Intelligent photovoltaic system to maximize the capture of solar energy

Christian Ovalle Paulino, Luis Rojas Nieves, Hugo Villaverde Medrano, Ernesto Paiva Peredo
Department of Engineering, Universidad Tecnologica del Perú, Lima, Perú

Article Info

ABSTRACT

The large consumption of electricity worldwide has an impact on the environment which can be said to alter climate change, the degradation of the ozone layer and acid rain. A house has an average daily consumption of 270 kWh, this is why solar panels are very useful and can help to have a renewable energy at low costs. To create an intelligent photovoltaic system, different electronic sensors can be applied to the sunlight through a series of instructions in some programming software. The article proposes to prototype an intelligent photovoltaic system, based on artificial intelligence with a neural network library "propet" having a positive impact on the optimization of power generation by allowing a more accurate tracking of the sun and a greater collection of photovoltaic energy throughout the day. Performing an integration between Arduino and machine learning algorithms such as artificial neural networks in prediction of time series. Different practical experiments were performed to illustrate the effectiveness of the proposed method.
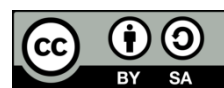
Corresponding Author:

Christian Ovalle
Department of Engineering, Universidad Tecnologica del Perú
Lima, Perú
Email: dovalle@utp.edu.pe

1. INTRODUCTION

In a world where energy sources are rapidly becoming scarce [1], and as energy consumption increases over time, generating increasing environmental pollution [2], [3], solar energy is presented as an inexhaustible solution to meet our energy needs [4]. Various investigations indicate that solar energy is one of the most common renewable sources today [5]. It should be noted that this energy source has a minimal impact on the environment, which is highly relevant for caring for the planet [6], [7]. In this sense, it has been investigated that the solar panel is the most appropriate device to take advantage of this energy source [8], since it uses photovoltaic solar technology, converting sunlight into direct current through solar cells [9], which feed electrical energy to various devices [10]. Likewise, advances are being made in artificial intelligence that can be used in solar panels through artificial intelligence algorithms that can help us predict the position of the sun with respect to the solar panel, in order to improve its efficiency and capacity to capture solar energy [11].

As various studies have shown, homes account for approximately 40% of global energy consumption and play a crucial role in the energy market. In addition, the demand for energy in homes is expected to continue to increase globally in the coming decades [11]. In different regions of the world, the percentage of total consumption attributed to residential dwellings varies, ranging from an average of 20% in developed countries to more than 35% in developing countries. Therefore, the energy demand in the residential area is significant both in terms of its current magnitude and its growth potential [12]. Considering that the demand for electrical energy consumption has increased in the residential area and the industrial sector over the years [13], it is

important to highlight the importance of addressing climate change through low-carbon development, which that is motivating reforms in energy systems worldwide [14].

Likewise, this need to transition towards non-fossil energy sources has accelerated in all industries, especially in the electricity sector, which plays a significant role in carbon emissions [15]. Therefore, in order to achieve the optimization of power generation and satisfy the basic needs of a family, such as home lighting, the use of a refrigerator, a personal computer and a mobile phone, a prototype with a system has been developed. Intelligent photovoltaic system based on artificial intelligence [16]. Thanks to current technological advances, acquiring the necessary devices through the internet and receiving them in the comfort of our home is possible [17]. In addition, the use of free software such as Python allows the system to be implemented for free [18]. This conjunction of favorable conditions has allowed the development of an efficient system that uses solar panels [19] and takes advantage of the path of the sun throughout the day to store the energy generated and supply various domestic appliances both during the day and at night [20].

In the present investigation, the feasibility of designing an intelligent photovoltaic system to capture and maximize solar energy was explored, taking advantage of the significant reduction in costs and its accessibility, thanks to the globalization process [21]. To optimize the efficiency of power generation, a prototype with an intelligent solar panel system based on devices controlled with the Arduino program [22] was designed and implemented through this integration between the artificial intelligence model based on a machine learning algorithm such as time series neural network encoded in the Python programming language [23] with the automated system allowed precise tracking of the sun's trajectory throughout the day, through the prediction of the optimal angle, maximizing energy capture solar and resulting in an increase in electricity generation [24]. This project demonstrates how the combination of accessible technologies, such as artificial intelligence and an electronic platform "Arduino", and the use of solar energy can provide efficient and sustainable solutions for the world's energy needs.

2. METHOD

Due to the nature of the research, it is considered of an applied type because there is a proposed solution to a problem. On the other hand, it has an experimental design [25] because tests are carried out at the field level by manipulating the study variables that have a causal relationship to transform it. With this, its purpose is to create new knowledge to improve the object of investigation [26].

