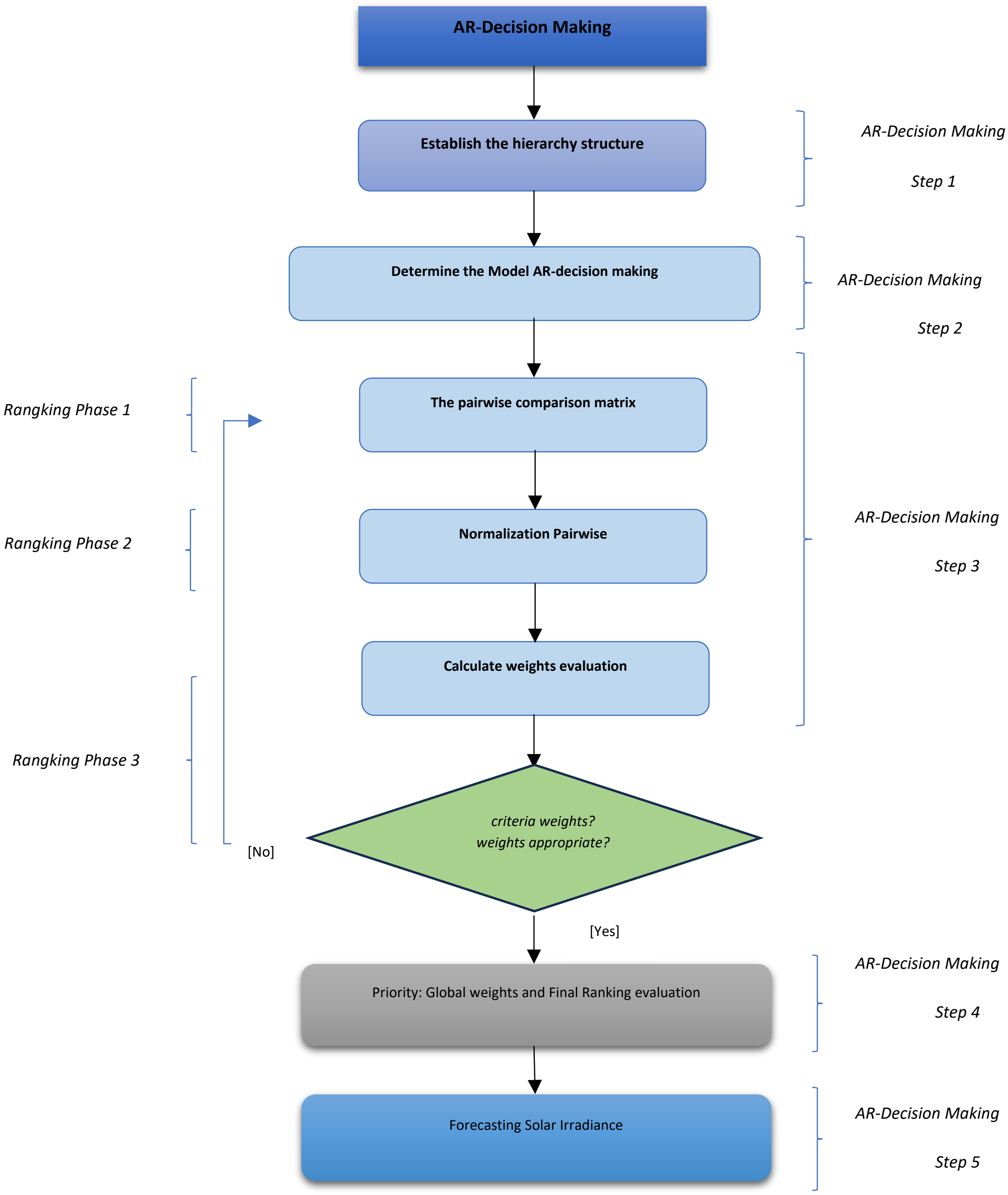

Fig. 4. The flowchart of the AR-F-MCDM

2.3.5. The weights evaluation of dimensions and criteria

The hybrid, asynchronous design model refers to the collaboration theory to achieve the goal of modeling solar irradiance prediction for PV station generation using AR-F-MCDM. This modeling has a positive impact, improving user experience and user engagement with the model. The implementation of the AR design model aims to develop an interface and hybrid technology integrated with artificial intelligence for AR-F-MCDM modeling. Collaboration or hybrid is part of the many applications of augmented reality in innovative design, education, culture, and technology development. Of all these applications, learning and education are the most important. Similar approaches have been used and validated in previous research, showing that collaboration using augmented reality has a very positive influence on users, especially students, in understanding artificial intelligence modeling lecture material for power systems. User collaboration is influenced by several main factors, including the location or position of the PV station, meteorological data-based forecasting, synchronization, and the user''s ability to use the application for solar irradiance forecasting. In addition, multi-device interaction can introduce novelty to collaboration through AR decision-making. In previous research, many user interface developments have used AR decision-making modeling applied to other fields.

