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Comparative study of the prediction of electrical energy from a photovoltaic system using the intelligent systems ANFIS and ANFIS-GA

Estudio comparativo de la predicción de energía eléctrica de un sistema fotovoltaico utilizando los sistemas inteligentes ANFIS y ANFIS-GA

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Abstract

To predict the electrical energy generation behavior in a photovoltaic system, we developed an adaptive neuro-fuzzy inference system (ANFIS) model which integrates an optimization through a genetic algorithm (GA). The evolutionary ANFIS-GA uses a geographical area's solar radiation and ambient temperature. This model uses the capacity to classify and identify data patterns of neural networks, and through fuzzy modeling, it calculates the optimal membership functions and fuzzy rules. The ANFIS-GA model is developed using MATLAB® software and is trained with the acquired data weather station and the electrical power output of the photovoltaic system located in Hermosillo, Sonora, México. The above was compared under the same parameters with an ANFIS model based on a hybrid algorithm. Reach values of RSME of 259.41, MAE of 132.7, MAPE of 4.56 for the ANFIS-GA model; RSME of 295.26, MAE of 149.58, and MAPE of 6.98 for the ANFIS model, respectively. The results indicate that the ANFIS-GA model emulates the power output with better precision, thus providing a valuable planning tool to predict photovoltaic system behavior.
Keywords: Photovoltaic systems; Solar power generation; Statistical methods; Genetic algorithms; ANFIS.

Resumen

Para predecir el comportamiento de generación de energía eléctrica en un sistema fotovoltaico, desarrollamos un modelo basado en un sistema de inferencia neuro-difuso adaptativo (ANFIS) que integra una optimización a través de un algoritmo genético (GA). El ANFIS-GA evolutivo utiliza la radiación solar y la temperatura ambiente de un área geográfica. Este modelo utiliza la capacidad de clasificación e identificación de patrones de datos de las redes neuronales y, a través del modelado difuso, calcula las funciones de pertenencia y las reglas difusas óptimas. El modelo ANFIS-GA se desarrolla utilizando el software MATLAB® y se entrena con los datos adquiridos de la estación meteorológica y la potencia eléctrica de salida del sistema fotovoltaico ubicado en Hermosillo, Sonora, México. Lo anterior se comparó bajo los mismos parámetros con un modelo ANFIS basado en un algoritmo híbrido. Alcanzando valores de RSME de 259,41, MAE de 132,7, MAPE de 4,56 para el modelo ANFIS-GA; RSME de 295,26, MAE de 149,58 y MAPE de 6,98 para el modelo ANFIS, respectivamente. Los resultados indican que el modelo ANFIS-GA emula la potencia de salida con mayor precisión, proporcionando así una valiosa herramienta de planificación para predecir el comportamiento del sistema fotovoltaico.
Palabras clave: Sistemas fotovoltaicos; Generación de energía solar; Métodos de estadística; Algoritmos genéticos; ANFIS.

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1 Introduction

Due to the fast growth of the application of photovoltaic energy, the operational performance of solar photovoltaic energy has turned out to be an essential issue of research. Particular areas such as the optimization of parameters of photovoltaic systems, the development of new technologies in photovoltaic cells and performance analysis, and the development of new techniques to predict the power output in actual weather conditions have been critical in the continuous improvement of the efficiency of the systems (Wang *et al*., 2021; Matsumoto *et al*., 2019; Ferrero- Bermejo *et al*., 2019; Ma *et al*., 2014). Research has shown the use of predictive tools through the development of intelligent systems such as learning machines (Xia *et al*., 2017), artificial neural networks (Di-Piazza *et al*., 2021; Rico-Contreras *et al*., 2014), and fuzzy logic (Yazdanbaksh *et al*., 2013; Virgen-Navarro *et al*., 2016). Also, hybrid systems, such as the adaptive neuro-fuzzy inference system (ANFIS) (dos- Santos *et al*., 2021), can provide a close prediction of the behavior of systems during their operation (Mellit and Kalogirou, 2008; Zor *et al*., 2017).

Several studies have reported data prediction relevant to different areas, such as meteorology, energy, industrial processes, communication, control, and pattern recognition (Brusamarello *et al*., 2020; Armaghani and Asteris, 2021; Gómez-Vargas *et al*., 2010; Figueroa-Garcia *et al*., 2021; Talebjedi *et al*., 2020; Ruz-Hernandez *et al*., 2019; Chalapathy *et al*., 2021). Tao *et al*. (2021) presented a novel model based on ANFIS to predict global solar radiation from the atmospheric temperature in different locations. An essential improvement in the efficiency of the ANFIS model was obtained by optimizing its internal parameters reaching results with R^2 between 0.769 and 0.802. Alamoudi *et al*. (2021) used an ANFIS system to analyze the performance of photovoltaic solar panels installed in a university hospital. They found the best working conditions and defined the self-expenditure rates and performance of the PV system. Pitalúa-Díaz *et al*. (2019) compared two deterministic models and ANFIS. The predicted electric power values from a photovoltaic system were compared with experimental data. The intelligent algorithm had lower deviation values computed with MAE and MAPE.

Aldair *et al*. (2018) developed an ANFIS-based controller for following an autonomous photovoltaic system. The conclusions disclose that the ANFIS model has a better active answer than the incremental conductance and constant voltage procedures. Bendary *et al*. (2021) developed an ANFIS system to search, monitor, and eliminate faults in photovoltaic modules. The environmental changes were considered. The simulation of the process improved the effectiveness of photovoltaics afterward the optimization process. Bilgili *et al*. (2021) applied ANFIS with Fuzzy-c-means and ANFIS with a Long Short-Term Memory neural network. The comparison was made of 4 types of renewable technologies. The results were evaluated, comparing them with the actual values and statistical evaluation criteria.