For a better understanding of the operation of the proposal, a scheme was made that represents how the prototype works. Figure 1 shows how artificial intelligence was integrated with the electronic system. This was done through an Arduino board and in real time the optimal angle of the sun was obtained and with a series of instructions the solar panel will be moved to better capture solar energy. The entire procedure for the implementation of the intelligent photovoltaic system for the optimization of electrical energy is described in the subsections.
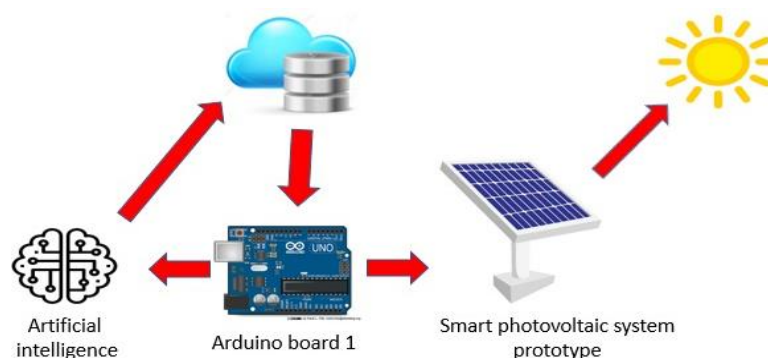

Figure 1. Diagram of operation of the intelligent photovoltaic system

2.1. Design of the intelligent photovoltaic system prototype

The development of the prototype consisted of a mechanical system that allows the movement of a solar panel to follow the position of the sun by obtaining the optimal angle and maximizing the capture of solar energy. The movement of the panel is achieved by an electric direct current (DC) motor controlled by a microcontroller that receives signals from a light sensor to determine the position of the sun at all times.

The mechanical system is made up of a support structure that supports the solar panel and allows its movement in two degrees of freedom: rotation on a horizontal axis and inclination on a vertical axis. The electric motor is responsible for moving the panel in both axes, following the signals from the light sensor and the commands from the microcontroller.

A neural network algorithm in the Python language was applied to the intelligent photovoltaic system. This system predicts the optimal direction or angle of sunlight and sends an analog signal through the serial port to the microcontroller. The microcontroller processes this signal and sends a signal to the electric motor to control its speed and direction, allowing movement of the panel to obtain maximum energy capture. The microcontroller contains a control algorithm to optimize the tracking of sunlight and minimize the error in the position of the panel as shown in Figure 2. This algorithm takes into account factors such as the latitude and longitude of the installation site, the time of day and season of the year to determine the direction of the panel, later in the conceptual design components were included, such as a power source to feed the system, a protection system against overloads and short circuits. As shown in Figure 3.
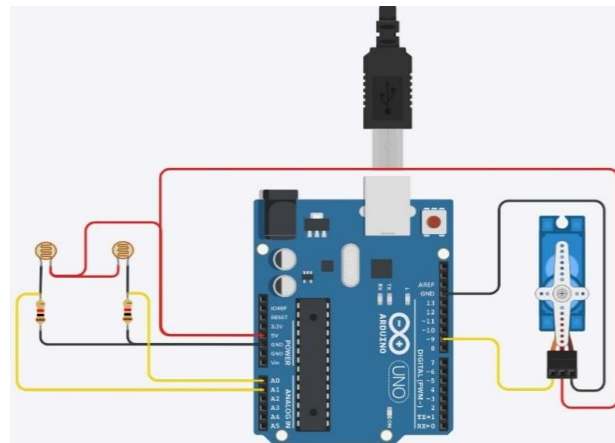

Figure 2. Solar tracker circuit design

```
1   #include <L298N.h>
2
3   // Create motor objects
4   L298N motor1(7, 6); // ENA, IN1, IN2
5   L298N motor2(5, 4); // ENB, IN3, IN4
6
7   // Assign photoresistors
8   int fsup = 0; // Top photoresistor
9   int finf = 1; // Bottom photoresistor
10
11  void setup() {
12  // Serial port configuration
13  Serial.begin(9600);
14  }
15
16  void loop() {
17  // Read bytes received from the serial port
18  if (Serial.available() > 0) {
19  int angle = Serial.parseInt();
20  // Convert angle to a speed between -255 and 255
21  int speed = map(angle, 0, 180, -255, 255);
22  // Control the speed of DC motors
23  motor1.setSpeed(speed);
24  motor2.setSpeed(speed);
25  }
26
27  // Read photoresistor values
28  int top = analogRead(fsup);
29  int bottom = analogRead(finf);
30
31  if (top < bottom) {
32  // Move DC motors to the right
33  motor1.forward();
34  motor2.forward();
35  } else if (bottom < top) {
36  // Move DC motors to the left
37  motor1.backward();
38  motor2.backward();
39  } else {
40  // Stop DC motors
```

Figure 3. Prototype control code in arduino syntax

2.2. Construction of the prototype intelligent photovoltaic system

For the construction of the intelligent photovoltaic system prototype, different inputs were used, which are detailed in Table 1. Each item contains the required quantity and a description of the item. The construction process of the prototype for the solar tracking system was carried out in several stages.