3. Analysis and Results

The research approach is used to inform decision-making for predicting SI at the system PV stations, especially in the very short term. In particular, the research presents an innovation forecasting model based on a collaborative mathematical model, AR-F-MCDM. The technology collaboration model integrated with the PV station process has the advantage of a position model, which can affect the PV station's performance in generating electrical energy based on meteorological data.

3.1. Criteria and Alternatives

First Step: The collaboration model using AR-F-MCDM consists of a problem-solving process, and the goal is to improve the selection of results for forecasting SI for PV station systems based on meteorological data. Within the scope of this research, there are five objectives, five variables b (b=1,2, ...,5), explained to characterize the Photovoltaic system. The following 16 module PV solutions are provided for solving the decision problem with alternative values of k (k=1,...,16). The decision-making model process, the components of criteria, and alternatives are implemented in the algorithm shown in Fig. 4. Each alternative is always related to the criteria. Table 1 illustrates the predictive value design model. So, analysis using AR-MCDM can be used directly with the numerical values to get the result variable r and Eq. (1). In particular, the five-criterion model and alternative model of the multi-criteria decision-making solution are obtained as follows:

Table 1. The criteria decision-making model for very short-term forecasting

Criteria Model	Description
Solar Irradiance ($b = 1$)	the surface power density per unit area of electromagnetic radiation within the wavelength limit of a measuring component received from the Sun, where for sunlight measurements are in watts per square meter (W/m2) in SI units.
Temperature ($b = 2$)	the heat or molecular level of a substance
Humidity ($b = 3$)	relative humidity value or dew point value
Wind Speed ($b = 4$)	relationship to the earth's surface per unit time with air movement
Wind Direct ($b = 5$)	the direction of the wind indicated by a particular indicator
Alternative Model	**Description**
Photovoltaic system ($k = 1, 2 ..... 16$)	A combination of multiple solar panels equipped with inverters and hardware using solar energy to produce electrical power.

3.2. Model Station of 3D Models Using Weight Analysis

The problem definition is the AR-Fuzzy decision-making collaboration using k-NN at the second step, which is implementation, and the hybrid method combined with design c associated with the PV systems alternative model variable j (j=1,...,16) is actual. In Fig. 5, an illustration of the resulting preferences of all users. AR-F-MCDM modeling is used to predict SI in the short term.

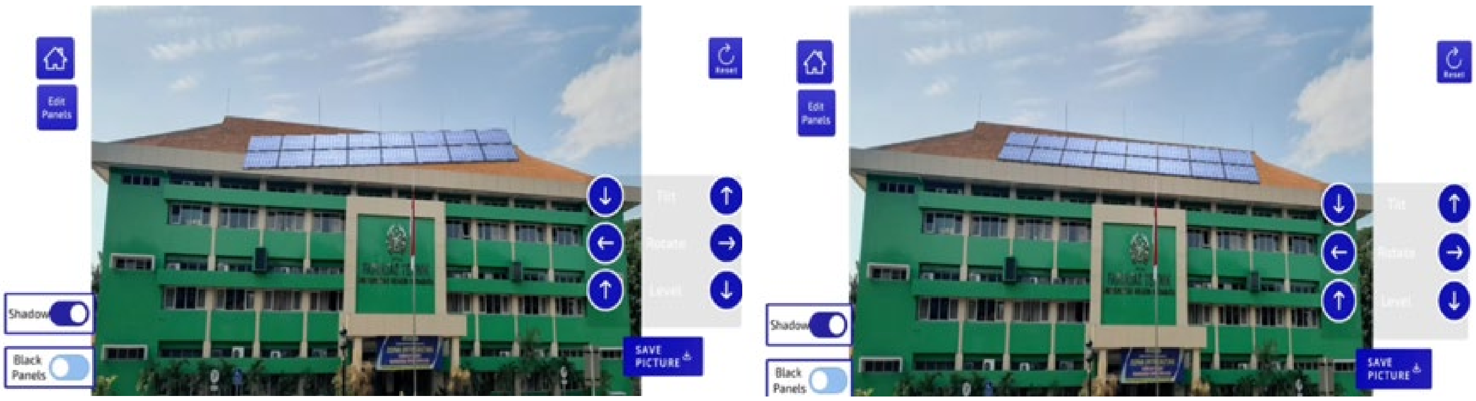

Fig. 5. Station PV system 16 panels in augmented reality

Table 2 explains the parameters, data positions and coordinates of each Photovoltaic System, i.e., angle, distance. Fig. 6 shows the position of the solar panels used by consumers, arranged in sequence.