ANFIS models use an intelligent neuro-fuzzy approach to model and control uncertain and unspecified systems (Jang, 1993). This model is applied to various fields as a system that combines artificial neural networks with learning capacity and fuzzy reasoning, like the ability of human thought (Jang *et al*., 1997). Firstly, the input and output values of the systems are analyzed and determined. Later, the fuzzy sets are created for the input variables, and the fuzzy rules are determined to develop and train the neural network that will constitute the predictive system (Stojčić *et al*., 2019). However, in certain situations, it is hard to delimit the set of fuzzy rules that show the information of a domain (Sugeno and Kang, 1998). In most cases, ANFIS uses gradient search techniques, resulting in difficulty in accurately defining and classifying the inputs that contribute to the prediction. Therefore, it is possible to automatically use an evolutionary computational system to generate fuzzy knowledge bases (Tien-Bui *et al*., 2018).

In recent years, there has been a growing interest in computational evolution, which has led to the development of many optimization algorithms (Sexton *et al*., 2011; Fernandez *et al*., 2019; Penghui *et al*., 2020; Kar *et al*., 2020; García-Muñoz *et al*., 2021). They can complete the prediction of systems by improving the speed of convergence and reducing the possibility of being trapped in local minima (Seifi *et al*., 2020). Orove *et al*. (2015) designed a computer code to predict the failure rate of students using an evolutionary algorithm. It was validated by feeding a test data set to evolved genetic programming models. The results showed a fast convergence and an excellent predictive capacity. Haznedar and Kalinli (2016) presented a study about the optimization of the premise and consequent parameters of ANFIS using a Genetic Algorithm (GA), which applied to the nonlinear dynamic system identification problem and was compared with a BP algorithm. They determined that optimizing GA is more successful. Khosravi *et al*. (2020) developed a model based on ANFIS adjusted with a genetic algorithm and an adjusting algorithm to support teaching-learning to determine the optimal design parameters of a system solar power tower (SPTS) with a thermal energy storage system. Vafaei *et al*. (2015) presented a study for modeling and controlling a photovoltaic system using ANFIS and a genetic algorithm. The results signify that the ANFIS-GA can match the load need with less uncertainty about the maximum point capacity. Arara *et al*. (2020) conducted an analysis that included the comparison of advanced learning algorithms. They evaluated the ANFIS model and three metaheuristic models. Eleven evaluation metrics were used to assess the models, showing that ANFIS-GA obtained better results than the other three models.

The literature survey indicates the absence of investigations on predicting the energy production of a photovoltaic system using neuronal networks and fuzzy systems coupled with a genetic algorithm. Therefore, this study aims to present the design and modeling of an intelligent ANFIS-GA system for predicting electrical energy generation from a photovoltaic system located in Hermosillo, Sonora, Mexico. To evaluate and process meteorological and electrical data and create the predictive model of the photovoltaic system performance, we have analyzed approximately 26,000 variable records. An ANFIS hybrid system optimized was developed using a genetic algorithm capable of processing information, learning, and convergence. The results are compared with an intelligent hybrid ANFIS system trained and tested under the same parameters (Cerecedo *et al*., 2021). The comparison has been made using rigorous statistical metrics. The ANFIS-GA system reached an RSME of 259.41, MAE of 132.7, and MAPE of 4.56, meaning a relative improvement against the ANFIS hybrid system that obtained an RSME of 295.26, MAE of 149.58, and MAPE of 6.98 under the same parameters. Additionally, when comparing one month, the MAPE values obtained were 4.78 for ANFIS-GA and 6.56 for ANFIS, respectively, determining that ANFIS-GA produces more accurate prediction results.

2 Materials and methods

The study photovoltaic system is located at the University of Sonora in Hermosillo, Sonora, Mexico. The system comprises rack-Mounted ten polycrystalline panels of the Phono Solar brand, model PS310P-24T, installed with an inclination of 25° concerning the horizontal. Each panel is made up of 60 cells with a combined capacity of 310 W and an efficiency of 15.98%. A pyranometer LI-COR LI-200 records solar irradiance. It features a silicon photovoltaic detector mounted in a fully cosine-corrected miniature head. It was calibrated against an Eppley Precision Spectral Pyranometer (PSP) under natural daylight conditions. The typical error under these conditions was ± 5%. It is installed at the same angle as the system. The ambient temperature was collected with a weather station model WIRELESS VANTAGE PRO2 installed on-site. The temperature sensor is mounted on a passive or fan-drawn radiation shield to minimize the impact of solar radiation on the sensor readings.

a) Photovoltaic system. b) Solar radiation sensor. c) Weather station.

Figure 1. Photovoltaic system and meteorological sensors.

The temperature sensor works from -40 to +74 °C with an accuracy of ± 1°C. A FRONIUS GALVO 3.1-1 208-240 inverter records the output power range of 2.5-4.5 kW, with a maximum efficiency of 96%. The development of the intelligent system, the data processing, the model training, and the predictive tests were carried out on a laptop with a CPU i3-1005G1 and 8 GB of RAM. Figure 1 shows the photovoltaic system and sensors.

3 Analysis of experimental data

The first step for any challenge related to the data is to conduct a rigorous review of the information. Studying the distributions of specific variables and determining their possible correlations is necessary to define the input variables with the most significant influence on the system's output power. It also indicates the association between the quantitative input and output variables (Asuero *et al*., 2006).

In this study, the correlation of six input meteorological variables against the output power was calculated to select the variables that have the most significant impact on electricity generation. Pearson's correlation coefficient (equation 1) (Benesty *et al*., 2009) and Spearman's correlation coefficient (equation 2) (Griffiths, 1980) were used:

$$r_p = \frac{SXY}{\sqrt{SX^2.SY^2}} \tag{1}$$

$$r_s = \frac{6\sum d^2(XY)}{n(n^2-1)} \tag{2}$$

Where n is the number of data points of the two variables, X, Y are the deviations of any pair of characteristics from their respective medians, XY is the product of the two previous values for any individual, SXY is the sum of said products for all individuals. SX^2 is the sum of the squares of all the various values of X, SY^2 is similar for Y, r_p is the Pearson correlation coefficient, $\sum d$ is the sum of the rank differences of all the individuals, and XY is the product of the two previous values for any individual, finally r_s is the Spearman correlation coefficient.

