Implementation of ANFIS +NN and nature-inspired optimization Algorithms for Solar Radiation Prediction.

Implementación de ANFIS + NN y Algoritmos inspirados en la naturaleza para predicción de radiación solar.

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Abstract- **This article presents a hybrid model that makes use of ANFIS (adaptive neuro-diffuse inference system) hybridized with Neural Networks (NN) and optimized with algorithms that are based on natural behaviors, in this case, ant colony (ACO). The model is designed to predict primary resources in a particular region subject to the planning and installation of distributed photovoltaic (PV) generation. The solar primary resource depends on the climatic conditions of the region to be evaluated, and its high variability in short periods presents a challenge in planning energy resources that use variable sources in the long term. In this article, the behavior of a hybrid ANFIS+NN+ACO model is designed, developed, evaluated, and validated. The methodology that is based on data analysis is detailed. First, work is done on climatic databases, which give guidelines for preprocessing and cleaning. Secondly, the climatic variables that predict solar radiation are established. The ANFIS membership functions are then based on the data to capture nonlinearity and extract relationships with predictors. Neural networks support the membership function optimization process, and finally, the optimizer refines and evaluates the response. The response is evaluated using metrics that demonstrate the robustness of the model when capturing and processing data. The study contributes to making visible tools and alternatives to determine energy potentials in climatic regions subject to the future for distributed generation.**

Keywords- **ANFIS, Fuzzy Systems, Neural Networks, Optimization Algorithms, Solar Radiation Prediction**

Resumen— **Este artículo presenta un modelo híbrido que utiliza ANFIS (sistema de inferencia neurodifusa adaptativa) hibridado con redes neuronales (NN) y optimizado con algoritmos basados en comportamientos naturales, en este caso, colonias de hormigas (ACO). El modelo está diseñado para predecir los recursos primarios en una región específica, sujeta a la planificación e instalación de generación fotovoltaica (FV) distribuida. El recurso solar primario depende de las condiciones climáticas de la región a evaluar, y su alta variabilidad en períodos cortos representa un desafío en la planificación de recursos energéticos que utilizan fuentes variables a largo plazo. En este artículo, se diseña, desarrolla, evalúa y valida el comportamiento de un modelo híbrido ANFIS+NN+ACO. Se detalla la metodología basada en el análisis de datos. En primer lugar, se trabaja con bases de datos climáticas, que proporcionan pautas para el preprocesamiento y la limpieza. En segundo lugar, se establecen las variables climáticas que predicen la radiación solar. Las funciones de pertenencia de ANFIS se basan en los datos para capturar la no linealidad y extraer relaciones con los predictores. Las redes neuronales respaldan el proceso de optimización de la función de pertenencia y, finalmente, el optimizador refina y evalúa la respuesta. Esta se evalúa mediante métricas que demuestran la robustez del modelo al capturar y procesar datos. El estudio contribuye a visibilizar herramientas y alternativas para determinar el potencial energético en regiones climáticas sujetas al futuro de la generación distribuida.**

Palabras clave— **ANFIS, Sistemas Difusos, Redes Neuronales, Algoritmos de Optimización, Predicción de la Radiación Solar**

I. INTRODUCTION.

Accurate solar radiation prediction is critical for managing and optimizing solar energy systems and is essential for sustainable development and reducing carbon emissions [1]. Solar radiation, which depends on various meteorological factors such as atmospheric pressure, clarity index, wind speed, and

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precipitation, is crucial in planning solar photovoltaic (PV) energy production [2].

Traditional forecasting methods, such as deterministic and statistical models, have shown limitations in handling the complexity and nonlinearity of weather data [3]. Climate nonlinearity, lack of complex data, and variable prediction horizons make traditional models increasingly challenging. In this context, artificial intelligence (AI) systems have emerged as powerful tools to improve the accuracy of solar radiation predictions [4]. Neural networks (NN), support vector machines (SVM), and Fuzzy Logic perform better when considering traditional techniques. However, new trends in research propose hybridization between AI algorithms and nature-inspired optimizers to address the issue of prediction with better results [5], [6].

Among the methods used, the Adaptive Neuro-Fuzzy Inference System (ANFIS) is a technique that integrates the advantages of artificial neural networks (ANNs) and fuzzy logic systems to model complex and nonlinear problems. ANFIS has been successfully used in various prediction and control applications due to its ability to learn from data and handle uncertainty [7], [8], [9]. However, the effectiveness of ANFIS is highly dependent on the proper selection of its input parameters and characteristics. Nature-inspired optimization algorithms, such as Ant Colony Optimization Algorithms (ACOs), offer a robust approach to finding optimal solutions in complex search spaces. ACO has been widely used in optimization problems because it can efficiently explore the search space and adapt to different scenarios. [10], [11]

In this study, we propose a hybrid approach that combines ANFIS with ACO for solar radiation prediction. This approach seeks to optimize the parameters and input characteristics of ANFIS using ACO to improve the accuracy of predictions. The meteorological data used in this study includes variables such as atmospheric pressure, clarity index, wind speed, and precipitation. Given the country's climatic variability, the model is applied to a city in Colombia. Section 2 shows a review of the literature and works related to the application of hybrid models for primary resource prediction. Section 3 presents the methodology for developing the model. Section 4 shows the application and results of the model and, finally, the conclusions. With this work, we aim to overcome the limitations of traditional methods and offer a more accurate and efficient tool for predicting solar radiation.

