Assessment of Future Performance of Hybrid Solar-Wind Street Lamp through Energy Generation Forecasting using Artificial Neural Network

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Abstract:
Hybrid solar-wind street lamps have gained popularity as a more efficient alternative to stand-alone street lamps, benefiting from the availability of two renewable energy sources: solar and wind. However, the system's energy generation is directly influenced by unpredictable weather parameters, posing a challenge for consistent performance. To overcome the declared challenge and concern, this study aimed to develop a forecasting model using Artificial Neural Network (ANN) to forecast the energy generation of a hybrid solar-wind powered lamppost. The forecasting model will aid in the assessment of the future performance of the street lamp. The accuracy of the forecasting model was validated through statistical analyses, including Mean Squared Error (MSE), Rall value, and Root Mean Squared Error (RMSE). The optimal number of hidden neurons was determined by modeling networks with different quantities, and 12 hidden neurons yielded the most satisfactory results. The researchers also assessed the parameter weights and biases using the Garson's Algorithm to provide insights into the causal relationships between inputs and outputs. Moreover, One-Sample T-test revealed a significant difference between forecasted and actual energy

Generation, indicating the need for prototype upgrade and calibration. The study recommends further research in different locations and highlights the need for prototype upgrades to enhance performance.
Keywords:
Hybrid solar-wind street lamp, Energy generation forecasting, Artificial Neural Network (ANN) MATLAB, Garson's algorithm, One-Sample T-test Analysis.

I. Introduction:

In recent years, renewable energy sources, including solar and wind power, have garnered considerable interest due to their capacity to alleviate worldwide energy and environmental challenges [1]. According to Reference [1], solar panels can harness the abundant solar energy available and convert it into electrical energy, while wind turbines are designed to capture the kinetic energy of wind and produce power. Nonetheless, solar and wind energy systems possess inherent limitations that can impact their efficacy and impede their widespread implementation.

The efficacy of solar panels is heavily dependent upon the availability of sunlight, making them vulnerable to variations resulting from meteorological factors, such as cloud obstructions in illumination [2]. Similarly, Wind turbines are susceptible to wind speed and direction fluctuations, which can affect their power production [3]. The outlined constraints present challenges to the dependable and consistent delivery of sustainable energy from solar and wind technologies.

In order to overcome these limitations and maximize the utilization of sustainable energy sources, researchers and industry professionals have investigated the concept of integrating solar and wind technologies. According to Reference [4], integrating solar panels and wind turbines in hybrid systems results in enhanced system performance due to the complementary power generation profiles. Hybrid systems can address the irregularity and reliability challenges commonly associated with solar and wind energy sources when used separately. This is achieved by combining the two sources, thereby improving their dependability and overall energy production.

The hybridization of solar and wind technologies offers numerous benefits. First, using multiple renewable sources simultaneously can augment the energy generation capacity. Furthermore, the combined utilization of solar and wind resources can lead to a more stable and reliable power supply, as the system can continue to produce electricity even in the event of lowered output from one of the sources. Hence, hybrid systems can enhance efficiency and optimize the usage of existing space and infrastructure [5].

Nonetheless, integrating and improving hybrid solar-wind systems necessitate intricate planning, design, and control methodologies. This is where the role of artificial neural networks (ANNs) becomes crucial in this study. Artificial neural networks (ANNs) are powerful machine learning algorithms that analyze complex datasets and identify patterns. This capability allows for precise forecasting and optimization of energy generation in hybrid systems [6]. The utilization of Artificial Neural Networks (ANNs) enables the assessment of the future performance of hybrid solar-wind street lamps, thereby facilitating informed decisions concerning system design, resource management, and operational planning.

Therefore, this study aimed to assess the potential of utilizing artificial neural networks to forecast energy production in hybrid solar-wind street lamps. By assessing the future system performance, it is possible to identify possibilities for enhancement, improve energy generation, and establish a path toward more effective and environmentally conscious street lighting alternatives.

This conceptual framework below outlines the process of utilizing Artificial Neural Networks (ANNs) to develop a forecasting model for energy generation. The framework begins with collecting essential input parameters through an experimental procedure conducted on the prototype, which involves monitoring weather and electrical parameters over 30 days. The collected data then undergoes preprocessing to ensure its suitability for ANN training. Next, the architecture of the ANN is formulated, determining the number of hidden layers and neurons within each layer. The ANN is trained iteratively to minimize the discrepancy between the predicted energy output and the measured values, using separate training and validation datasets. The training continues until the researchers are satisfied with the model's performance. The framework emphasizes the importance of data preprocessing, architectural design, and iterative training to achieve accurate energy generation forecasting for the prototype.