The data used to develop the model in this study were global horizontal solar radiation and ambient temperature as input variables and the electrical power generated by the system as the output variable. A correlation comparison of the output variable (electrical power) was made with six input meteorological variables (solar radiation, ambient temperature, humidity, dew point, wind speed, and atmospheric pressure). Only global horizontal solar radiation and ambient temperature significantly correlated with the output variable. It was done with approximately 26,000 records of each variable captured every 5 minutes for 268 days. The programming and development of the model were carried out using Matlab software. The leading causes for poor results when training different predictive models are overfitting and underfitting. In overfitting, the model will only adjust the cases we teach it and will be unable to recognize new input data. Underfitting the model considers valid data identical to that used in training. It cannot correctly distinguish the inputs if they are slightly out of the pre-established ranges (Hawkins, 2004; Belkin *et al*., 2018). These two cases cause an inability of the model to make optimal predictions, so it is necessary to partition the data system for training and validation to find a balance between bias and variance, which means that a model must reach an equilibrium between underfitting and overfitting (Belkin *et al*., 2019).

Regarding the above, empirical studies show that the best results are obtained using 70-80% of the data for training and the remaining 20-30% for testing. It is recommended to avoid overfitting (occurs when the data set from which they have been created is adjusted so precisely that they lose much of their predictive power) and underfitting (occurs when the set of training data is insufficient or unrepresentative) (Gholamy *et al*., 2018).

In the present ANFIS-GA model training, 70% of the total universe of registered data was used for training, and the remaining 30% was used to carry out the prediction or testing tests. Therefore, it could be considered that the range used in this model falls within the sweet spot margin reported in the literature (Nguyen *et al*., 2021).

4 Methodology of the predictive algorithm

The ANFIS-GA generates a Sugeno-type FIS structure consisting of membership functions (MF) that can learn fuzzy sets in neurons. The MF must be found and understood by the system. It is characterized by clarity, excellent precision, and few rules (Kukolj and Levi, 2004). ANFIS uses a systemic methodology for data modeling.

The ANFIS-GA model finds the mapping relationship between the input and output data through hybrid learning to determine the optimal distribution of the membership functions. The learning algorithm adjusts all the weights to fit the training data, usually using least squares methods and stochastic gradient descent (SGD) versions, with backpropagation to calculate partial derivatives (Hecht-Nielsen, 1992). The inclusion of the genetic algorithm aims to optimize the ANFIS classifier model to obtain a more accurate estimate.

The basic principle of this type of model is based on the mathematical model of neurons. In this calculation model, an input vector from the variables or other neurons provides an output response where each input x_i is affected by a weight w_i, which represents the intensity of interaction between each presynaptic and postsynaptic neuron (Kröse, 1993).

In this case, a multilayer perceptron was obtained by adding intermediate (hidden) layers to a simple perceptron (MLP). It is a type of ANN formed by multiple layers composed of several interconnected neurons, organized by input, an output layer, and two hidden layers. It can be used to solve mathematical models that are not linearly separable (Kröse, 1993; Yousif, 2019). The structure of the MLP constitutes a universal function approximator (Brio and Molina, 2001).

Finally, the training of the neurons of the layers of the multilayer architecture is provided by the error backpropagation algorithm (BP). For this, an error function similar to equation 3 is used. It is derived based on the weights of the output layer and as a function of the weights of the hidden neurons, using the chain rule. Given an input pattern x^μ ($\mu = 1,\ldots,p$), the global operation is expressed by equation 4, determined in (Brio and Molina, 2001).

$$E = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} T_i - (\mathcal{F}_{outi})^2 \tag{3}$$

Where, E_i is the error measure for the i-th input of the given training data set, T_i is the desired output of the i-th input, and $\mathcal{F}_{outi}$ is the output of the system using the i-th input, then:

$$z_k^\mu = \sum w_{kj}^1 y_j^\mu - \theta_k^1 = \sum_j w_{kj}^1 f\left(\sum_i w_{ji} x_i^\mu - \theta_j\right) - \theta_k^1 \tag{4}$$

On the other hand, according to Jang (1997), fuzzy logic uses values that are continuous between 0 (the facts are entirely false) and 1 (the facts are quite true). In this way, fuzzy sets can be used where the concepts are associated with groups in a process called fuzzification. Fuzzy values can be used in language rules and obtain a result that can remain fuzzy or defuzzify to get discrete values. Model fuzzy clustering is a process that assigns input data to one or more clusters using membership levels. Therefore, the fuzzy systems are based on fuzzy partitioning of information, where their decision capacity depends on base rules and a fuzzy reasoning mechanism.

In the most general form, the knowledge encoding of a multiple-input and a single-output (MISO) system can be defined by different partitions of the input-output space based on various IF-THEN rules consisting of fuzzy variables in both its antecedent and its consequent. Each compartment is represented by a membership function, as observed in the example below and explained in detail in Emami *et al*. (1998).

IF U_1 is B_{11} AND U_2 is B_{12} AND … AND U_r is B_{1r}
THEN V is D_1 AND V_2 is D_{12} AND … AND V_s isD_{1s}
ALSO
…
ALSO
IF U_1 is B_{n1} AND U_2 is B_{n2} AND … AND U_r is B_{nr}
THEN V is D_{n1} AND V_2 is D_{n1} AND V_2 is D_{n2} AND …AND V_s isD_{ns}

Where, U_1, U_2, … U_r are the input variables, V_1, V_2, …, V_s are the output variables, B_{ij} ($i = 1,\ldots,n, j = 1,\ldots,r$), D_{ik} ($i = 1,\ldots,n, k = 1,\ldots,s$) are the fuzzy set of the universe of discourse X_1, X_2,…, X_r; Y_1, Y_2, …, Y_s of U_1, U_2, …, U_r and V_1, V_2, …, V_s, respectively.