II. LITERATURE REVIEW

Optimization algorithms are widely used in primary resource quantification, prediction, and the energy industry [12]. The concepts of fuzzy logic and neural networks are combined in the adaptive neuro-fuzzy inference system (ANFIS), an artificial intelligence system [13]. Complex systems that behave nonlinearly and uncertainly may be modeled using ANFIS. Fuzzification, inference engines, and defuzzification are the three essential components of any fuzzy system [14]. The human expert in fuzzy systems obtains fuzzy rules. Fuzzy systems were enhanced with artificial neural networks to use learning algorithms to gather the knowledge of human experts. The neuro-fuzzy system is the name of this link (ANN to fuzzy system) [5].

Much research has been done to evaluate the ANFIS model concerning solar radiation. The work focused on applying the ANFIS model to identify the essential factors that may scatter solar energy. To analyze the impact of such predictions, as stated in Kerman City, the research relied on 10 essential factors. According to the study's results, the length of sunlight is crucial since it impacts how solar radiation diffuses. The mix of sunlight, horizontal global solar radiation, and extraterrestrial solar radiation are crucial factors. The subjects of similar research were the relevance of horizontal sun radiation and the location of interest in affecting thermal or photovoltaic systems. The research aimed to maximize the essential ANFIS model inputs, such as air temperature, month, day, relative humidity, longitude, latitude, and wind speed. The results provide evidence for the influence of global horizontal irradiance on solar radiation and the growth of such systems. Discuss the current state of research on diffuse irradiance and evaluate three reliable machine learning models using almost eight years of hourly observations from Almeria, Spain. The authors suggest that future machine learning models can benefit from advanced optimization techniques, such as evolutionary algorithms and nature-inspired optimization, which can fine-tune the models' parameters and improve their performance on a given dataset. The study compares different types of machine learning models and finds that hybrid models show promise in predicting diffuse fractions. The authors recommend further exploration of hybrid and ensemble models to address gaps in current research.[5], [14], [15], [16]

In work, hybrid models and a standalone adaptive neuro-fuzzy inference system have been created to estimate monthly global solar radiation from various meteorological indicators, such as sunlight duration and air temperature. The findings demonstrated that the hybrid models created had the most dependable and precise estimating capabilities and are thought to be the most effective way of forecasting global solar radiation for diverse purposes [17].

According to this, the SVM approach was used to apply the strategy for attaining the clearness index using the performance metrics for the ANFSI model. It was clear that the ANFSI model and the photovoltaic systems performed better because of the alien solar radiation. Considering this, it is reasonable to use this to estimate solar system radiation [7].

The study [5] discussed the model's importance in correctly forecasting solar diffuse fraction. Following a discussion of the status of diffuse irradiance research, three reliable machine learning (ML) models are tested against a large dataset (spanning over eight years) of hourly observations from Almeria, Spain. The ANFIS model, the multilayer perceptron (MLP), and the hybrid multilayer perceptron grey wolf optimizer (MLP-GWO) were all used in the research. The results showed that the ANFIS model performed better when calculating solar diffuse percentage and was effective.

The ANFIS [18], the adaptive system, and the standard solar radiation prediction model were contrasted. The goal was to comprehend the adaptive system's relevance as a precise and accurate model for calculating and forecasting solar radiation. This worked well since it demonstrated the value of the ANFIS model in increasing solar radiation efficiency.

Some more advanced empirical models can be used to forecast solar radiation. However, this work aims to evaluate the efficiency and dependability of the ANFIS model. It was simpler to connect the meteorological parameters with the present change in duration values for the sunlight and temperature using data from the Hunan province in China, situated in a subtropical monsoon climatic zone. Intriguingly, a model's alteration might affect how accurately a prediction is made; other researchers utilizing the ANFIS model are interested in implementing this [19].

The work uses air temperature to forecast solar radiation. Consistency in air temperature was crucial for solar energy gathering in the North Dakota experiment. The ANFIS model was crucial in establishing the ideal air temperature for optimizing solar energy harvesting worldwide, even though they could have chosen any number of models to analyze the performance accuracy of solar energy harvesting. The results showed that applying the ANFIS model increased the prediction accuracy when using the temperature alone to estimate solar radiation. As a result, it demonstrated its advantages and the necessity of applying it to North Dakota and other places with comparable climatic and meteorological characteristics. A novel intelligence model by fusing the Adaptive Neuro-Fuzzy Inference System (ANFIS) with two metaheuristic optimization algorithms, Salp Swarm Algorithm and Grasshopper Optimization Algorithm, to predict the global solar radiation at various locations in North Dakota, USA. The findings suggest the potential of boosting prediction accuracy by integrating ANFIS with metaheuristic optimization methods [20]. The work conducted a study to predict monthly solar radiation for semi-arid, dry, and wet regions. To estimate solar radiation, they utilized several models, including the multilayer perceptron, radial basis function neural network, and adaptive neuro-fuzzy interface system (ANFIS). The Grasshopper algorithm was utilized to improve the performance of the ANFIS, RBFNN, and MLP models. Three Iranian stations, namely Rasht (with a humid climate), Yazd (with a semi-arid climate), and Tehran (with a slightly arid environment), were used as case studies. The results revealed that relative humidity, wind speed, rainfall, and temperature were these locations' most influential input variables. The study's primary contribution is the development of innovative hybrid ANFIS models for forecasting monthly solar radiation in various locations [21].

To estimate the daily global solar radiation in Iraq using several metrological properties, the work developed multiple linear regression (MLR) and numerous other AI models, including ANFIS. According to the findings, the results provided by ANFIS are more accurate than those from other prediction models [22].

TABLE I.
REPRESENTATIVE WORKS IN THE USE OF OPTIMIZATION ALGORITHMS INSPIRED BY NATURE+ANFIS.