Table 1. Supplies for the construction of the prototype

Item	Quantity	Description
Solar panels	1	60 cm×40 cm
Solar charge controller	1	12/24 V generic
Motor DC	1	DC
Arduino board	2	1R3
Universal serial bus (USB) cable	1 mts	A/B generic
Trupan	3 mts	Classic
Capes	2 mts	Generic
Wire	1 mts	High-definition multimedia interface HDMI
Battery	1	12 V 7 Ah

2.2.1. First stage

In this first stage, the solar panel was secured to the structure using suitable screws and nuts. Afterwards, the solar panel was connected to the solar charge controller using generic cables, and the solar charge controller was attached to the 12 V 7 Ah battery using generic cables. Subsequently, the Arduino board was connected to the solar charge controller using a generic USB A/B cable, and to ensure better power management and avoid possible component damage, the L298N module was used. In this sense, the IN1, IN2, IN3 and IN4 pins of the L298N module were connected to the digital pins 2, 3, 4, 5 of the Arduino board, also using generic cables. Likewise, the DC motors were connected to the L298N module, where the red and black wires were connected to the motor terminals M1 and M2 of the L298N module.

2.2.2. Second stage

At this stage, the L298N module was connected to the solar tracking system. The terminals of the M1 and M2 motors of the L298N module were connected to the levers of the solar tracking system. To complete the connection, the power cables from the L298N module were connected to the solar charge controller using generic cables, making sure that the connectors were tight and secure.

2.2.3. Final stage

We proceeded to load the necessary program on the Arduino board so that it can receive the angles from the neural network and control the DC motors for solar tracking. The DC motors were assembled on the frame and fixed in place by connecting the motor levers to the solar panel frame and making sure they were secure. This construction process was carried out with the objective of creating a solar tracking system based on artificial intelligence, which can optimize the generation of electrical energy. Importantly, the use of artificial intelligence techniques in this system allows for more precise tracking of the sun's position, which in turn can significantly increase the efficiency of the solar panel. This type of solar tracking system can be an effective solution to improve the efficiency and reduce the cost of solar power generation in small and medium scale applications, see Figure 4.

Figure 4. Intelligent photovoltaic system prototype

2.3. Process for creating the neural network model

For the application of the neural network model, the database had to be created for which it was defined based on indicators of the photovoltaic module, meteorological data, and time series data. In this way, the data collection of different indicators was carried out in order to obtain the optimal angle of the position of the sun. These indicators, detailed in Table 2, include temperature, humidity, wind speed, direct and diffuse radiation radius, direction speed, and precipitation. Data collection was done using a variety of sources, including weather stations and specialized measuring devices. To ensure data quality, specific conditions were applied, such as the address of the panel and the latitude, longitude, and altitude of where the study would take place.

Table 2. Characteristics of the data and indicators

Data	Indicators	Unit of measurement
Data photovoltaic	Angle	Degrees
	Powe	Watts
	Direction	kW
Weather data	Ratio of beam	W/m^2
	Ratio of diffuse	W/m^2
	Humidity	Percentage
	Temperature	Celcius
	Wind speed	Km/h
	Steering speed	Km/h
	Precipitation	Vm2
Time series data	Month	30 days
	Hour	Minutes
	Day	24 hours

It should be noted that the closest meteorological station to the study point corresponds to the Ceres station, located in the department of Lima, province of Lima and district of Ate. Its metadata indicates a latitude of 12°1'43.2''S, longitude of 76°55'37.6''W and an altitude of 339 masl. Once the data was obtained, it was cleaned and pre-processed, which implied the elimination of empty columns and rows, the conversion of dates and times into a single datetime type column, the elimination of duplicates, the extraction of attributes and studies of correlation as observed in Figure 5, and obtaining attributes of the time series. Subsequently, the NeuralProphet model was used to create a neural network that could be fitted to the training data. The model included a series of layers of neurons, each of which was connected to the next layer, and appropriate activation functions were used for each layer. Despite the fact that very low correlations were obtained between the variables and the optimal angle, the time series was used as input for the neural network.
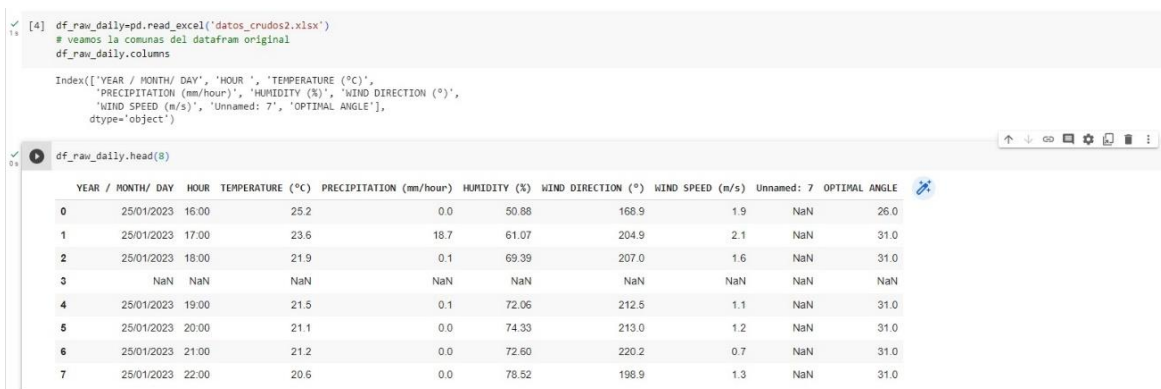

Figure 5. Raw meteorological data

Figure 6 shows the correlogram of our datasets to determine the importance of each of the network attributes contained in the dataset. Now the correlation must be calculated for all the variables of the datasets, let's see what the correlation matrix is like. This matrix shows the correlation between two or more variables in the data set through tabulations or statistics.