It is observed that the fuzzy sets B_{ij} and D_{ik} make up the fuzzy model parameters, and the number of rules determines its structure.

This model can estimate the output of the inputs based on the calculations of the five layers used to build the inference system. The equations for its development are widely explained and adapted from (Jang, 1993; Ying and Pan, 2008; Kohonen, 1988; Lippmann, 1987; Jang and Sun, 1995).

Layer 1. Fuzzification is performed in the first layer. In this process, the neurons transfer the previously received signals according to their programming. Each node in this layer generates degrees of membership based on a linguistic label, where the node function of the i-th node can be:

$$O_i^1 = \mu A_i(x), i = 1,2; \mu A_i(x) = \exp\left\{-\left(\frac{x-c_i}{\alpha_i}\right)^2\right\} \quad (5)$$

Where x is the entry of node i, and A_i is the linguistic label (high, medium, low, etc.) associated with the function of the node, i.e., O_i^1 is the membership function of A_i, and specifies the degree to which the $A_i(x)$ given satisfies the quantifier A_i. in addition, α_i, c_i are premise parameters, being α_i the adjustable center and c_i the variances center. As the values of these parameters change, the functions vary accordingly, thus exhibiting various forms of membership functions in the linguistic label A_i.

Layer 2. In this layer, the weights of the membership functions are calculated. This layer is called the ruler layer. The firing strength of each rule is calculated with the degrees of affiliation that come out of the previous layer. Each node in this layer is a circular node labeled T_z that multiplies the incoming signals and sends them out.

$$O_i^2 = w_i = \mu A_i(x) x \mu B_i(y), i = 1,2 \quad (6)$$

Each node output represents the firing strength of a rule.

Layer 3. In this layer, the fuzzy rules are determined, and the beginning of each of them is calculated. It is called the normalization layer. Each node in this layer is a circular node labeled N. The ith node computes the ratio of the ith rule's firing strength to the sum of all firing rules.

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \quad (7)$$

The outputs of this layer are known as normalized firing forces.

Layer 4. Called the defuzzification layer. In this layer, the output values are computed. The output value for each rule is calculated using the trigger strength value from previous layers. Every node i in this layer is a square node with a function node.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (8)$$

Where $\overline{w}_i$ is the output of layer three and $\{p_i, q_i, r_i\}$ are the set of parameters. The parameters in this layer are called consequent parameters.

Layer 5. It is the addition layer. In this layer, the total output is calculated as the sum of all the previous signals. The production of ANFIS is obtained by collecting the output values of each rule obtained in the defuzzification layer. The only node in this layer is a circular node labeled $\sum$ that computes the total output as the sum of all input signals, i.e., the output has a continuous type of value instead of a fuzzy set type.

$$O_i^5 = overall\ output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1,2 \quad (9)$$

The neurons in each layer receive prior information from other neurons to calculate the output signal propagated to other neurons. Figure 2 shows an ANFIS structure with two inputs and one output, where the model is composed of five layers.

In general, the search space in ANFIS during data processing can have a high computational load, hindering its convergence and even getting trapped in local minima or maxima. As noted above, optimizing the ANFIS parameters using GA can help solve this problem.

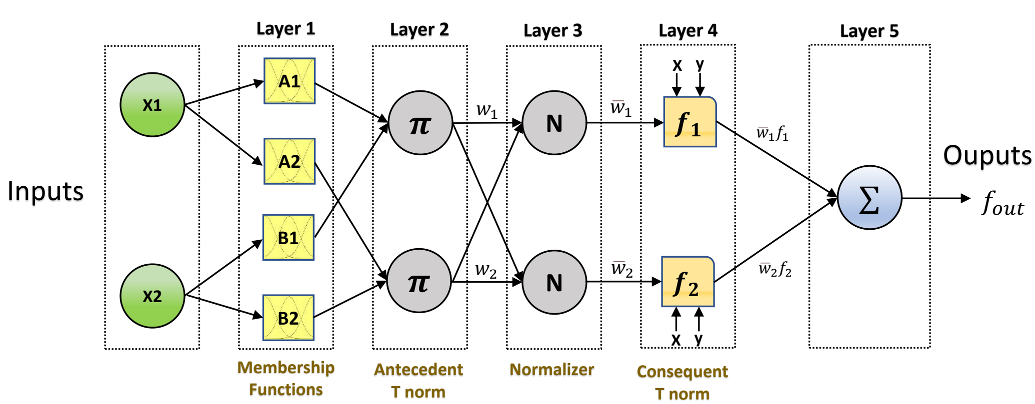

Figure 2. Structure of adaptive neuro-fuzzy inference based on two inputs variables and one output variable.

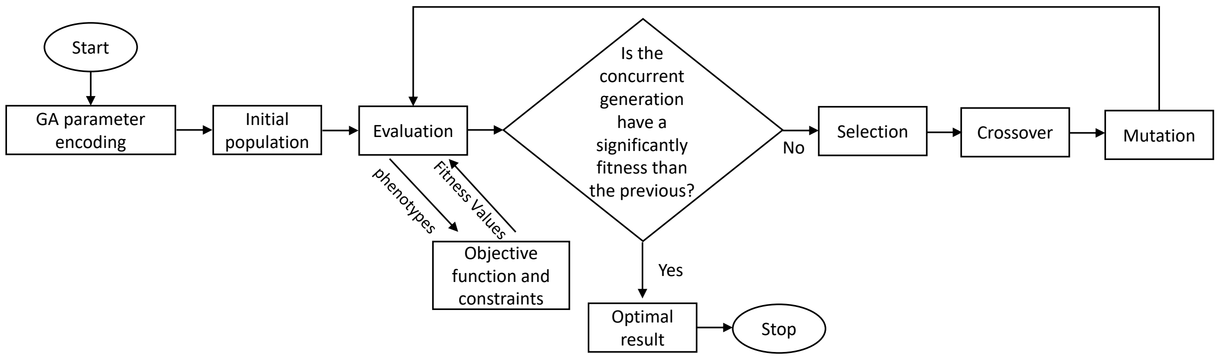

Figure 3. Genetic algorithm flowchart.