References	Case study	Input parameters	Output parameter	AI model	Optimization algorithm	Data scale	Research remark	Other if you find appropriately	Performance metrics
[23]	Kerman Iran	Daily diffuse solar radiation on a horizontal surface, global solar radiation on a horizontal surface, sun shine duration, minimum air temperature, maximum air temperature, average air temperature, relative humidity, and water vapor pressure, as well as the calculated values of daily maximum possible sunshine duration, solar declination angle and extraterrestrial solar radiation on a horizontal surface.	Horizontal diffuse solar radiation	ANFIS	-	Daily	The literature does not research the selection of the most crucial variables for predicting diffuse solar radiation well. This study (ANFIS) selects the essential elements impacting horizontal diffuse solar radiation using the adaptive neuro-fuzzy inference method.	The findings indicated that considering the most relevant combinations of two or three ideal inputs offers a compromise between ease of use and high accuracy.	MAPE, MABE, RMSE and R,
[24]	Iran	Global solar radiation in terms of month, day, average air temperature, maximum air temperature, minimum air temperature, air pressure, relative humidity, wind speed, top-of-atmosphere insolation, latitude and longitude	predict the daily global solar radiation	(GMDH) type neural network (MLFFNN) ANFIS	ANFIS-PSO ANFIS-GA ANFIS-ACO	Daily	The findings showed that the GMDH model beats the other produced models even though all studied models can accurately estimate the global horizontal irradiance.	This research has been done to evaluate and compare the accuracy of six artificial intelligence systems since it is crucial to comprehend the availability of solar Energy and the lack of monitoring stations in particular regions.	RMSE, MSE, R2,
[25]	Malaysia	Global solar radiation, including s sunshine duration S (h), and air temperature	Monthly Global Solar Radiation	ANFIS	ANFIS- PSO, ANFIS-GA and ANFIS-DE	Monthly	The importance of this study stems from the need for more precise measurements of solar radiation that may be employed in various applications across a range of sectors, in addition to the measured meteorological parameters that are now accessible.	The results show how effectively ANFIS predicts the level of solar radiation globally and how well it may be used with other soft computing methods.	Clearness index
[26]	Yucatan Peninsula, Mexico	measured meteorological variables: minimum and	predicting daily horizontal	-	ANFIS, SVM, and ANN	Daily	The evaluation shows that the SVM technique performs better than the other techniques. This suggests that the SVM	According to the study's findings, using SVM improves the precision of forecasting global solar radiation in tropical	RMSE, MAE, and R2

		maximum air temperatures, rainfall, and global solar radiation	global solar radiation				technique may offer a promising alternative to the conventional methods for predicting solar radiation.	warm and humid regions such as Mexico's Yucatán, particularly when rainfall is factored into the equation.	
[27]	Almeria, Spain	Global Irradiance, Beam Irradiance, Sunshine Duration Index, (Global/Extraterrestrial-Clearance Index), (Diuse/Extraterrestrial)	Solar (Global/Diuse-Diuse Fraction) (DF)	ANFIS, MLP,	MLP-GWO	Hourly	The results demonstrated that the MLP-GWO model performed better in the training and testing processes, followed by the ANFIS model.	Subsequent investigations ought to employ more advanced hybrid machine-learning techniques. Through hybridization, machine learning models have become more effective and precise. As a result, upcoming models could significantly benefit from tailored evolutionary algorithms and nature-inspired optimization methods to enhance their parameters and scrutinize their algorithmic influence on the quality control of a particular dataset.	MAE, ME, and RMSE
[28]	10 different cities worldwide	Latitude, longitude, minimum and maximum temperatures (°C), relative humidity (%), wind speed (m/s), surface pressure (kPa), amount of air pollutants (O3, NO2, PM2.5, PM10), dew frost point, wet bulb temperature (°C) and mean solar radiation (MJ/m2 /day) on a horizontal surface	Mean monthly global solar radiation	ANN and ANFIS	GA-ANN	Daily	Based on the number of statistical indices specified in this study, the offered model is roughly more formidable in accuracy and credibility than other models created by other researchers.	It may also be expensive or impossible to objectively measure global solar radiation in certain locations since it requires specific equipment. The authors consequently recommend replacing the empirical approach with artificial intelligence to anticipate mean monthly global solar radiation while accounting for input factors in light of the modeling results, particularly the ANFIS method.	RSME= 5.90E−05 , R2 = 0.999, ASM = 5.50E−04, EBM = 0.425
[29]	China	Daily sunshine duration (S), relative humidity (RH), precipitation (Pre), air pressure (AP), daily mean/maximum/minimum temperature (DT/Tmax/Tmin)	Daily global solar irradiance (Hg)	ANFIS, E-IBCM, IYHM		Daily	The findings show that the enhanced empirical models (E-IBCM and IYHM) are more accurate than the original models and that the ANFIS model is more accurate in predicting Hg than the E-IBCM and IYHM models.	The ANFIS model offers the highest accuracy in calculating daily global solar irradiance in China compared to the other E-IBCM and IYHM models. Our future work will enhance the ANFIS model with additional methodologies and combine more diverse input factors to increase modeling accuracy.	RMSE and MAE
[30]	North Dakota, USA	maximum, mean, and minimum air temperature	Solar radiation	ANFIS	ANFIS-SSA, ANFIS-GOA	Daily	The most intriguing finding is that almost every prior SR prediction model was created	It can be claimed that the performance of the hybridized ANFIS-muSG model proved	RMSE. At Baker, Beach, Cando, Crary, and Fingal