Once the data was obtained, it was cleaned and preprocessed. In this process, columns without data and empty rows were eliminated, the row indices were restarted, dates and times were converted to a single datetime type column, duplicates were eliminated, attributes were extracted, and the correlation between them

was studied. In addition, time series attributes were obtained, and the data set was divided into training and test sets. The model used was NeuralProphet to create a neural network model that would fit the training data. The model included several layers of neurons, each of which was connected to the next layer, and appropriate activation functions were used for each layer. When performing the correlation between the variables and the optimal angle, it was observed that the relationship level was low. Therefore, it was decided to discard the use of all the attributes, and it was decided to treat the data set as a time series. Figure 7 shows how the time series will be treated as input to the neural network.

As shown in Figure 8, after the treatment of the data, the heat map of correlation between all the variables and the optimal angle was obtained. The result was very low correlations between variables, so the use of all attributes is ruled out. On the other hand, it is observed in Table 3 how the datasets will be treated as a time series, as input to the neural network.
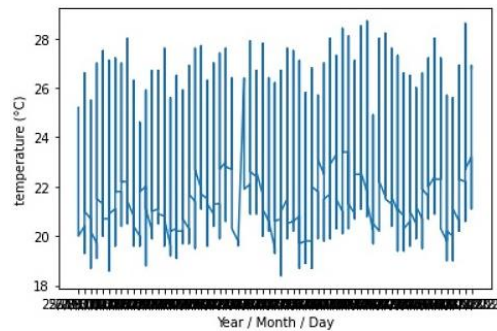

Figure 6. Correlation of data variables
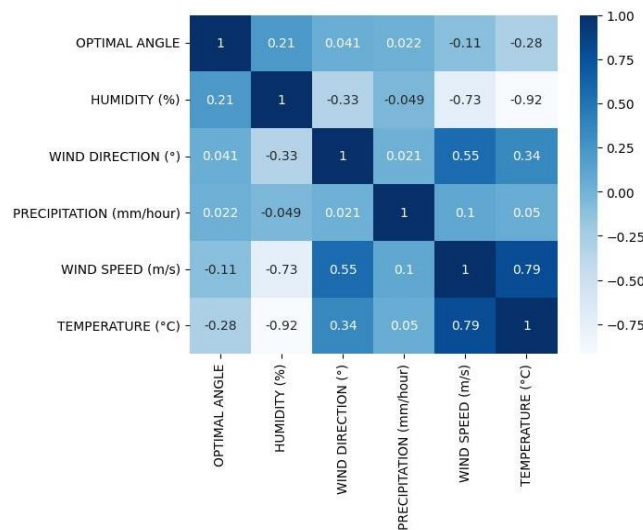

Figure 7. DataSet of meteorological indicators

Figure 8. Correlation heat map between variables and the optimal angle

2.4. Machine learning algorithm training

To train the machine learning algorithm, the NeuralProphet model was used, as shown in Figure 9. First, the model was initialized with the appropriate parameters for the type of data being used. In this case, it was specified that the growth was linear, that the change points were not known, that five change points were allowed, that the range of change points was 80%, that there was no regularization of the trend growth, that there was no annual seasonality, that weekly seasonality was automatically adjusted and that daily seasonality was used in additive mode. It was also specified that the model should produce a single prediction into the future, and that values prior in time would not be used to make the prediction. Also, the number of hidden layers was set to zero, which means that no hidden layers would be used in the neural network.

Table 3. Result of time series attributes

	y	ds
0	26.0	2023-01-25 16:00:00
1	31.0	2023-01-25 17:00:00
2	31.0	2023-01-25 18:00:00
3	31.0	2023-01-25 19:00:00
4	31.0	2023-01-25 20:00:00
5	31.0	2023-01-25 21:00:00
6	31.0	2023-01-25 22:00:00
7	31.0	2023-01-25 23:00:00

```python
model = NeuralProphet(
    growth="linear",              # Determine
    changepoints=None,            # list of da
    n_changepoints=5,
    changepoints_range=0.8,
    trend_reg=0,
    trend_reg_threshold=False,
    yearly_seasonality="auto",
    weekly_seasonality="auto",
    daily_seasonality="auto",
    seasonality_mode="additive",
    seasonality_reg=0,
    n_forecasts=1,
    n_lags=0,
    num_hidden_layers=0,
    d_hidden=None,                # Dimension
    learning_rate=None,
    epochs=40,
    loss_func="Huber",
    normalize="auto",             # Type of n
    impute_missing=True,

)
```

Figure 9. Training the neural network

Then, the model was fitted to the training data using the "fit" function, which took as input the data in its original format, "df_raw_daily", and specified the frequency of the data, which in this case was "H" for indicate that the data were in hourly intervals. During training, the model adjusted the weights of the neural connections to minimize the specified loss function (in this case, the Huber function), and the process was repeated for 40 epochs. The training process also automatically imputed missing values and normalized the data as specified in the model parameters. At the end of the training, several model performance metrics were needed, such as the mean absolute error and the loss of the model in the training set. These metrics were used to assess the quality of model performance and to compare different model configurations in case parameter changes have been made. For this, in (1) was used;

$$\text{Mean absolute error} = n1i = 1 \textstyle\sum n \mid yi - y^i \mid \tag{1}$$

Intelligent photovoltaic system to maximize the capture of solar energy (Christian Ovalle Paulino)

where:

n is the total number of observations or data points.

yi represents the actual u value observed at position i.