Genetic algorithms transform individual populations of binary character strings into new populations using operations modeled on natural genetic processes (Koza, 1990). The population of candidate solutions progresses towards better solutions. Each potential solution has a set of characteristics known as genotype, which can be mutated and changed, and where the fittest individuals are randomly selected from the current population. The genome of individuals is adjusted by applying a set of genetic operators (selection, crossover, mutation, evaluation, and replacement) to provide a new and optimized generation.

The optimized generation of the candidate solutions is utilized in the next iteration of the algorithm (Carrascal *et al*., 2009). The GA stops when the optimal solution is obtained. The algorithm runs a defined maximum number of iterations until there is no change in the population. The cycle repeats systemically from selection, crossbreeding, mutation, evaluation, and replacement in each process. Figure 3 shows the flow chart of the genetic process.

The premise and the consequent parameters in ANFIS can be optimized (Haznedar and Kalinli, 2016). The premise parameters are related to the membership functions in the first layer of the ANFIS structure, and the consequent parameters are used in the fourth layer for the defuzzification process.

The adjustable parameters of the membership functions are α_i, c_i, which are indicated in equation (5). The optimization of the ANFIS model using the GA starts with the random production of the initial population from binary strings, where each represents a solution for the fuzzy components of the antecedent part (Azimi *et al*., 2019). Once the initial population is calculated, the function for each chromosome is determined in such a way that it allows training the data of the output matrix and defining its relative output error.

Table 1. Parameters of ANFIS-GA.

Process	Value
Alpha (α)	0.7
Betha	8
Crossover percentage	0.4
Iterations	1000
Membership function	10
Mutation percentage	0.7
Mutation rate	0.15
Train Population	18241

The process continues to generate new populations using the crossover operator. The two chromosomes with the best fitness of the previous generation are selected, forming a new chromosome with better characteristics. Subsequently, the mutation operator selects a chromosome of the prior generation and randomly alters one of its bits to avoid getting stuck in the optimal local points. This process produces a new chromosome and a new generation, thus continuing a process of evolution for a specified number of generations until the optimal population is reached.

The ANFIS membership function parameters were updated during the optimization process. Figure 4 presents the ANFIS-GA process. Parameters initialized randomly in the first step are updated using GA, and all parameters are updated iteratively until the objective function is achieved. Table 1 shows some details of the ANFIS and GA parameters configured in the process.

After the development and training process of the ANFIS-GA model, the outputs can be estimated. The outputs are evaluated with rigorous statistical methods explained extensively by Yousif *et al*. (2019).

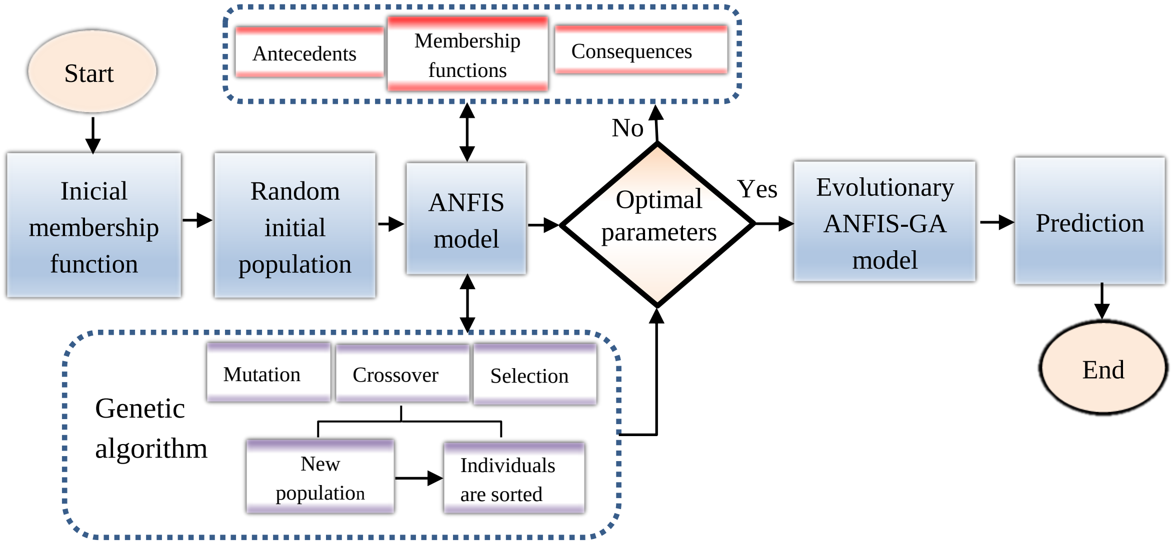

Figure 4. Flowchart of ANFIS-GA.

In this investigation, to verify the functioning of the model, the root means square error (RMSE), the mean square error (MSE), and the mean absolute error in percentage (MAPE) were used. Equations 10, 11, and 12 were used for model verification.

$$RMSE = \sqrt{\frac{1}{a}\sum_{i=1}^{a}(d_i - y_i)^2} \quad (10)$$

Where, d_i is the predicted values and y_i are the observed values, and n is the number of observations.