					(ANFIS-muSG)		using a variety of parameters. However, the model suggested in this research was built using temperature, and it performed well with an R2 in the range of 0.769 to 0.802.	the muSG algorithm's usefulness for enhancing ANFIS parameters when just one predictor (in this instance, air temperature) is used. This demonstrates the possibility of the proposed method being extensively used for accurate SR prediction.	stations, respectively, the ANFIS-muSG demonstrated a prediction boost compared to the conventional ANFIS model by 42.2%, 32.6, 54.8%, 25.7%, and 49.0% in terms of RMSE.
[31]	Three stations in Iran, namely Rasht (humid climate), Yazd (semi-arid) and Tehran (slightly arid),	relative humidity, wind speed, rainfall, and temperature	monthly solar radiation	ANFIS, RBFNN, MLP	GOA, PSO, SSA	Monthly	The primary contribution of the research is the development of novel hybrid ANFIS models for monthly solar radiation forecasting in various regions.	Future researchers may simultaneously choose the best input combinations and seek the optimal model parameter values using multi-objective optimization methods. Furthermore, prediction models, climatic scenarios, and climate models may be used to forecast solar estimates for the future. Utilizing solar Energy for electricity generation in the future may assist decision-makers.	mean absolute error (MAE), RMSE, NSE, P BIAS
[32]	Iranian city of Tabass	by day of the year (day) as the only input	Estimating the horizontal global solar radiation	an intelligent optimization scheme based upon the adaptive neuro-fuzzy inference system (ANFIS)		Daily	The survey's findings strongly supported using ANFIS to calculate daily worldwide horizontal sun radiation using just n_{day}.	There are two benefits to basing global solar radiation predictions on the day of the year. First, there is no reliance on any input component, such as weather information. Additionally, no pre-calculation analysis is required.	Bias error (BE) ranges from –3 to 3 MJ/m2, mean absolute percentage error (MAPE) = 3.9569%, mean absolute bias error (MABE) = 0.6911 MJ/m2, root mean square error = 0.8917 MJ/m2 (RMSE), and correlation coefficient (R) = 0.9908.
[33]	Iraq	daily meteorological data of maximum temperature, minimum temperature, mean temperature, relative humidity, and wind speed	Daily Global Solar Radiation	Artificial Neural Network, adaptive neuro-fuzzy inference		Daily	The study's findings confirmed that the ensemble techniques may improve the performance of single models in the training, validation, and testing processes by up to 19.19%, 7.59%, and 16.81%, respectively.	It might be proposed that additional AI-based models, like SVM, must be used in future research and that their outputs be incorporated in ensemble modeling in light of the study's findings,	Determination coefficient (DC or Nash–Sutcliffe efficiency criterion) and root mean square error (RMSE)

				systems, Meza–Varas, Hargreaves–Samani, and Chen, multi-linear regression (MLR) model				demonstrating that more diverse inputs for ensemble modeling can result in better overall outcomes.	

A. SURVEY ASSESSMENT

According to research by and, the adaptive neuro-fuzzy inference system (ANFIS) model is crucial for accurately forecasting solar radiation. There has always been interest in employing renewable energy to solve the issues of resource depletion and the need for renewable energies [34]. The ANFIS model demonstrates that solar radiation may be forecasted accurately utilizing a variety of factors and suggested performance criteria, including the correlation coefficient, root mean square error, mean absolute percentage error and mean absolute bias error. These are all crucial in evaluating the accuracy of solar radiation and the steps to minimize any inaccuracies that could occur [20]

The results are compared with earlier research conducted in several places throughout the globe to offer a fair evaluation of the chosen ANFIS-muSG model in solar radiation prediction. In this respect, a fair evaluation is carried out to confirm the efficacy of the chosen model in forecasting solar radiation. Notably, in contrast to other research in the literature, the suggested ANFIS-muSG model study attained the desired accuracy. The most intriguing finding is that almost every prior model for predicting solar radiation was built using a variety of inputs. However, the model suggested that the research was building temperature and performed well with an R[20]^2 between 0.769 and 0.802.

One of the most effective modeling methods for AI models is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines ANN and FL methodologies. According to many studies, ANFIS is more accurate in estimating solar radiation.[3]

For instance, a station in Kuala Terengganu, Malaysia, employed a conventional and hybrid ANFIS model to forecast monthly global solar radiation using several metrological characteristics, such as maximum and lowest air temperature, rainfall, clearness index, and sunlight duration. This model integrated ANFIS with genetic algorithms, particle swarm optimization, and differential evolution methods. Results indicate that the hybrid ANFIS-PSA model predicts solar radiation better than the other models. According to the findings, the results provided by ANFIS are more accurate than those from other prediction models.[17]

Due to its capacity to capture the uncertainty associated with time series data, a comparison of several AI models for solar radiation prediction found that ANFIS is best for solar radiation modeling. However, tuning ANFIS hyperparameters, such as optimizing membership function parameters, is the main issue with this approach. As a result, in earlier research, the classic ANFIS model was hybridized with other optimization techniques to enhance its performance. Although the performance of the current hybrid ANFIS model is promising, it is still necessary to improve the prediction capabilities, given the significance of the precision required in solar radiation measurement. In addition, one of the main drawbacks of current solar radiation prediction models is the need for various input variables that are not always accessible in certain places owing to a lack of monitoring infrastructure.[35]

III. METHODOLOGY OF THE MODEL.

A. DATA TO USE IN THE MODEL.

Various databases and variables are used in resource quantification-prediction in solar primary resource models. According to [36], databases should have features such as:

- Geographical location
- Prediction Horizon
- Co-dependent variables of solar radiation.
- Geographical mesh.

Detailed meteorological data was used to develop and validate the hybrid ANFIS model optimized with ACO, covering multiple variables that directly influence solar radiation. This dataset includes daily atmospheric pressure measurements, clarity index, wind speed, and precipitation collected from reliable weather stations in strategically selected locations.