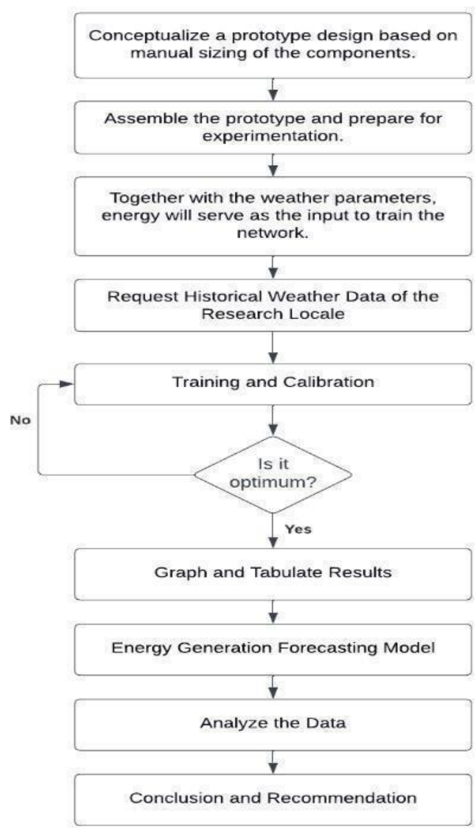


Figure 1.1 Conceptual Framework

for this study, the researchers focused on utilizing an Artificial Neural Network algorithm to generate an energy generation forecasting model based on the trained input data, which were obtained from the weather parameters, such as; wind speed, solar irradiance, temperature, humidity, and time factor at Tagalag, Valenzuela City, and the measured energy generation of the constructed prototype of hybrid solar-wind powered street lamp as the target data. The researchers selected Brgy. Tagalag as the research locale because it has good wind circulation, for there is no disturbance in the air due to minimal buildings, trees, and its location, which is in the middle of the body of water. Moreover, the said forecasting model was used to forecast the energy generation of the hybrid solar-wind-powered street lamp, establishing a fundamental basis for its future optimization. The forecasting model aided in forecasting the energy generation of the prototype itself, hence, establishing advanced management plan regarding its future performance. In addition, the researchers also checked and tabulated the energy consumption of the prototype, as it was needed and helpful for the One-Sample T-test Analysis statistical treatment.

Hence, this study did not have an in-depth discussion about the other components of the prototype, such as the pole, enclosure of the control and monitoring system, and the base of the pole, since this study only focused on the prototype's energy generation and consumption aspect. Additionally, to avoid intervention and measurement errors during the data gathering period, the researchers limited the height of the pole to 3 meters due to the limitations on the wire length for the sensors and voltage drop. Thus, the data gathering of the weather parameters, such as wind speed, relative humidity, and temperature, and the electrical parameters, including current and voltage, was done between 6 am to 6 pm. The Arduino monitoring system and the weather instrument used for data gathering were not designed to withstand strong weather conditions, including typhoons. Therefore, when such weather events occur, the researchers did not gather data for that specific day to avoid potential damage to the prototype. In addition, the researchers can only offer a fundamental basis and advanced management plan for the future optimization of hybrid solar-wind street lamp.

Hybrid solar-wind street lamps have increasingly become popular due to the availability of two renewable energy sources; the solar and wind energy, making the system more efficient compared to stand-alone street lamps. However, due to the unpredictability of weather parameters, which directly affects the energy generation of the system, one of the underlying concerns with hybrid solar-wind energy system is its need to undergo optimization to allow the system to constantly meet the demand that the load requires for it to efficiently operate. Thus, for this study, the researchers aimed to generate a forecasting model using Artificial Neural Network that will forecast the energy generation of the prototype of a hybrid solar-wind powered street lamp, to have an assessment for its future performance.

This was further assessed by answering the following questions:

1. How can the Artificial Neural Network be used for the assessment of the future performance of the energy generation of hybrid solar-wind powered street lamp?
2. How accurate is the forecasting model in forecasting the energy generated of Hybrid Solar-Wind Energy System that power the street lamp?
3. How does the method used to train the input data influence the accuracy of the output?
4. How does the energy generation forecasting model be used to assess the future performance of the hybrid solar-wind powered street lamp?

Moreover, the researchers formulated the following hypotheses to establish a systematic approach in proposing for the possible relationship of two variables – energy generation and consumption. The establishment of the conclusion and recommendation for this study will be facilitated by determining which hypothesis is deemed acceptable based on the obtained results.

Ho: The prototype does not require an upgrade and calibration, for there is no significant difference between the energy generation and energy consumption.

Ha: The prototype does require an upgrade and calibration, for there is a significant difference between the energy generation and energy consumption.

Objectives of the study:

The main objective of this study is to provide a forecasting model using Artificial Neural Network that will forecast the energy generation of hybrid solar wind powered lamppost given the weather conditions at Tagalog, Valenzuela City where the prototype was installed. The forecasting model will serve as the basis for future assessment of the performance of the street lamp itself.