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - x_i)^2 \quad (11)$$

Where, y_i is n number of predictions, and x_i is n number of actual values.

$$MAPE = \frac{1}{N}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (12)$$

Where n is the number of fitted points, A_t is the actual value, F_t is the forecast value, and $\sum$ is the summation notation (the absolute value is summed for each point in the forecast time).

5 Results

The characteristics used for developing and modeling the ANFIS-GA system are shown below. The total days of the study period were 258, with recording intervals of 5 minutes, for a total of 26058 records for each variable. The training used 70% of the data collected, and the remaining 30% were used to measure the system's performance.

For the selection of the input variables, the correlation process was carried out, selecting the variables with the most significant influence on the system's energy generation. In this investigation, the selected variables were global solar radiation and ambient temperature. In this process, 18,241 records for training and 7817 for testing were used. As it was described in the materials and methods section, these data were collected through instrumentation installed on the site. The smooth function of Matlab was applied to the training data. The process of smoothing data improves the predictive capacity of the model. This method uses locally weighted linear regression. Each smoothed value is determined by the neighboring data points defined within the period. Because a weighted regression function is established for the data points included in the span, the procedure is weighted. The moving average was used for outliers as points more than three local scales mean absolute deviations away from the local median within a sliding window, where the location of the outlier relative to the other points in a sliding window is found. 5 minutes. The r_p (Eq. 1) for the Solar Radiation-Electric power variables was 0.967, and the r_s (Eq. 2) for Ambient Temperature-Electric power variables was 0.272.

An ANFIS structure consisting of two inputs and one output was created for the modeled dynamical system. The inputs of the built ANFIS structure used the Gaussian membership function with ten parameters. Hence, there are $10n$ rules in the model. Initially, the model generates a FIS (fuzzy inference system) using fuzzy c-means (FCM) clustering by extracting a set of rules that model the behavior of the data. As input arguments, the function needs separate input and output data sets. Genfis3 can create an initial FIS for ANFIS training when there is just one output. The rule extraction method employs the fuzzyc-means to define the number of rules and membership functions for the antecedents and consequents. It should be noted that initially, when generating the FIS, the type of membership function of the input variables is of the Gaussian type and the output variable is of the linear type. It can be adjusted according to the training.

In the optimization process through GA, an improved fuzzy grouping and efficient strategy were developed to select significant system inputs and their membership functions, which is very useful in reducing the computational load and the effects of the curse of dimensionality (Cui, 2021).

Figure 5 shows in its section: (a, b) the initial membership functions created by the model of the solar radiation variable where (a) is before optimization and (b) once the MF were optimized and, in its section (c, d) the initial membership functions created by the model of the ambient temperature variable where (c) is before optimization and (d) once the MF were optimized. The comparison of the algorithm before and after being optimized with the GA shows a reduction of the membership functions and a dynamic adjustment of the membership ranges of each function. This optimization process represented an improvement in the predictive capacity of the model.

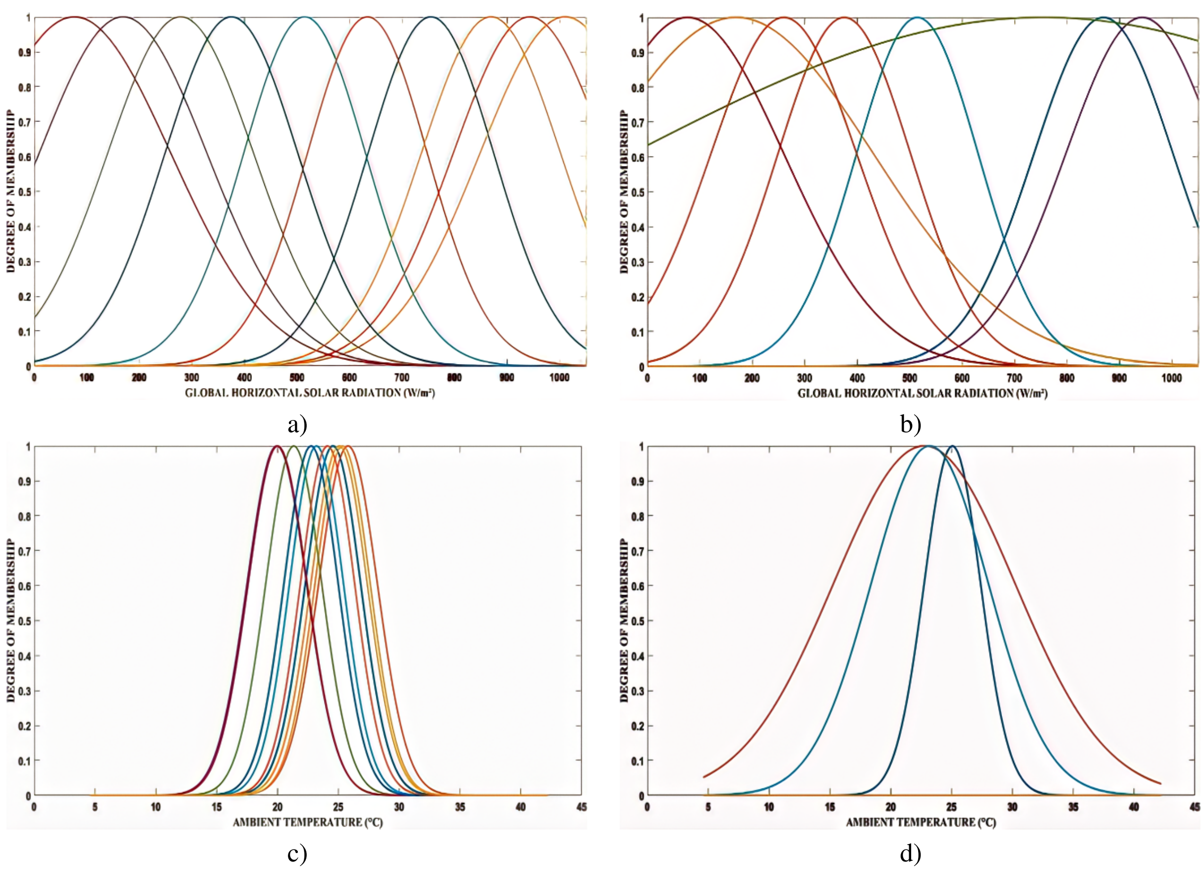

Figure 5. Membership functions before training of variables (a) Solar radiation and (c) Ambient temperature and membership functions of the optimized model of the input variables: (b) Solar radiation and (d) Ambient temperature.