Atmospheric pressure is a crucial variable that affects air density and, consequently, the amount of solar radiation that passes through the atmosphere. Variations in atmospheric pressure can influence the scattering and absorption of solar radiation. The clarity index is a dimensionless measure representing the fraction of diffuse global solar radiation. This index is critical for understanding the ratio of direct to diffuse radiation, which is essential for modeling the availability of solar Energy under different atmospheric conditions. Wind speed, measured in meters per second (m/s), can affect the scattering of clouds and aerosols in the atmosphere, altering the amount of solar radiation that reaches the Earth's surface. In addition, strong wind conditions are often associated with weather systems that can reduce direct solar radiation. Precipitation, measured in millimeters (mm), indicates the presence of clouds and storm systems that block solar radiation. Periods of high precipitation generally correspond to conditions of low solar radiation due to dense cloud cover.[37]

The data used in this study were obtained from weather stations such as those provided by NASA POWER DAVE V2.0.5 weather services. According to technical documentation, each station provides highly accurate data updated and maintained to rigorous quality standards. Before using the data in the model, a preprocessing process was carried out to ensure its quality and consistency. This process included the elimination of outliers, identifying and eliminating values significantly outside the normal ranges, and using statistical techniques such as percentile analysis and standard deviation. Missing data were imputed using advanced methods such as interpolation, minimizing bias and loss of information. All variables were normalized to a standard scale to ensure that machine learning algorithms can effectively handle differences in variable scales. The typology to develop the model is shown below [38].

B. TYPOLOGY TO BE USED IN THE HYBRID MODEL

The model typology used in this study combines an Adaptive Neuro-Fuzzy Inference System (ANFIS) with Neural Networks (NN) and an Ant Colony Algorithm (ACO) [19], [39]. This combination is chosen due to ANFIS's ability to model complex nonlinear systems, NN's effectiveness in finding optimal solutions in large and complex search spaces, and ACO's robustness in parameter optimization.

ANFIS is a hybrid model that integrates the advantages of neural networks and fuzzy logic systems. Its structure is based on a network of five layers, each of which plays a crucial role in the inference process [39]

1. **Input Layer:** Receives inputs from the system (in this case, weather variables such as pressure, clarity index, wind speed, and precipitation).

2. Fuzzification Layer: Transform inputs into fuzzy values using membership features.

3. Rules Layer: Applies the fuzzy rules that represent the expert knowledge of the system.

4. Normalization Layer: Normalizes the fuzzy values resulting from the rules.

5. Output Layer: Generates the system's output using a set of inference functions.

ANFIS is trained using a supervised learning process that adjusts the parameters of membership functions and fuzzy rules using optimization algorithms. This allows it to capture the nonlinear relationships between input and output variables [7].

The neural network (NN) is a computational model inspired by the workings of the human brain. This algorithm can learn complex patterns from data by optimizing their weights and biases through backpropagation processes [40], [41]. The NN optimizes the parameters of the ANFIS model and selects the most relevant features from the dataset. The NN process includes the following steps:

1. Initialization: It starts with a defined neural network structure and establishes random initial weights.

2. Forward propagation: The input data is propagated through the network, calculating activations at each layer until it reaches the output.

3. Error calculation: The error between the output predicted by the network and the actual values is calculated using a loss function, such as mean square error (MSE).

4. Backpropagation: The error propagates backward through the network, adjusting weights and biases to minimize the error.

5. Optimization: The iterative process continues until a stopping criterion is reached, such as a maximum number of iterations or a convergence in error reduction.

The Ant Colony Algorithm (ACO) is an optimization algorithm inspired by the behavior of ants in foraging. This algorithm is characterized by its ability to find optimal graph paths using pheromones, which are chemical substances that ants deposit to mark effective routes. ACO is used to optimize the parameters of the ANFIS model and select the most relevant features from the dataset [42]. The implementation of the ANFIS+NN+ACO hybrid model follows the following steps:

1. Data Preprocessing: Weather data is preprocessed to remove outliers, impute missing data, and normalize variables.

2. Initial ANFIS Training: An initial ANFIS model is trained using the full features of the dataset.

3. Optimization with NN: NN is used to adjust ANFIS parameters and select the most relevant features, iteratively improving the model's accuracy.

4. Optimization with ACO: ACO is used to fine-tune the parameters of the NN-optimized model and select the most relevant features, iteratively further improving the model's accuracy.

5. Model Evaluation: The optimized model is evaluated using a validation set to measure its performance in terms of mean square error (MSE) and other relevant metrics [39].

This typology combines the learning and adaptability of ANFIS with the robustness of NN and ACO in parameter optimization, providing a powerful and efficient approach to solar radiation prediction. The integration of these techniques makes it possible to capture the inherent complexity of weather data and significantly improve the accuracy of predictions. Below is the application in a particular region and the model results.

IV. APPLICATION AND RESULTS OF THE MODEL

A. DATA USED IN THE MODEL.

The data used in this study contains meteorological data relevant to the prediction of solar radiation from 1-01-2020 to 20-07-2024. The city chosen is Pasto, located in southwestern Colombia (Latitude 1°12'52.48"N ·Longitude 77°16'41.22" W). This dataset includes six key variables, as shown in Table 2

.

TABLE II. PHYSICAL VARIABLES USED IN THE DATABASE- SOURCES: AUTHORS.