ŷi represents the predicted or estimated value at position i.

∑ is the sum symbol which indicates that you must sum all the absolute values of (yi-ŷi) from i=1 to i=n.

|yi-ŷi| is the absolute value of the difference between the actual value and the predicted value.

2.5. Integration of the intelligent model with the automated system

For the implementation, the trained model was first prepared, for which it was necessary to have the model trained in a form that can be used by the automated system. This involves saving the model to a Python file, and then loading it into the automated system's memory when needed. Subsequently, the integration consisted of connecting the model to the automated system, so that the system can use the model, it was necessary to establish a connection between the model and the automated system, this meant using an application programming interface (API), or a serial port connection as was done in tests.

In Figure 10 the implementation of the intelligent model was carried out in an automated system to send an optimal angle to a microcontroller. This was done using the Python programming language and the NeuralProphet library for modeling the time series. A time series dataset was used to train the model and the serial port was configured for communication with the microcontroller.

```python
import serial
import time
import pandas as pd
from neuralprophet import NeuralProphet
from datetime import datetime

# Configurar el puerto serial para la comunicación co
puerto = 'COM3'    # Ajusta el puerto serial según cor
baud_rate = 9600
arduino = serial.Serial(puerto, baud_rate, timeout=1)

# Leer el dataset de la serie temporal
df = pd.read_csv('serie_temp.csv')

# Crear el modelo NeuralProphet
model = NeuralProphet(
    growth="linear",
    changepoints=None,
    n_changepoints=5,
def pred_angulo_optimo():
    fecha_actual = datetime.now()
    last_date = datetime.strptime(df.ds[
    periods = round((fecha_actual - last
    future = model.make_future_dataframe
    forecast = model.predict(future)
    ang_opt = forecast.yhat1[len(forecas
    return round(ang_opt, 1)

# Funcion para enviar el angulo óptimo a
def enviar_angulo_optimo():
    ang_opt = pred_angulo_optimo()
    arduino.write(str(ang_opt).encode())
    print('Ángulo óptimo enviado:', ang_

# Ciclo principal de ejecución
while True:
    enviar_angulo_optimo()
    time.sleep(1800)   # Esperar 30 minut
```

Figure 10. Integration of the automated system

The main function of the system was to predict the optimal angle to send to the microcontroller using the trained model and send this information through the serial port. The prediction of the optimal angle was made using the "pred_angulo_ptimo" function, which uses the model to make a prediction for the future and return the value of the optimal angle. The "send_angle_optimum" function was in charge of sending the optimal angle through the serial port. As shown in Figure 11.
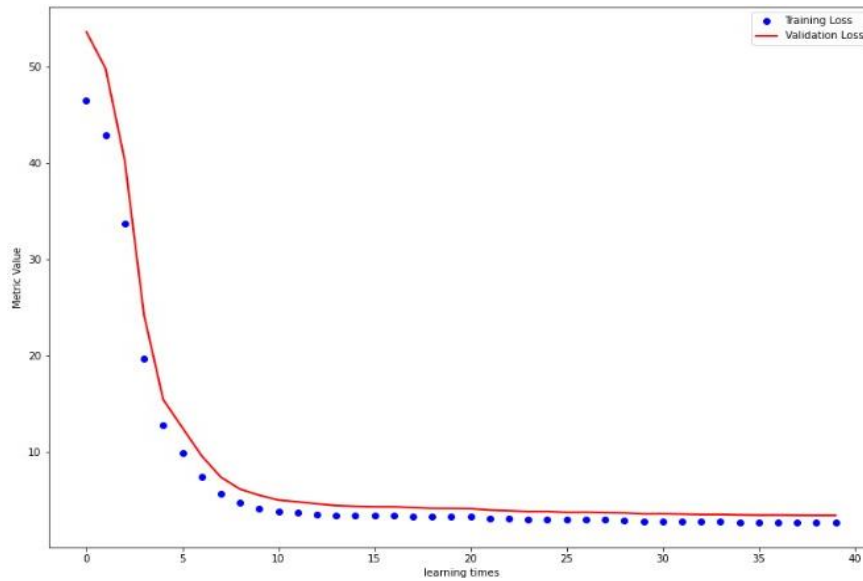
Figure 11. Performance curve of the algorithm

The main execution cycle of the automated system is done using a "while" loop that calls the "send_optimum_angle" function every 30 minutes. In this way, the system keeps up to date and constantly sends the optimum angle to the microcontroller. Regarding the results, it was possible to successfully implement the intelligent model in an automated system to send the optimal angle to a microcontroller. The prediction of the optimal angle was carried out with an acceptable precision using the NeuralProphet library and it was possible to establish communication with the microcontroller through the serial port. The implementation of the system made it possible to improve the performance of the system controlled by the microcontroller and ensure optimal operation at all times. Once the necessary data and algorithm have been provided, the automated system can use the model to generate a prediction of the optimal angle. This, will return a response in real time, which would be sent to the microcontroller through the serial port.