The following research objectives facilitated the achievement of this aim:

1. Utilize the Artificial Neural Network algorithm to assess the energy generation of a hybrid solar-wind energy system;
2. Test the forecasting model's accuracy in forecasting the energy generated of the Hybrid Solar-Wind Energy System to power street lamp post.
3. Apply a training method applicable to the forecasting model to ensure its accuracy
4. Determine how the optimized energy generation forecasting model be applied to assess the future performance of hybrid solar-wind street lamp.

Review of Related Literature:

After reviewing all the gathered research and literature for this study, it is clear that opting for renewable energy sources can positively impact the environment. In particular, a hybrid solar-wind energy system has been shown to be helpful, especially because it makes consumers less reliant on the traditional power grid, which cuts down on electricity use and costs [7]. As the reviewed studies and literature suggested, the presence of both the solar panel and wind turbine will allow the hybrid system to harness solar and wind energy simultaneously at any time of the day [8]. In designing the prototype of the hybrid solar-wind-powered lamp post, the components' specifications should be considered. It is to ensure that the quantity, the required rating, and other specifications are accurate to what the prototype needs for it to work effectively. Some main components include; a solar panel, wind turbine, charge controller, batteries, and LED lamp.

Additionally, the location and position of installing the lamp post are crucial things to consider to maximize energy production and harness solar and wind energy efficiently [9]. Since two energy supplies are being utilized in a hybrid solar-wind-powered lamp post, the circuit configuration of the system should be in parallel so that each power supply provides the required load voltage, thus increasing the load current and power [10]. Also, street lamps are widely used to illuminate alleys or roads, which is why utilizing renewable energy from the sun and wind will be ideal for powering street lamps, as it will be easier to harness solar and wind energy.

However, due to the unpredictability of the weather conditions which directly affects the energy generation of the system, accurate forecasting of energy generation of hybrid renewable energy system is a crucial thing to do. Unlike other energy sources, power generation that comes from solar and wind heavily depend on the meteorological conditions and environmental factors. Forecasting energy generation in a general context is essential to provide crucial information on the projected changes in the to-be-generated energy in the future, which subsequently allows for the advanced management of the energy system itself. Thus, in a study conducted by Reference [11], the authors utilized machine learning (ML) based approaches to forecast the power generation of various hybrid renewable energy system (HRES).

Utilizing Artificial Neural Network for training and developing a forecasting model to forecast the energy generation of the HRES require for various things that should be considered. Selecting the optimal amount of data influences the quality and accuracy of the output, hence, the forecasting model itself [12]. The input parameters should have a strong correlation with the target output. It is also necessary to consider the weight and bias of the input data as it will affect the training of neural networks. For this study, Garson’s algorithm was used to assess the said weights and biases and determine which input parameter has the highest relative importance to the output [13].

There are various types of activation functions and training methods in ANN, but for this study, the researchers only covered the discussion of Tangent Sigmoid (tansig) function and Levenberg-Marquardt (LM) method since it was used in this study and it was asserted to be the most efficient function to use since it resulted to the most satisfactory results compared to other activation functions and training methods. However, along with the training period of neural networks, problems may occur. These are called overfitting and under fitting. Overfitting happens when there is too much data and the network is too complex; hence, to prevent it from happening, the model's complexity should be reduced by utilizing an optimal number of neurons or layers. On the other hand, under fitting occurs when the complexity of the neural network is too low for it to learn the underlying mathematical mapping from input features to output labels. It occurs when the network cannot produce precise predictions on the training set [14]. In this regard, determining the number of hidden layers and hidden neurons is critical because it significantly impacts the outcome of the training process [15]. Thus, the input data will mainly undergo training, validation, and testing. The process will continue until the researchers are satisfied with the output;

hence, an accurate forecasting model is generated.
Consequently, numerous studies and articles concerning the forecasting of energy generation of hybrid solar-wind energy systems (HRES), which is the focus of this study, have been reviewed throughout the completion of this paper; thus, only minimal studies that specifically used the Artificial Neural Network method and focused on employing it to HRES in street lighting. Most have just focused on simulating and modeling hybrid electrification for microgrids. Additionally, many studies have been found to utilize ANN to forecast the power generation of single energy sources, such as PV power output and WP generation. A study has also been reviewed where it developed a High-Order Multivariate Markov Chain forecasting model to predict the power generation of a PV-Wind energy system [16]
To overcome the declared gap, the researchers aimed to have an assessment regarding the future performance of the hybrid solar-wind street lamp. ANN was utilized to generate a forecasting model that will accurately forecast the energy generation of hybrid solar-wind, allowing its users to have a basis for its future optimization. The findings and suggestions from the reviewed studies and literature were beneficial and aided in the justification of the present study.