Variable Name	**Physical Variable**	**Units**	**Min Value**	**Max Value**	**Variable Type**
PS	Atmospheric pressure	kPa	0.0016	101.40	
WS10M	Wind speed at 10 meters	M/s	0.00	12.20	
T2M	Temperature at 2 meters	°C	-16.60	41.60	Predictor
QV2M	Humidity at 2 meters	g/kg	0.0027	24.20	
RIGHT CORR	Corrected precipitation	mm/hour	0.00	63.70	
CLRSKY_SFC_SW_DWN	Surface radiation	Wh/m^2	0.00	1268.57	Target Variable

The preliminary analysis of the predictors shows that the data are in good condition. The distributions of the variables indicate variability and diversity in the meteorological conditions captured. As shown in Figure 1, the variables do not have anomalous data and high variability is not shown in a few periods, which influences the quality of the model results. The climate predictors that act as input to the model

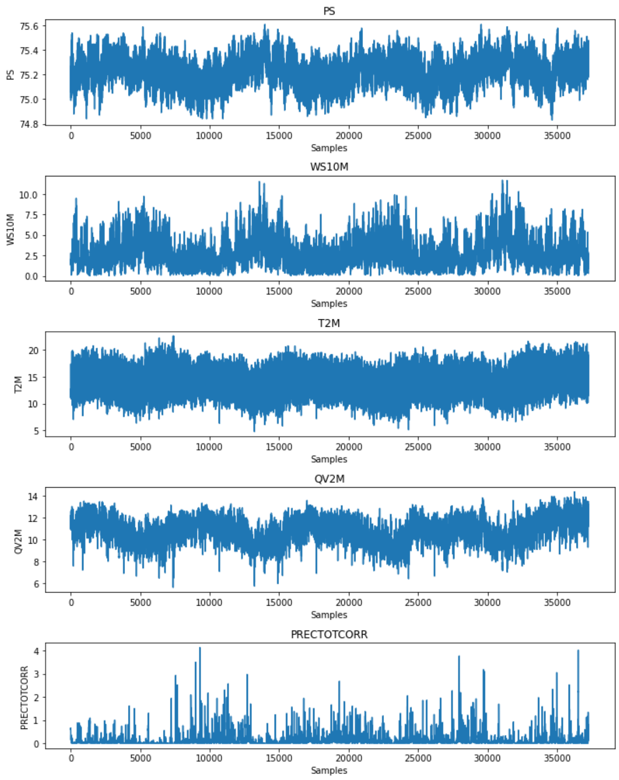

Fig 1. Predictors used in the ANFIS+NN+ACO model. Source: Authors

Figure 2 shows solar radiation in Pasto, the primary resource in the region, which shows high variability. The region's high variability suggests the presence of cloudiness patterns over time and fluctuations in the clarity of the sky, an essential variable in solar PV power generation planning. In addition, seasonal patterns must be captured and predicted by the model.

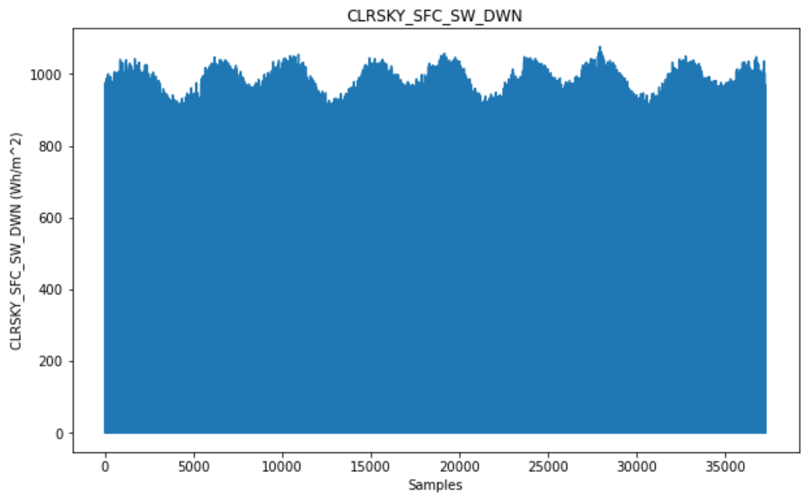

Fig 2. Solar radiation of the particular region in the period. Source: Authors.

B. APPLICATION OF THE MODEL

Figure 3 shows the model's design. The preprocessing and data cleansing stages are responsible for looking for anomalous data or null values that the dataset may have to have continuous inputs to the model. Subsequently, the dataset is normalized to have the predictor variables in the same range. Finally, the dataset is mixed so that the model can capture nonlinearity without redundancy.

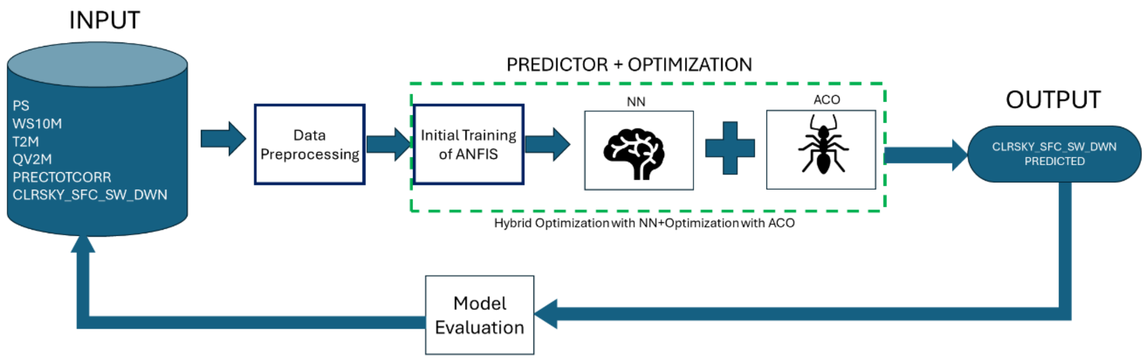

Fig 3. ANFIS+NN+ACO Predictor Model Schema. Own source.