For example, Fig. 7 shows the hybrid AR-decision-making model and explains the alternative model of the station PV system with all the multilayers explained.

Table 2. Data position and coordinates of the PV stations

No	Photovoltaic	Distance (d)	Angle (°)	Coordinate (x_i,y_i)
1	PV5	0	0	(0,0)
2	PV1	66	180	(-6.6,0)
3	PV2	132	180	(-13.2,0)
4	PV3	198	180	(-19.8,0)
5	PV4	66	0	(6.6,0)
6	PV6	132	0	(13.2,0)
7	PV7	198	0	(19.8,0)
8	PV8	264	0	(26.4,0)
9	PV9	165	217	(-6.6,-9.9)
10	PV10	108	217	(-13.2,-9.9)
11	PV11	51	217	(-19.8,-9.9)
12	PV12	0	0	(0,-9.9)
13	PV13	51	323	(6.6,-9.9)
14	PV14	108	323	(13.2,-9.9)
15	PV15	165	323	(19.8,-9.9)
16	PV16	222	323	(26.4,-9.9)

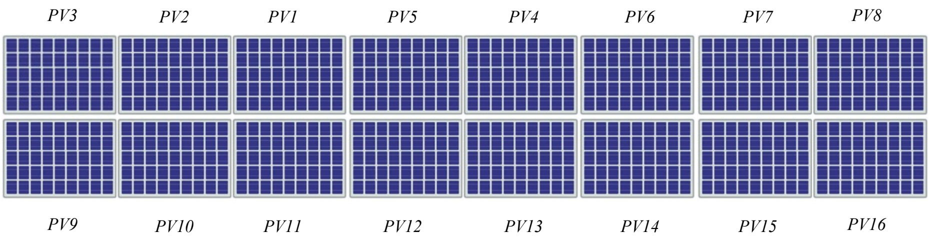

Fig. 6. PV panel position in augmented reality

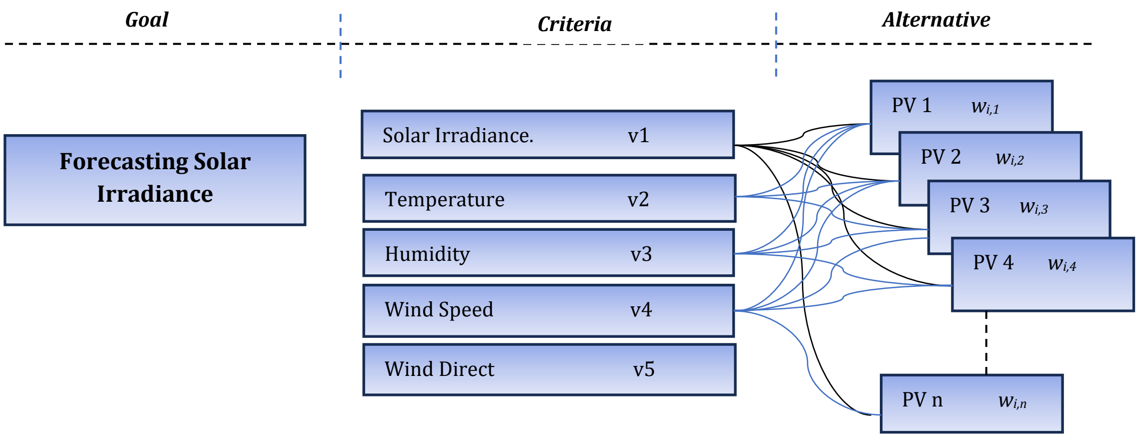

Fig. 7. Design of the problem of the research forecasting SI

In the third step of AR-fuzzy decision-making, the design criteria models are optimized to determine the weights for the input variables. Determine model criteria and alternative value set for the forecasting simulation analysis $Y_1 = \{b|b = 1, \ldots, 5\}$ and $Y_2 = \{k|k = 1, \ldots, 16\}$. The decision-making models are defined:

- v_b is the criteria input model relation and b-th criteria $\forall b \in Y_1$;
- $w_{b,k}$ is an associated PV model and the k-th alternative and the b-th ($\forall b \in Y_1$; $\forall k \in Y_2$)

The decision model evaluates AR-decision making to identify variable value $w_{b,k,}$ and $v_{b,}$ which is developed for variable criteria. Specifically, local weights v_i are computed based on Eq. (1) by considering $p = b$. Next, the weight value for $w_{b,k}$ is shown in Eq. (2).

$$w_{b,k} = \frac{r_t}{\sum_{q=1}^{p} r_y{}'} \quad , \forall b \in Y_1 , \forall k \in Y_2 \tag{2}$$

Table 2. The terms fundamental, pairwise and linguistic rules of transformation

A Set of Eight Terms Fundamental scale pairwise comparison			A Set of Seven Linguistic for importance weights of factor		
Set	Linguistic	Fuzzy Set	Set	Linguistic	Fuzzy Set
	Equality especially Important	(0,1,2)		Extremely High (XI)	(0,0,0.6)
	For compromise between the above values	(1,2,3)		Very High (EI)	(0.6,1.8,3)
	Moderate Importance	(2,3,4)		High (I)	(2,3.7,6)
L₁	For compromise between the above values	(3,4,5)	***L₂***	Fair (A)	(5,7,8)
	Strong Importance	(4,5,6)		Low (O)	(8,9,10.5)
	For compromise between the above values	(5,6,7)		Very Low (EO)	(10,11.5,20)
	Very Strong on demonstrated importance	(6,7,8)		Extremely Low (XO)	(22,23.5,25)
	For compromise between the above values	(7,8,9)			
	Extreme Importance	(8,9,10)			

The first AR-F-MCDM supported monitoring and by considering several alternatives as a basis for evaluation $j \in N*$ about the meteorology data (b=1). The model design is associated with other options (PVj) based on its meteorological data, i.e., SI, temperature, humidity, wind speed, and wind direction. In the process, following the AR-decision-making hybrid model in stage-2, a collection of empty spaces is identified and used to improve two sequential alternatives. The third step is to repeatedly apply the criteria, values and weighted alternatives. Table 2 explained the achieved linguistic terms and the rules transforming fundamental scales and importance weights of the factor.

Table 3. The average F-MCDM forecasting for SI value

Alternative	w'_b
Solar Irradiance (w1)	0.15,0.19,0.23
Temperature (w2)	0.12,0.1,0.165
Humidity (w3)	0.066,0.085,0.11
Wind Speed (w4)	0.1,0.1,0.155
Wind Direct (w5)	0.165,0.2,0.15

In Table 3, the average result of decision-making forecasting for SI. After performing the calculation and obtaining all the weight values of each criterion and alternative, to evaluate all the weights, w- (fourth stage for AR-F-MCDM), explained the effectiveness. Specifically, the formula is used to obtain the main, which can be denoted as Eq. (3). Fig. 8 explains collaboration with 3D for PV systems.