II. Methodology

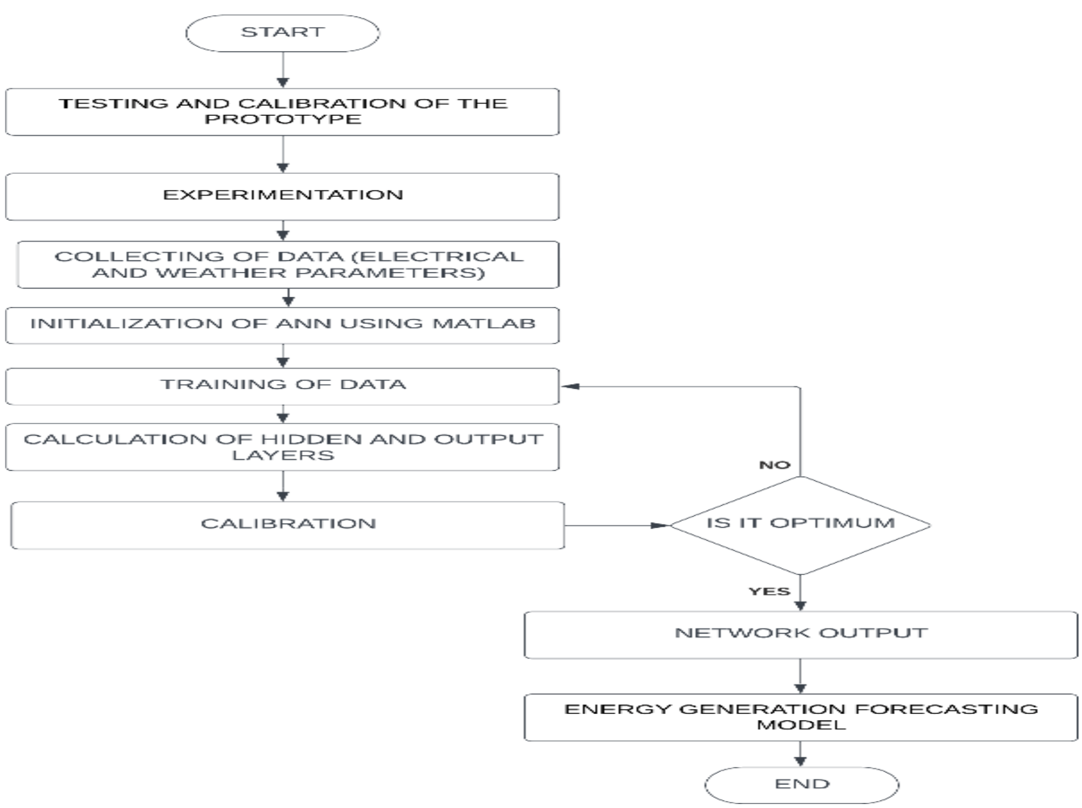


Figure 2.1 Overview of the Methodology

To complete this study, the first step the researchers have taken was constructing a Street lamp that a hybrid solar-wind energy system will power. The sizing of the prototype's components was manually computed to ensure that wind and solar energy sources will efficiently supply the load requirement. Following the completion of the prototype, the researchers embarked on a 30-day experimental period. Within that time range, the researchers gathered the measured voltage and current data and weather parameters in the chosen research locale where the prototype was installed. These data were all used as input data and normalized before being used for proper training. The data training was simulated using MATLAB software. Once the researchers are satisfied with the network output, an accurate forecasting model will be generated, which was then used to forecast the energy generation of the prototype, providing an accurate foundation for future optimization.

Moreover, the Arduino smart energy system was utilized to collect the necessary data, as it can measure various electrical parameters required to justify the data gathering approach. Multiple data collection instruments were used to collect the necessary data for this study. The materials' information and the cost of constructing the hybrid solar-wind LED lamp posts are also tabulated below. Thus, the researchers intend to present a conclusion and recommendations at the end of this study, which will also serve as a guide for future researchers who wish to pursue a topic related to this.

Figure 2.2 Actual Design of the Prototype

DATA GATHERING PROCEDURE
Data Gathering Procedure:

Weather Data

Due to the limitations of the weather instrument used in this study to record real-time weather data, it only records three of the four weather parameters needed in the study. As for the data of solar irradiance, the researchers used Solcast as a credible source of solar irradiance data. Solcast is a company that specializes in providing real-time and historical solar irradiance data to businesses and organizations worldwide. Their data is derived from satellite imagery, ground measurements, and advanced algorithms, ensuring high accuracy and reliability. The data was collected hourly from 7 am to 6 pm. On the other hand, the researchers obtained historical weather data from the National Renewable Energy Laboratory (NREL) at hourly intervals daily since they needed it to support the training of ANN. NREL is a reliable source of historical meteorological data. It is a reliable and widely used source of long-term meteorological data, offering high-quality data to researchers and professionals involved in designing and analyzing renewable energy systems. NREL's main feature is the National Solar Radiation Database, which contains historical weather data.