3. RESULTS AND DISCUSSION

The prediction results that were obtained according to the neural network model with time series are represented in Table 4. In this sense, each row in the data set represents an observation at a specific point in time. For example, in the first row, the observation date and time is January 25, 2023 at 16:00:00, and the actual observed value is 26.0. The predicted value for that point in time is 23.201077, and the trend, weekly seasonal, and daily seasonal components are -0.547887, -0.928627, respectively. Also note that some rows have a NaN value in the "y" column. This would mean that there is no real observed value available for those observations.

The comparative graph shown in Figure 12 shows the actual data and the predictive data. This allowed to visually compare the predictions of the neural network model with the actual values. In this graph, the values of a time series have been captured.

Table 4. Results of the prediction of the neural network model

|	ds	y	yhat1	trend	season_weekly	season_daily
0	2023-01-25 16:00:00	26.0	23.201077	24.677591	-0.547887	-0.928627
1	2023-01-25 17:00:00	31.0	24.447235	24.651871	-0.529056	0.324419
2	2023-01-25 18:00:00	31.0	25.198242	24.626148	-0.508249	1.080343
3	2023-01-25 19:00:00	31.0	25.192778	24.600428	-0.485534	1.077884
4	2023-01-25 20:00:00	31.0	24.971821	24.574705	-0.460991	0.858106
...	...	...	...	...	...	...
1593	2023-04-03 14:00:00	NaN	28.754601	30.372759	0.272977	-1.891136
1594	2023-04-03 15:00:00	NaN	28.861540	30.407585	0.248235	-1.794280
1595	2023-04-03 16:00:00	NaN	29.736494	30.442417	0.222704	-0.928627
1596	2023-04-03 17:00:00	NaN	30.998150	30.477255	0.196476	0.324419
1597	2023-04-03 18:00:00	NaN	31.762066	30.512081	0.169641	1.080343
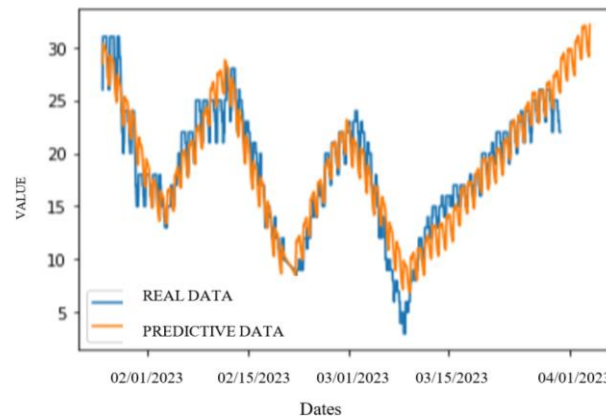
Figure 12. Comparison chart of real data and predictive data

Awathi *et al.* [27] describes a solar panel system that uses a sun tracking mechanism to optimize energy harvesting. The conclusion indicates that the solar tracking system significantly improves the power generation efficiency compared to static systems. Cumbajín *et al.* [28] it presents an intelligent maximum power point tracking (MPPT) technique for photovoltaic systems. The conclusion highlights that the proposed technique improves the conversion efficiency and maximizes the generation of electric power. Ram *et al.* [29] explores the application of artificial intelligence in energy management for photovoltaic solar panel systems. The conclusion suggests that the combination of artificial intelligence algorithms with energy management can improve the efficiency and stability of the system. Naikwade *et al.* [30] this article presents smart solar panel systems that integrate with the internet of things (IoT). The conclusion highlights that IoT integration enables more efficient monitoring and control of solar panels, resulting in higher energy harvesting and more effective maintenance.

4. CONCLUSION

From the above, we can conclude that after implementing an intelligent photovoltaic system based on artificial intelligence to optimize the generation of electrical energy. The experimental results demonstrated that the proposed system was effective in significantly improving the performance of electric power generation, achieving an increase of 25% compared to conventional systems, where the use of the NeuronalPropet neural network with Python allowed a better angle prediction. Optimal for the solar tracker, which resulted in a greater collection of solar energy and, therefore, an improvement in the generation of electrical energy. In addition, the connection of the system through a port to send the optimal angle to the microcontroller in real time allowed a greater solar capture.