Figures 6a and 6b show the comparative graphs of the prediction of the ANFIS model described by Cerecedo *et al*. (2021) and the ANFIS-GA model developed in this study, both compared with the experimental records of the photovoltaic system. This comparison was made over a non-arbitrary period of 9 days from April 23 to 30, 2019. This phase is within 30% of the total records destined for model testing. In some cases, it was observed that the predictive data of the model, compared to the data recorded experimentally, showed some inaccuracies in the prediction, especially in the highest points of the Gaussian bell. The day compared to the case of April 29, was a day that presented a greater trend of solar radiation variation (the most significant variable), showing a non-normal distribution.

The model predicts power electricity output every 5 minutes throughout the day. These radiation variations caused the model to not hold the prediction at some points within the MAPE range reported in the results. However, in the Total MAPE measurement of the predictive stage shown in Table 2 and the electrical power estimate reported in Figure 9, these inaccuracies were insignificant in the results. When we compared the values of the solar radiation variable from the experimental data, specifically on April 29, where the predictive model presented the peaks or outliers, we took that range that shows the most significant peak line. It is made up of values from 11:00 am to 12:00 pm. These records had a standard deviation of 198.52. If we take the same range of radiation values from April 30, the standard deviation is 10.97. It probably derived from MAPE values above the average on April 29, specifically in this range where the radiation variations presented experimentally were very significant, affecting the estimation capacity of the model in that range, but not the average estimate of the period reported in the results.

Figure 8 compares both models with the experimental data for more precise visual detail. Both models show acceptable estimates from the experimental data. However, it is possible to observe that the ANFIS-GA GA model was more accurate in approximating the peaks of the Gaussian distribution. The r^2 between the experimental data results compared to the test data obtained by the model was equal to 0.97.

The models were evaluated with rigorous statistical parameters indicated in the methodology. Both the training and the predictive phase are shown in Table 2. It is observed that the ANFIS-GA model emulated with greater precision the behavior of the experimental data in the compared period. The ANFIS-GA has an RSME value of 259.41, MAE of 132.7, and MAPE of 4.56 compared to the values obtained with the ANFIS model, which has an RSME value of 295.26, MAE of 149.58 and MAPE of 6.98. It is possible to observe that the percentage error throughout the period is lower in the ANFIS-GA model. Although there are some peaks in the daily estimate, the monthly MAPE for the ANFIS-GA model is 4.56%, whereas, for the ANFIS model, it was 6.98%.

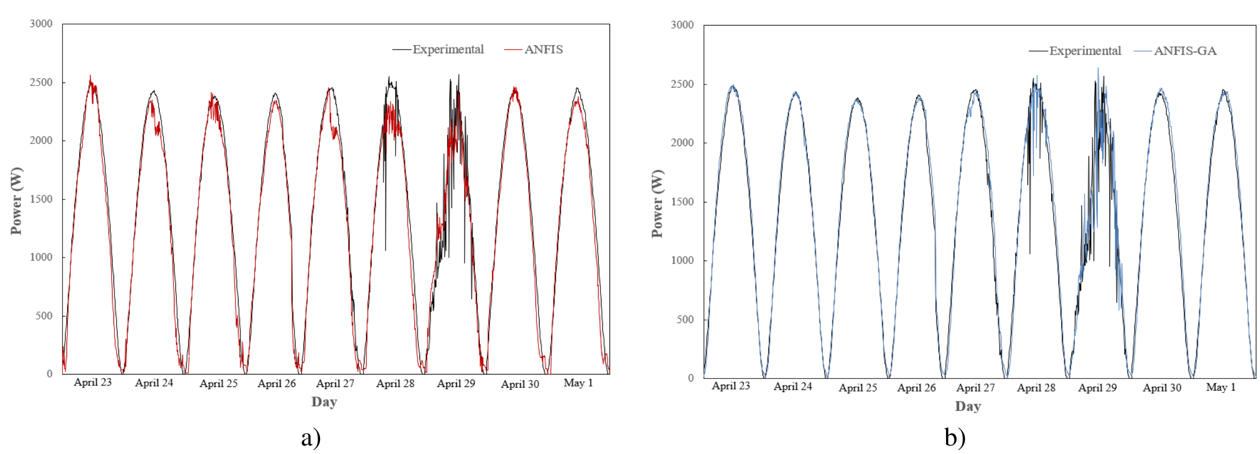

Figure 6. Comparison of experimental records over nine days with (a) ANFIS forecast and (b) ANFIS-GA forecast.