Experimentation:

The experimentation stage primarily focused on gathering the input data and data processing. The researchers classified the input parameters based on the factors affecting the Hybrid Solar-Wind Energy System. Five input parameters for the ANN Model, wind speed, relative humidity, temperature, solar irradiance, and time were recorded during the monitoring hours. The target parameters were the prototype's energy generation, which was recorded simultaneously as the input parameters. The researchers monitored the generation data with 1-hour intervals, from 6 am until 6 pm. The electrical parameters of the prototype are recorded to the data logger every 5 minutes, while the researchers record the weather parameters manually at the specified interval. In addition, the researchers programmed the Arduino Smart Energy Monitor to record the energy generation and consumption of the prototype. All the data were tabulated following the experimentation phase, and it also served as a guide for the researchers in resizing the components when the forecasting model had been finalized.

Before the experimentation stage, a mock experiment was performed to prepare the overall system to undergo such tests and data gathering. Also, to ensure that the Arduino measures the data accurately and efficiently, the researchers did an accuracy test between the measured data in Arduino and the mustimeter. After completing the mock experiment, the researchers proceeded to the testing period

ANN Model:

After gathering the essential data from the conducted experiment, the researchers moved to the simulation phase, which mainly involved the Artificial Neural Network. The ANN algorithm was used to establish an accurate forecasting model that will forecast the energy generation of the prototype for the following months. With the help of the optimized energy generation forecasting model, it can provide an accurate basis for the future optimization of the prototype itself. The input parameters are the weather conditions such as; solar irradiance, wind speed, temperature, and relative humidity, as well as the time factor that affect the prototype's energy generation; the algorithm is the process of identifying complex relations between input variables in order to produce a predicted output; the area in which the algorithm resides is known as the hidden neurons. The outcome of the hidden neurons is sent to the output layer, where it will be calibrated. Once the researchers are satisfied with the output, an optimized forecasting model can now be established to forecast the energy generation of the prototype.