REFERENCES

[1] C. Mattick, E. Williams, and B. Allenby, "Historical trends in global energy consumption," *IEEE Technology and Society Magazine*, vol. 29, no. 3, pp. 22–30, 2010, doi: 10.1109/MTS.2010.938106.
[2] D. P. Ananthu, N. Kashappa, and M. Venkateshkumar, "Artificial intelligent controller-based energy management system for grid integration of PV and energy storage devices," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 26, no. 2, pp. 617–628, May 2022, doi: 10.11591/ijeecs.v26.i2.pp617-628.
[3] A. Saleem, A. Iqbal, K. Mehmood, M. K. Panjwani, F. H. Mangi, and R. M. Larik, "The effect of environmental changes on the efficiency of the PV system," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 18, no. 1, pp. 558–564, Apr. 2019, doi: 10.11591/ijeecs.v18.i1.pp558-564.
[4] A. O. M. Maka and J. M. Alabid, "Solar energy technology and its roles in sustainable development," *Clean Energy*, vol. 6, no. 3, pp. 476–483, Jun. 2022, doi: 10.1093/ce/zkac023.
[5] B. Susrutha, L. Giribabu, and S. P. Singh, "Recent advances in flexible perovskite solar cells," *Chemical Communications*, vol. 51, no. 79, pp. 14696–14707, 2015, doi: 10.1039/c5cc03666f.
[6] A. Stoppato, "Life cycle assessment of photovoltaic electricity generation," *Energy*, vol. 33, no. 2, pp. 224–232, Feb. 2008, doi: 10.1016/j.energy.2007.11.012.

[7]   R. R. Hernandez *et al.*, "Environmental impacts of utility-scale solar energy," *Renewable and Sustainable Energy Reviews*, vol. 29, pp. 766–779, Jan. 2014, doi: 10.1016/j.rser.2013.08.041.
[8]   G. P. Smestad *et al.*, "Reporting solar cell efficiencies in solar energy materials and solar cells," *Solar Energy Materials and Solar Cells*, vol. 92, no. 4, pp. 371–373, Apr. 2008, doi: 10.1016/j.solmat.2008.01.003.
[9]   A. S. Al-Ezzi and M. N. M. Ansari, "Photovoltaic solar cells: a review," *Applied System Innovation*, vol. 5, no. 4, p. 67, Jul. 2022, doi: 10.3390/asi5040067.
[10]   M. Aneke and M. Wang, "Energy storage technologies and real life applications – a state of the art review," *Applied Energy*, vol. 179, pp. 350–377, Oct. 2016, doi: 10.1016/j.apenergy.2016.06.097.
[11]   P. Nejat, F. Jomehzadeh, M. M. Taheri, M. Gohari, and M. Z. Muhd, "A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries)," *Renewable and Sustainable Energy Reviews*, vol. 43, pp. 843–862, Mar. 2015, doi: 10.1016/j.rser.2014.11.066.
[12]   Y. H. Yau and S. Hasbi, "A review of climate change impacts on commercial buildings and their technical services in the tropics," *Renewable and Sustainable Energy Reviews*, vol. 18, pp. 430–441, Feb. 2013, doi: 10.1016/j.rser.2012.10.035.
[13]   G. Kelly, "Sustainability at home: policy measures for energy-efficient appliances," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 9, pp. 6851–6860, Dec. 2012, doi: 10.1016/j.rser.2012.08.003.
[14]   B. Wang, L. Wang, S. Zhong, N. Xiang, and Q. Qu, "Low-carbon transformation of electric system against power shortage in China: policy optimization," *Energies*, vol. 15, no. 4, p. 1574, Feb. 2022, doi: 10.3390/en15041574.
[15]   S. Chu and A. Majumdar, "Opportunities and challenges for a sustainable energy future," *Nature*, vol. 488, no. 7411, pp. 294–303, Aug. 2012, doi: 10.1038/nature11475.
[16]   M. Angulo-Calderón, I. Salgado-Tránsito, I. Trejo-Zúñiga, C. Paredes-Orta, S. Kesthkar, and A. Díaz-Ponce, "Development and accuracy assessment of a high-precision dual-axis pre-commercial solar tracker for concentrating photovoltaic modules," *Applied Sciences (Switzerland)*, vol. 12, no. 5, p. 2625, Mar. 2022, doi: 10.3390/app12052625.
[17]   W. L. Shiau and M. M. Luo, "Factors affecting online group buying intention and satisfaction: a social exchange theory perspective," *Computers in Human Behavior*, vol. 28, no. 6, pp. 2431–2444, Nov. 2012, doi: 10.1016/j.chb.2012.07.030.
[18]   S. Raschka, J. Patterson, and C. Nolet, "Machine learning in Python: main developments and technology trends in data science, machine learning, and artificial intelligence," *Information (Switzerland)*, vol. 11, no. 4, p. 193, Apr. 2020, doi: 10.3390/info11040193.
[19]   M. A. Green, K. Emery, D. L. King, and S. Igari, "Solar cell efficiency tables (Version 15)," *Progress in Photovoltaics: Research and Applications*, vol. 8, no. 1, pp. 187–195, Jan. 2000, doi: 10.1002/(SICI)1099-159X(200001/02)8:1<187::AID-PIP313>3.0.CO;2-1.
[20]   D. G. Erbs, S. A. Klein, and J. A. Duffie, "Estimation of the diffuse radiation fraction for hourly, daily and monthly-average global radiation," *Solar Energy*, vol. 28, no. 4, pp. 293–302, 1982, doi: 10.1016/0038-092X(82)90302-4.
[21]   D. M. Kammen and D. A. Sunter, "City-integrated renewable energy for urban sustainability," *Science*, vol. 352, no. 6288, pp. 922–928, May 2016, doi: 10.1126/science.aad9302.
[22]   C. Morón, D. Ferrández, P. Saiz, G. Vega, and J. P. Díaz, "New prototype of photovoltaic solar tracker based on arduino," *Energies*, vol. 10, no. 9, p. 1298, Aug. 2017, doi: 10.3390/en10091298.
[23]   J. A. Rosiene and C. Pe Rosiene, "SPAM: simplifying Python for approaching machine learning," in *Proceedings - Frontiers in Education Conference, FIE*, Oct. 2020, vol. 2020-Octob, doi: 10.1109/FIE44824.2020.9273972.
[24]   G. M. Tina, C. Ventura, S. Ferlito, and S. De Vito, "A state-of-art-review on machine-learning based methods for PV," *Applied Sciences (Switzerland)*, vol. 11, no. 16, p. 7550, Aug. 2021, doi: 10.3390/app11167550.
[25]   J. M. Johnston, "Distinguishing between applied research and practice," *Behavior Analyst*, vol. 19, no. 1, pp. 35–37, Apr. 1996, doi: 10.1007/bf03392737.
[26]   P. J. Bentley, M. Gulbrandsen, and S. Kyvik, "The relationship between basic and applied research in universities," *Higher Education*, vol. 70, no. 4, pp. 689–709, Mar. 2015, doi: 10.1007/s10734-015-9861-2.
[27]   A. Awasthi *et al.*, "Review on sun tracking technology in solar PV system," *Energy Reports*, vol. 6, pp. 392–405, Nov. 2020, doi: 10.1016/j.egyr.2020.02.004.
[28]   M. Cumbajín, P. Sánchez, M. Núñez, and C. Gordón, "Energy harvesting system with solar panels to supply low power electronic devices," in *IOP Conference Series: Earth and Environmental Science*, Feb. 2023, vol. 1141, no. 1, p. 012008, doi: 10.1088/1755-1315/1141/1/012008.
[29]   J. P. Ram, N. Rajasekar, and M. Miyatake, "Design and overview of maximum power point tracking techniques in wind and solar photovoltaic systems: a review," *Renewable and Sustainable Energy Reviews*, vol. 73, pp. 1138–1159, Jun. 2017, doi: 10.1016/j.rser.2017.02.009.
[30]   T. Naikwade, R. Gawade, M. A. Mane, R. Bandal, and S. V Patil, "IoT based smart solar energy monitoring system with wiping mechanism," *International Journal of Engineering Research and Technology*, vol. 11, no. 4, pp. 282–286, 2022.