$$w_j^{'} = \sum_{i=1}^{16} v_i \, x \, w_{i,j}, \forall_j \in Y_2 \tag{3}$$

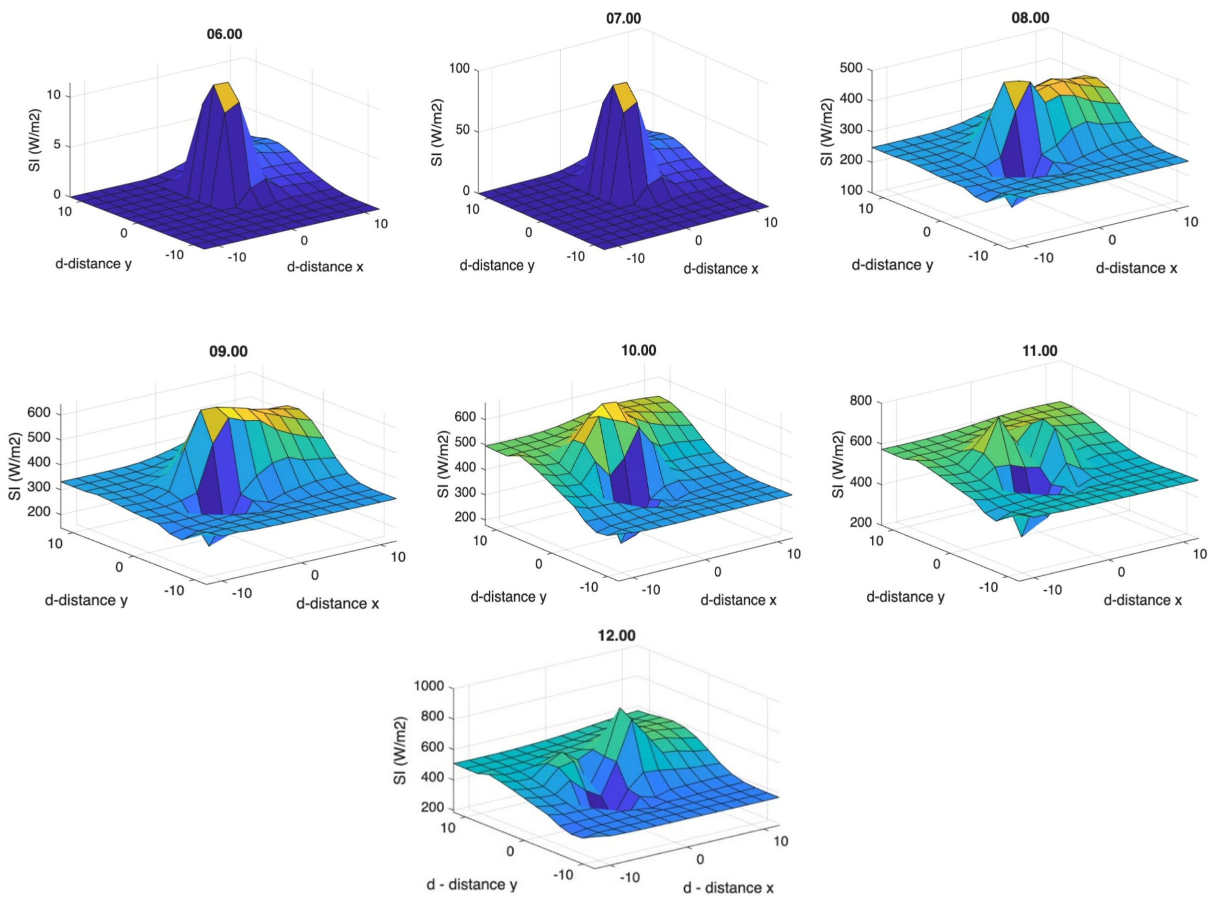

Fig. 8. Collaboration 3D alternative model of the station PV system (from 06:00 a.m to 12.00)

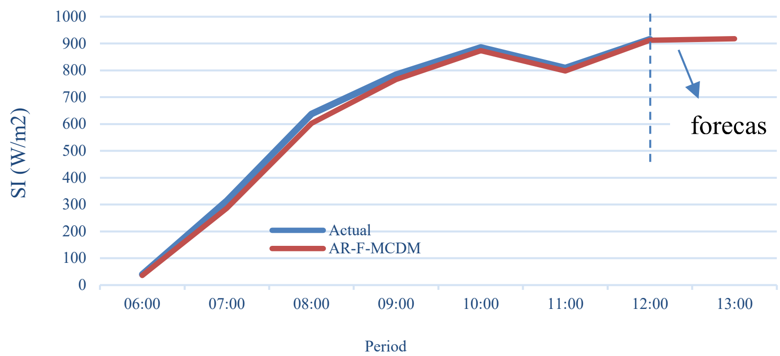

Fig. 9. Comparison of SI forecasting of the hybrid model and measured data

In Fig. 9, explains the comparison of the hybrid model using measured data from the SI and PV station estimation. Highly accurate and favorable agreement between actual values and simulation results is predicted using the hybrid AR-F-MCDM model. The result is determined by the weight value. The hybrid AR-decision-making model is in good agreement with measured data in the object position system PV generation. The result is very short-term solar irradiation forecasting. Fig.10. explained error calculation, using the MAPE value for the hybrid model and actual data. The actual and hybrid model prediction variable data are well-fitted for the prediction of very short-term SI. Using equation (4), the error value obtained is used as a statistical indicator. MAPE is calculated according to Eq. (4):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\left|\frac{G_{f,i} - G_{m,i}}{G_{m,i}}\right|\right)\times 100 \tag{4}$$

Where $G_{f,i}$ the SI prediction value and $G_{m,i}$ the actual value, and N is the number of irradiances.