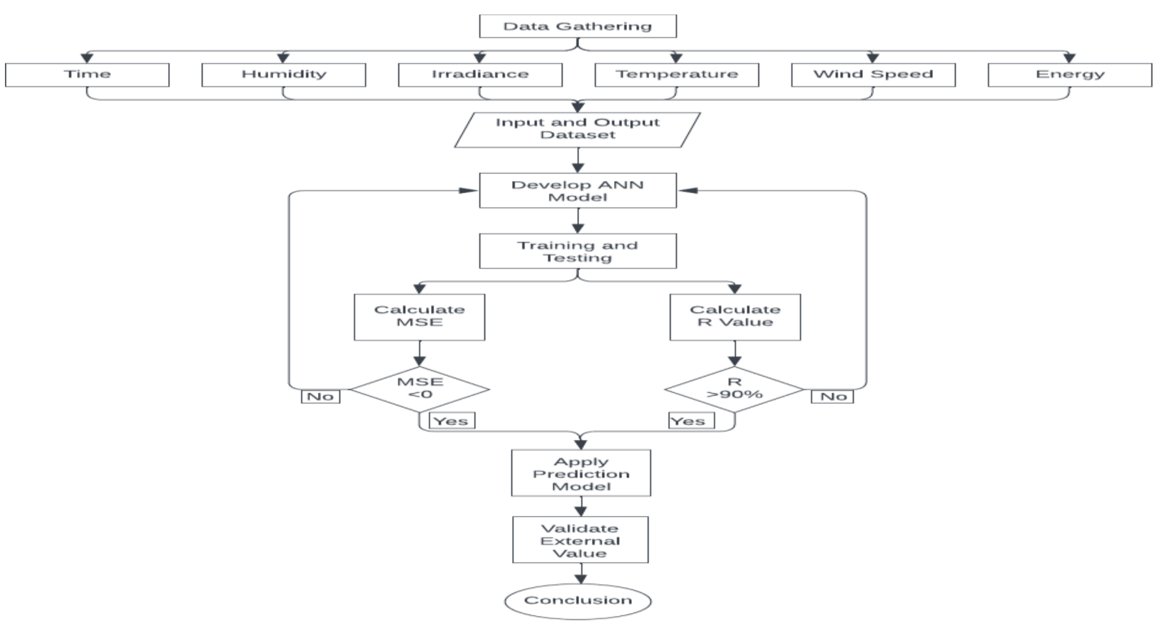


Figure 2.3 Process Flowchart of ANN

After gathering the essential data from the conducted experiment, the researchers moved to the simulation phase, which mainly involved the Artificial Neural Network. The ANN algorithm was used to establish an accurate forecasting model that will forecast the energy generation of the prototype for the following months. With the help of the optimized energy generation forecasting model, it can provide an accurate basis for the future optimization and assessment of the performance of the prototype itself. The input parameters are the weather conditions such as; solar irradiance, wind speed, temperature, and relative humidity, as well as the time factor that affect the prototype's energy generation. The algorithm is the process of identifying complex relations between input variables in order to produce a predicted output; the area in which the algorithm resides is known as the hidden neurons. The outcome of the hidden neurons is sent to the output layer, where it will be calibrated. Once the researchers are satisfied with the output, an optimized forecasting model can now be established to forecast the energy generation of the prototype.

III. Results and Discussion:

Assessment of ANN Training, Validation, and Testing Using MATLAB

In performing ANN simulation, various conditions should be taken into consideration. The first thing is normalizing all the input data to fit the behavior of the activation function used in the simulation, which is the tansig. Knowing what to set as the input and target data is also crucial for the overall training, as it will highly influence the outcome. The researchers used the Levenberg-Marquardt (trainlm) training function since various studies suggested it was the best training algorithm. This claim was strengthened when the researchers completed the ANN simulation, resulting in a satisfactory value and meeting the conditions. All of the input data was partitioned for the ANN simulation and put through Training, Validation, and Testing. As shown in the ANN process flowchart in the Figure 2.2, it indicates that in order to meet the training and testing period conditions and achieve the best possible outcome, the target R-value (All) should be more than or equal to 0.90 or 90%, while the Mean Squared Error (MSE) should be approaching 0. The researchers have tried modeling networks with three to seventeen hidden neurons in order to determine the optimum number of hidden neurons that yields acceptable Rall and MSE values. Detailed findings for each hidden neuron are summarized in the table below.

Table 3.1 Selecting the optimal number of hidden neurons

Hidden Neuron	Training	Validation	Test	R (ALL)	MSE
3	0.86223	0.88504	0.83751	0.86153	0.06921
4	0.8627	0.87656	0.8685	0.86381	0.06629
5	0.85642	0.82722	0.91427	0.86112	0.08576
6	0.86014	0.90133	0.90869	0.87055	0.06465
7	0.87148	0.83377	0.87227	0.86613	0.07024
8	0.86031	0.88923	0.88143	0.86799	0.06954
9	0.8776	0.85703	0.85086	0.86985	0.06254
10	0.87601	0.86898	0.91719	0.88194	0.0642
11	0.88254	0.86334	0.88416	0.88121	0.05067
12	0.90972	0.89999	0.8669	0.90373	0.04048
13	0.90171	0.85778	0.86031	0.88932	0.06413
14	0.86984	0.863	0.88774	0.87153	0.06377
15	0.86853	0.87091	0.86919	0.86906	0.07597
16	0.85651	0.87612	0.94071	0.87386	0.0698
17	0.88169	0.88816	0.83346	0.8762	0.05203