The prediction stage consists of the **ANFIS predictor** first. In its initial training stage, Gaussian membership functions are defined to model the input variables. The inputs are then transformed into fuzzy values using the built-in Fuzzification engine. Then, by applying rules based on fuzzy logic, relationships are established between the input and output variables. Finally, the output of this predictor is the initial training with parameter adjustment of memory functions and fuzzy rules employing a supervised learning algorithm. From a mathematical point of view, ANFIS takes each input variable. $x_i(i = 1,2,3,\dots,n)$ defines the fuzzy membership functions, where being Gaussian, we have as in Equation (1):

$$\mu A_j(x_i) = exp\left(-\frac{(x_i - c_j)^2}{2\sigma_j^2}\right) \quad (1)$$

Where $\mu A_j(x_i)$, is the degree of membership of the function of membership, is the center of the function, and is the standard deviation.$x_i A_j c_j \sigma_j$

For each Fuzzy rule R_j

$$R_j\colon if\ x_1\ is\ A_{1j}\ and\ x_2\ is\ A_{2j}\ and\ \dots and\ x_n\ is\ A_{nj}, then\ y_j = a_j x_1 + b_j x_2 + \cdots + z_j x_n$$

The weight of the ruler is calculated as shown in Equation 2:

$$w_j = \prod_{i=1}^{n} \mu A_j(x_i) \quad (2)$$

Finally, the output of the ANFIS model, defuzzification, is calculated as shown in Equation 3:

$$y = \frac{\sum_{j=1}^{m} w_j y_j}{\sum_{j=1}^{m} w_j} \quad (3)$$

Where m, is the number of rules.

The **neural network and ACO** stages optimize the response of the ANFIS model. With forward typology and hidden layer, the neural network compares the predicted output of ANFIS with the actual values, employing a loss function that adjusts the weights and biases of the network to minimize error. The process is repeated until a stopping criterion is reached, which is the convergence in reducing error for this study. Layers of neurons represent the optimization neural network. For a layered network, the output of the layer is shown in Equation 4:

$$a^l = f(W^l a^{l-1}) + b^l \quad (4)$$

Where

$a^0 = X$ Network Input
W These are the weights and biases of the layer b^l l
f is the activation function, in this case, sigmoid

The training process adjusts weights and biases to minimize the loss function J, as indicated by Equation 5:

$$J(\theta) = \left(\frac{1}{m}\right) \sum_{i=1}^{m} (h_\theta(x^i) - y^i)^2 \quad (5)$$

The ants in ACO build a solution by moving through the graph and choosing paths based on the probability determined by the number of pheromones and the local heuristic. The pheromones are updated according to the quality of the solutions found by the ants, reinforcing the paths that lead to better solutions. The integration of ACOs for feature selection optimizes the model's parameters, and finally, in the results stage, the performance against standardized metrics is evaluated.

It starts with a population of ants and establishes an initial level of pheromones in the paths of the graph. Each solution is built by moving across the graph and choosing probability-based paths, as shown in Equation 6, which are determined by the number of pheromones and the local heuristic. $\tau_{ij}\eta_{ij}$.

$$P_{ij} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{k\, callowed} \tau_{ij}^{\alpha}\eta_{ij}^{\beta}} \quad (6)$$

where are parameters that control the influence of pheromone and heuristics, respectively α, β

The pheromones are updated according to the quality of the solutions found by the ants, reinforcing the pathways that lead to better solutions, as shown in Equation 7:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{ant\ k} \Delta\tau_{ij}^{k} \quad (7)$$

Where is the rate of pheromone evaporation, and is the amount of pheromone deposited by the ant.$\rho\Delta\tau_{ij}^{k}k$

The results are then described, and the model is validated.

C. RESULTS AND VALIDATION OF THE MODEL

Figure 4 shows the results of the primary resource prediction. The ANFIS +NN+ACO model performs well. The membership functions implemented in the model, of Gaussian type, can consolidate a solid base of prediction based on fuzzification processes. In addition, the linguistic rules used cover all the spectra found in the cleaning and characterization part of the dataset. The configuration of 64 input layer neural networks and 48 hidden layer neural networks can take resource variations and predictors. By implementing optimization functions represented in Nested and Loss ACOs, the model can capture and respond to the nonlinearity of climate resources.

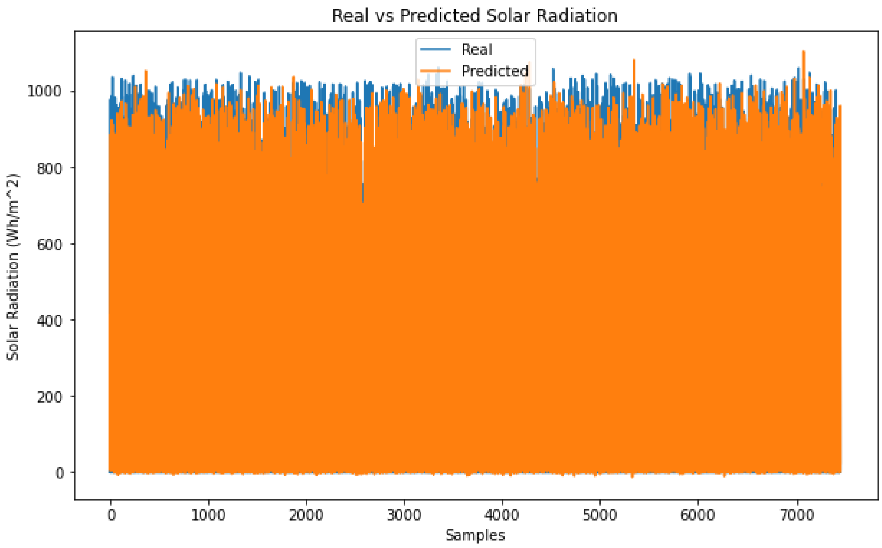

Fig 4. Measured solar radiation vs. predicted solar radiation. Source: Authors

Figure 5 shows the evolution of the data during the model's training and validation stages over 200 epochs. The portion of data used to train-validate the model has a ratio of 70-30. The curves in the graph decrease rapidly at first and then stabilize, suggesting that the model is learning effectively and shows no signs of significant overfitting. The generalization of the model represented by the loss of validation, which is slightly more significant than the training loss, suggests that the model is robust.