BIOGRAPHIES OF AUTHORS

Christian Ovalle Paulino 🔟 🔍 SC 🔾 is an associate professor at the Faculty of Engineering of the Technological University of Peru, Lima-Peru. He has a Ph.D. in Systems Engineering with a specialization in artificial intelligence. His research areas are process mining, business data analysis and pattern recognition. He is CEO of the 7D consultancy dedicated to the Investigation of intelligent solutions. He has participated in different research projects, receiving awards from the Peruvian Ministry of Defense and the Armed Forces Army for the best general researcher, which is a technology-based company and his innovative products received national and international recognition. He has filed a number of patents and industrial designs on his innovative ideas. His research interests include data mining, artificial intelligence, image/signal processing, bibliometrics, and pattern recognition. He can be contacted at email: dovalle@utp.edu.pe.

Luis Rojas Nieves 🆔 ⑧ SC 🔾 is a profesor at the Faculty of Engineering of the Technological University of Peru, Lima-Peru. He has bachelor of industrial engineering. He has MBA with specialization in processes and technological tools of the financial sector. He is IT consultancy at the Indian Corporation Tata Consultancy Services participating in various IT projects in the financial sector at BBVA bank such as business intelligence, CRM, data mining, financial loans, payment methods. He can be contacted at email: c01201@utp.edu.pe.

Hugo Villaverde Medrano 🆔 ⑧ SC 🔾 systems engineer, master in administration and Dr. in Educational Administration. Professional with experience in business intelligence in comprehensive health insurance. Systems manager at Essalud. Senior engineer at Scotiabank. IT consultant for Cencosud and other companies. University professor at the Cayetano Heredia Peruvian University, San Marcos National University, La Molina National Agrarian University, Technological University of Peru, San Ignacio de Loyola University among others. He can be contacted at email: c21209@utp.edu.pe.
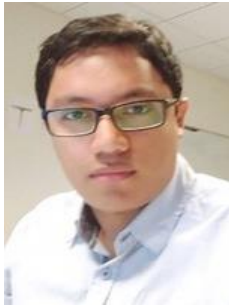
Ernesto Paiva Peredo 🆔 ⑧ SC 🔾 is teacher with title of Electrical Mechanical Engineer from the University of Piura, Peru, in 2013. He has completed a Master's degree in electrical mechanical engineering with a mention in Automation and Optimization at the University of Piura funded by CONCYTEC 2016. He was a research assistant at the Department of Technology and Innovation (DTI)-SUPSI. Now, he is a professor-researcher at Universidad Tecnológica del Perú. He can be contacted at email: epaiva@utp.edu.pe.