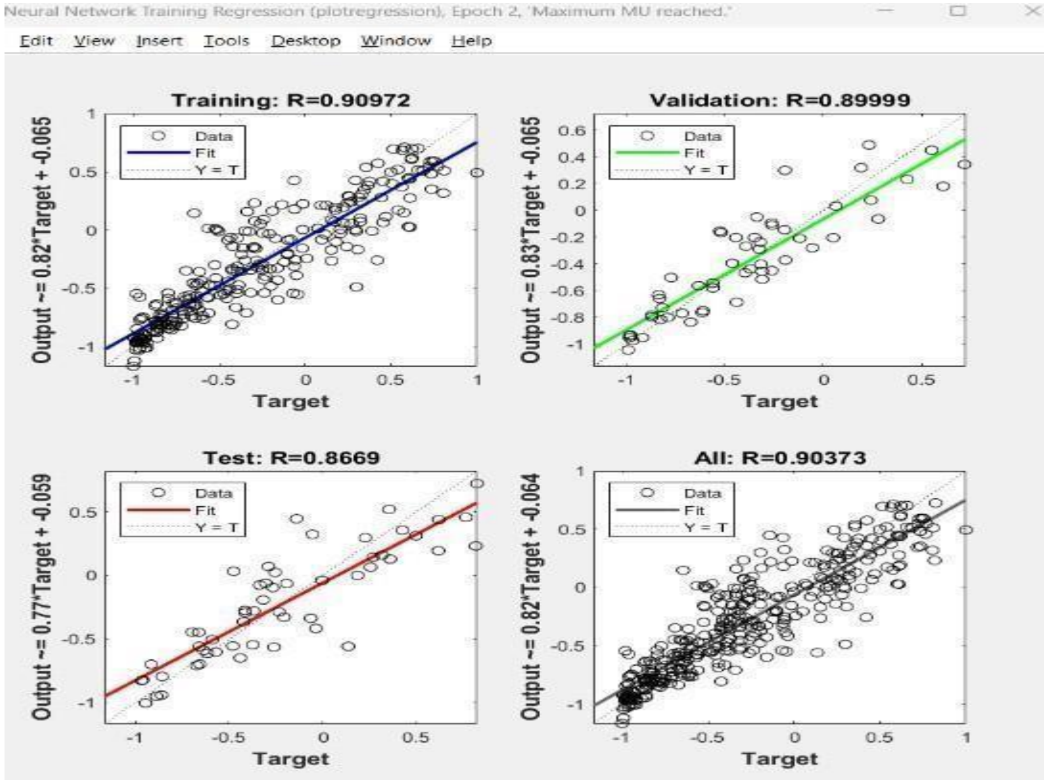


Figure 3.1 R-value using 12 Hidden Neurons

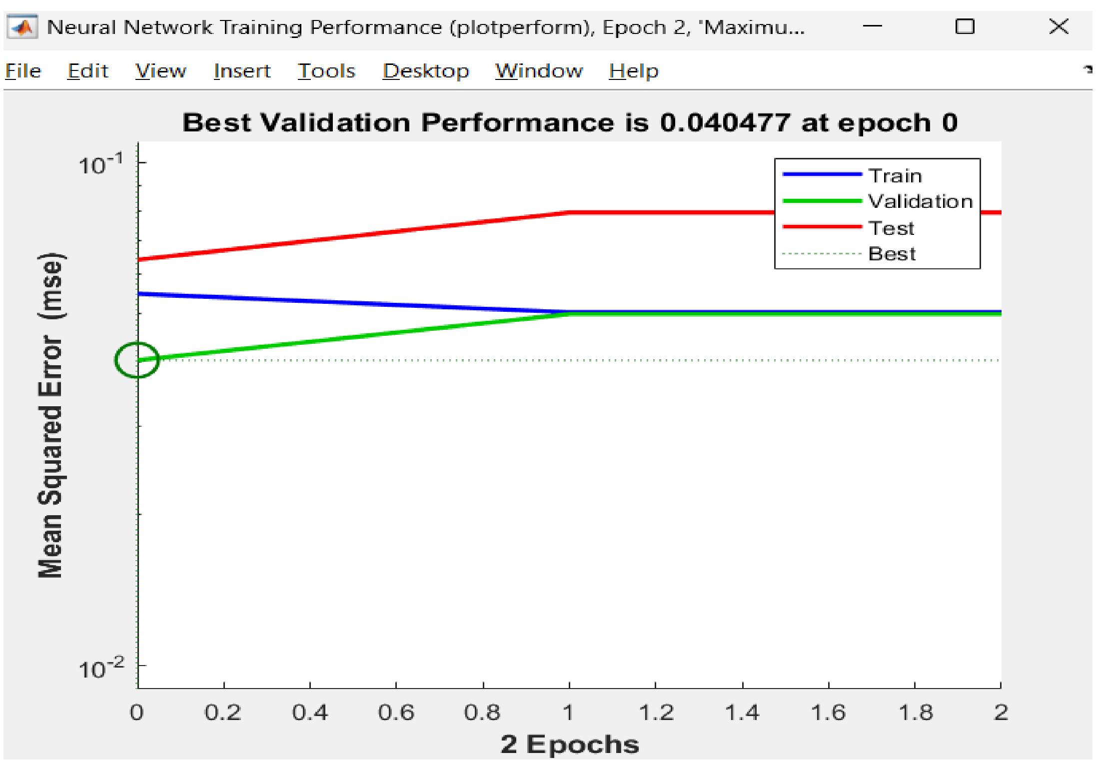


Figure 3.2 MSE using 12 Hidden Neurons

Figure 3.3 shows the neural network of the model that is consists of 5 inputs, 12 hidden neurons, and 1 output.