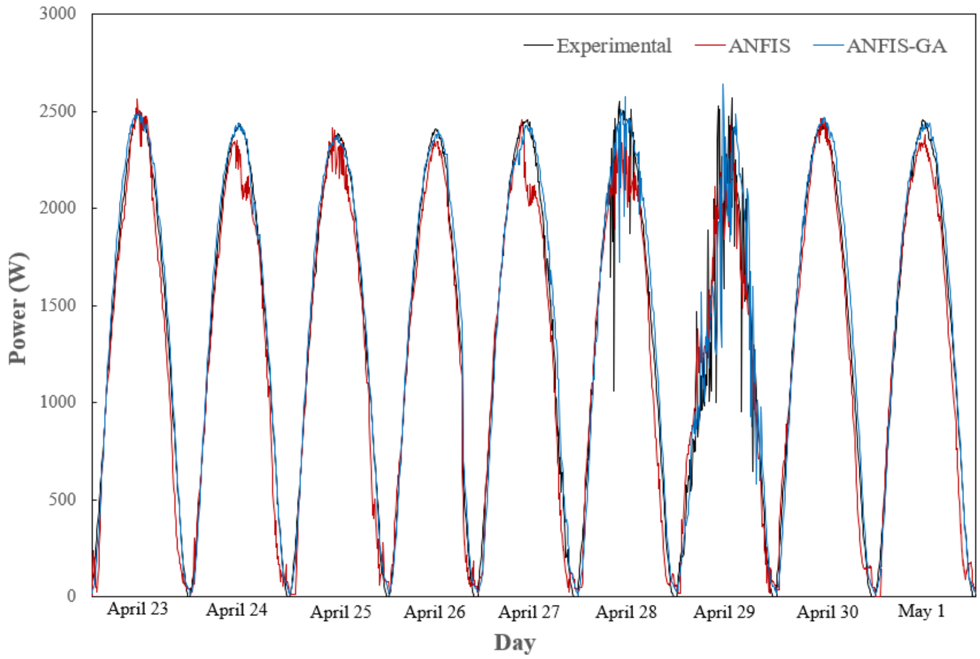

Figure 7. Comparison of experimental records with ANFIS forecast and ANFIS-GA forecast.

Table 2. Comparison of errors for the ANFIS and ANFIS-GA models in the training phase (70%) and the predictive stage (30%).

MODEL	FIS structure	RSME		MAE		MAPE	
		Train	Test	Train	Test	Train	Test
ANFIS	Grid Partitioning approach	254.93	295.26	149.58	218.69	4.99	6.98
ANFIS-GA	Fuzzy c-Means Clustering	189.87	259.41	126.35	132.7	4.1	4.56

Table 3. Comparison of the MAPE (%) values of both models.

MODEL	MONTH	WEEK 1	WEEK 2	WEEK 3	WEEK 4
ANFIS	6.56	7.47	5.86	7.09	6.54
ANFIS-GA	4.78	6.39	3.78	5.08	3.77

Table 3 presents the weekly variability of the MAPE during the month. Based on the analysis of both models, it is determined that the optimized ANFIS-GA model produces better results in the predictions for every week of the month.

However, the daily variation of the MAPE from April 13 to May 12, 2019, is shown in Figure 8. Each peak represents the MAPE of one day of the models. It is observed that on most days, the ANFIS-GA has a MAPE value below that the corresponding of ANFIS.

Figure 9 shows the electricity generation produced by the photovoltaic system in a bar graph based on the experimental data recovered from the inverter and counted per week for one month. These data are compared with predicted data from both models over the same date range from April 13 to May 12. A numerical integration process was carried out using the trapezoidal rule to obtain the predicted values in kW. The graph allows us to compare the predictive capacity of the models in terms of kW when considering them against the electrical generation of the system measured in the inverter. In this case, the percentage predictive error of the models concerning the experimental data was 5.28% for ANFIS and 2.73% for ANGIS-GA.

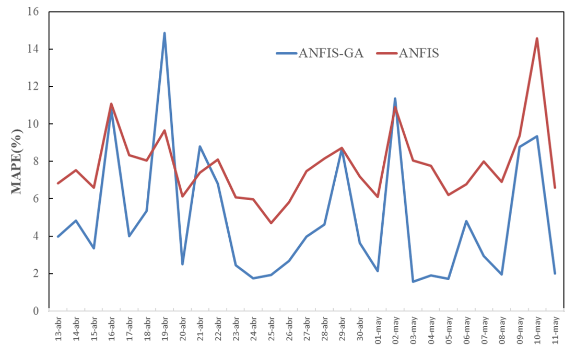

Figure 8. MAPE curves of intelligent models for a month.

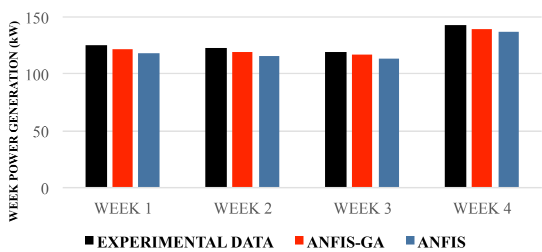

Figure 9. Comparison of electric power generation of the photovoltaic system and the predictive models ANFIS and ANFIS-GA.

Conclusions

This study presented an intelligent neuro-fuzzy model optimized using a genetic algorithm, which was evaluated with statistical models to determine the predictive error. Likewise, it was compared with an ANFIS not optimized model.

The optimized ANFIS-GA model has a better predictive capacity. It shows a better approach in the peaks of the Gaussian bells (which indicate the highest values of daily electric generation). It registers a better evaluation of statistics errors, where values were obtained for the ANFIS model of RSME of 295.26, MAE of 149.58, and MAPE of 6.98, and for the ANFIS-GA model of RSME of 259.41, MAE of 132.7, MAPE of 4.56.

Additionally, it was observed that the ANFIS-GA provided a better approximation to the electrical generation recorded experimentally in the inverter of the photovoltaic system, where the percentage of predictive error of the models compared to the experimental records was 5.28% for ANFIS and 2.73% for ANGIS-GA.

According to the tests on this model, the number of initial MF with the best results was 10. Under greater demand for data processing, this parameter can be adjusted to balance the computational load and the optimal results.

The optimization method, based on a genetic algorithm, improved the predictive capacity of the intelligent system. Therefore, considering the satisfactory results of this study, it may be of interest to use the ANFIS-GA model in different photovoltaic systems with other geographic, climatic, and system size conditions.

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