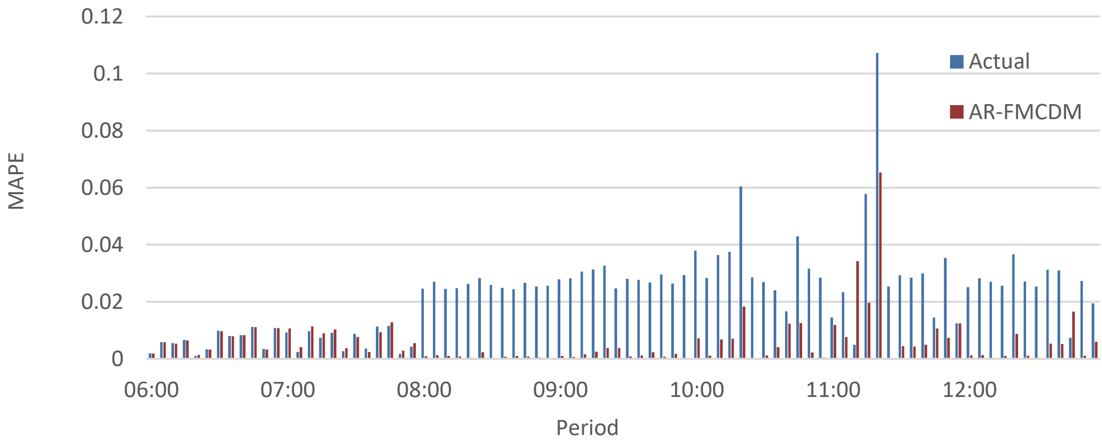

Fig. 10. MAPE calculation result for the actual data and AR-F-MCDM hybrid model

In the calculation, an absolute ratio is obtained by summing the estimated SI values per hour for each PV system, then dividing by the number of points *m*. The statistical indicators for the AR-F-MCDM design model, MAPE, are 5.6%. The AR-F-MCDM combination model provides a better forecast than the other design models.

4. Conclusion

This study, which uses a hybrid collaborative mathematical model, proposes a fuzzy multi-criteria decision-making method supported by AR-F-MCDM. This innovative design modeling approach is based on the multi-step F-MCDM process and utilizes a 3D visual-based parameter comparison inspired by the k-nearest neighbors algorithm. In the AR-F-MCDM hybrid model, decision-making and comparison are performed in an augmented reality environment that provides useful visual design information for prediction. The new model of the proposed method is: i) based on a visual, fast, and innovative procedure and collaboration using the AR-F-MCDM hybrid model; ii) can be used directly and quickly to select the best option for decision making problems combining 3D visual information of the virtual model of planning and the system of PV station locations and positions; iii) In conclusion, the proposed approach is applied to select the best option based on the k-nearest neighbor model. The hybrid modeling study analyzes the characteristics of the input data, including meteorological data used in the testing and training simulation processes. In this study, the proposed AR-F-MCDM hybrid model shows excellent results in forecasting compared to actual data. The evaluation of the ultra-short-term solar intensity forecast using the AR-F-MCDM hybrid method was carried out every hour, and the results showed that the AR-F-MCDM model outperformed the results of other models. For the statistical error indicator of the actual data model, the MAPE was 5.6%. The results of the proposed AR-F-MCDM hybrid method can be used effectively and with high accuracy to forecast ultra-short-term irradiance, with outputs that are closer and in accordance with the actual data. Therefore, the performance of the proposed AR-F-MCDM hybrid model is better compared to other methods

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Author Contributions

Unit Three Kartini contributed to the conceptualization and design model, modeling the experiments, modeling software, preparation materials, validation data, data analysis, and model analysis tools, writing the original draft of the article, editing the draft of the article, project research administration, and funding acquisition data. Fajar Arianto contributed to the conceptualization and design of the model, performed the experiments, contributed to the investigation, wrote the original draft of the article, reviewed the simulation results, edited the article, administered the data, validated the simulation data, analyzed, and funded the model. Priyo Heru Adiwibowo contributed to the conceptualization and design of the model, performed the experiments, contributed to the investigation, prepared the original draft, conducted reviews and edits, handled project administration, data collection, methodology, software, validation, analysis, manuscript editing and funding acquisition

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Declaration of Artificial Intelligence (AI) Tools

The authors confirm that no AI tools were used in the preparation of this manuscript.

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