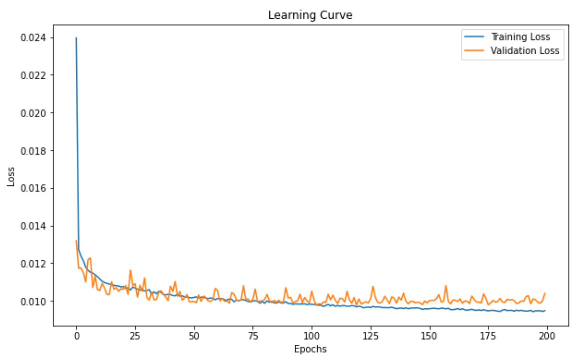

Fig 5. Learning curve of the ANFIS +NN+ACO model. Source: Authors.

Regarding the metrics analysis, shown in Table 3, the MSE (Mean Square Error) indicates that the mean square error between the predicted and actual values is low, suggesting strengths in the model's performance. The RMSE (Root Mean Square Error) makes interpreting the error in the units more accessible. The MAE (Mean Absolute Error) shows that, on average, the model's predictions are 3.07 units away from the actual solar radiation values, which is a relatively low error. Finally, the correlation coefficient indicates that the model explains approximately 91% of the variability of solar radiation data. The metric results are pretty explicit in determining that the model has strengths and can capture the high nonlinearity of the region's data.$Wh/m^2 R^2$

TABLE III. MODEL PERFORMANCE EVALUATION METRICS. FUETNE AUTORES.

Metric	**Value**
MSE	12.818108
RMSE	3.5023
R^2	0.912214

V. FUTURE RESEARCH.

Future researchers may simultaneously choose the best input combinations and seek the optimal model parameter values using multi-objective optimization methods. Furthermore, prediction models, climatic scenarios, and climate models may be used to forecast solar estimates for the future. Utilizing solar Energy for electricity generation in the future may assist decision-makers.

To estimate global sun radiation at various places in North Dakota, USA, Tao et al. (2021) suggested a unique intelligence model by fusing two metaheuristic optimization algorithms with the Adaptive Neuro-Fuzzy Inference System (ANFIS). The study's findings showed that by properly optimizing ANFIS parameters, solar radiation forecast capacity may be increased. The models used in this work can only estimate solar radiation from readily accessible temperatures (maximum, mean, and lowest) in any place. Such less resource-intensive models are crucial for underdeveloped nations with limited access to meteorological information besides rainfall and temperature. The ANFIS-muSG model created in the Tao et al. (2021) research may thus be used for energy harvesting and monitoring in various geographical areas. However, future research may assess how well the model performs when additional meteorological factors include wind speed, cloud cover, sunlight, humidity, and rainfall (Tao et al., 2021).

Additionally, data from satellite remote sensing may be used as an input to enhance model performance in solar radiation forecasting. Using an ensemble strategy, the performance of the hybridized ANFIS-muSG model might be significantly enhanced. In addition, additional cutting-edge optimization methods like quantum-behaved PSO and the Firefly Algorithm may be used to choose input predictors that have been proven successful in model input selection. Empirical mode composition and wavelet transform could also be additional data analysis methods.

VI. CONCLUSIONS

This work presented the design and development of an ANFIS+NN+ACO model. The latter is representative of nature and is an inspiration in data-driven model optimizers. The model is robust in predicting primary solar resources in a particular region. ANFIS settings can be managed so that different strategies are considered in membership functions that can provide greater modeling capacity for nonlinear data. Parameter optimization using ACO is a process of trial and error to determine the best combination(s) for the totalized model. Finally, hybridizing ANFIS with other models, such as neural networks (NN), can leverage the strengths of both approaches, where ANFIS handles uncertainty and fuzzy logic, and NN captures the complex nonlinear relationships, thus achieving greater accuracy in predictions. However, several limitations must be acknowledged. First, the model relies on the availability and quality of meteorological data, which may be limited in some regions. Second, although the model was trained and tested using data from a specific geographic area (Pasto, Colombia), its generalization capability to other climatic zones remains to be validated. Third, the computational cost of hybrid models that include metaheuristic optimization can be relatively high, especially for large datasets or longer prediction horizons. Finally, the current model does not incorporate satellite-based inputs or multi-objective optimization, which could further enhance its accuracy and adaptability.

Despite these limitations, the hybrid ANFIS+NN+ACO model provides a strong framework for evaluating solar energy potential and supporting the planning of distributed generation systems. Future work should address these constraints by incorporating diverse geographic datasets, reducing computational load, and integrating additional optimization strategies to improve generalizability and scalability.

Models of this nature are essential inputs to quantify the solar potentials of regions subject to distributed generation installation with variable primary resources.

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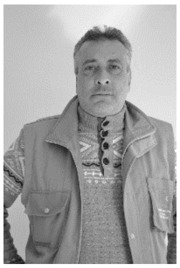

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