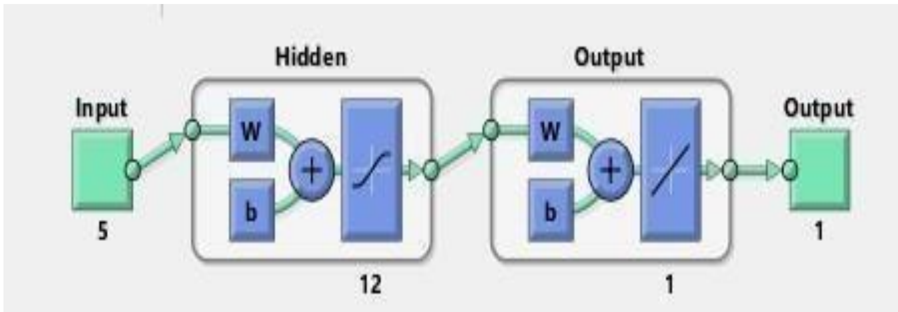


Figure 3.3 Neural Network of 12 Hidden Neurons

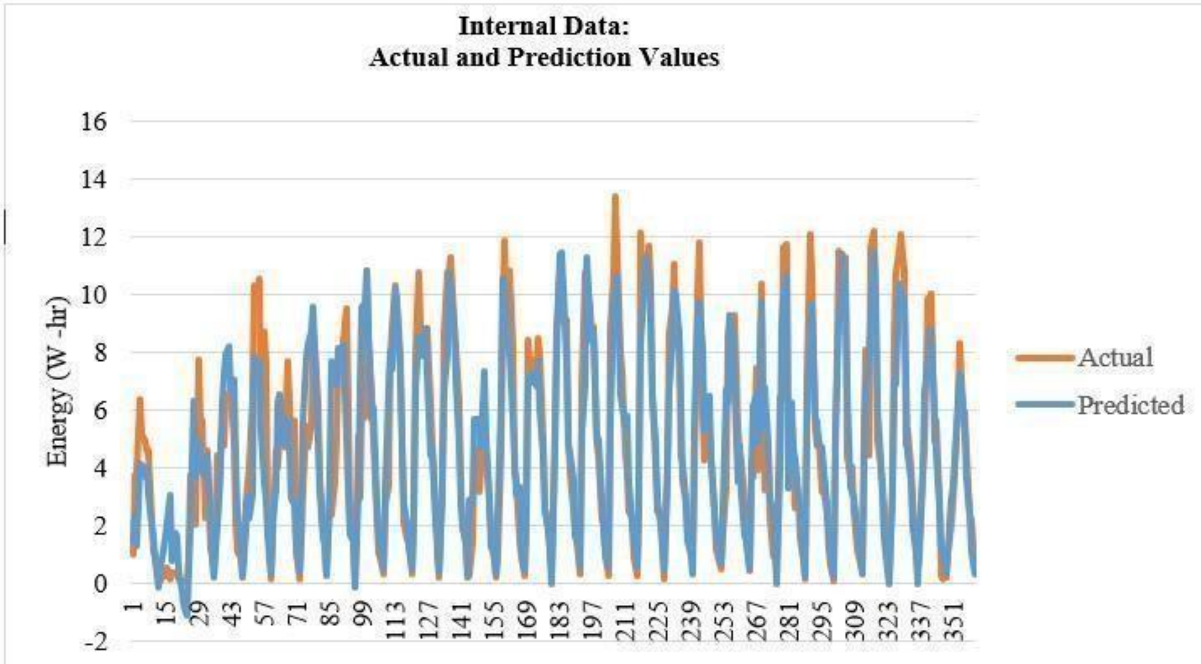
Table 3.2 Used Model in the Energy Generation Forecasting Model

ANN Model	Use in the Model
Training Algorithm	Levenberg-Marquardt
Training Function	Hyperbold Tangent Sigmoid
Number of Hidden Neuron	12
Number of Hidden Layer	1
Performance Criteria	R Value and MSE

The presented graphs and table show that 12 hidden neurons yielded the most satisfactory Rall and MSE values among the other quantities. The Rall value reached the researcher has targeted value of 0.9037 or 90.37%, whereas the MSE resulted in a value-approaching zero, particularly 0.04. After obtaining favorable results, the researchers modeled the forecasting model.

Accuracy of the Forecasting Model:

To test and verify the accuracy of the generated forecasting model, the researchers employed various statistical analyses to calculate the error of the simulated network. The Mean Squared Error (MSE) showed a result of 0.04, which is considered satisfactory since the goal for this metric is to get a value that is close to 0. As for the Rall value, the result was able to reach the target value of 90.37%, which also satisfies the set condition for this error metric. As for the Average Root Mean Squared Error (RMSE), it exhibited a value of 1.10 and 1.34 for internal and external data, respectively. Moreover, the accuracy of the network model highly depends on the hidden neurons used. In selecting the optimal number of hidden neurons, the researchers have modelled networks with different number of hidden neurons, ranging from 3 to 17 to assess which quantity would yield the most satisfactory values, and as the results revealed, using 12 hidden neurons generated the most acceptable Training, Testing, and Validation values among the other quantities, which are 90.97%, 86.69%, and 89.99%, respectively


Internal Data:
Actual and Prediction Values
Energy (W -hr)
Actual
Predicted

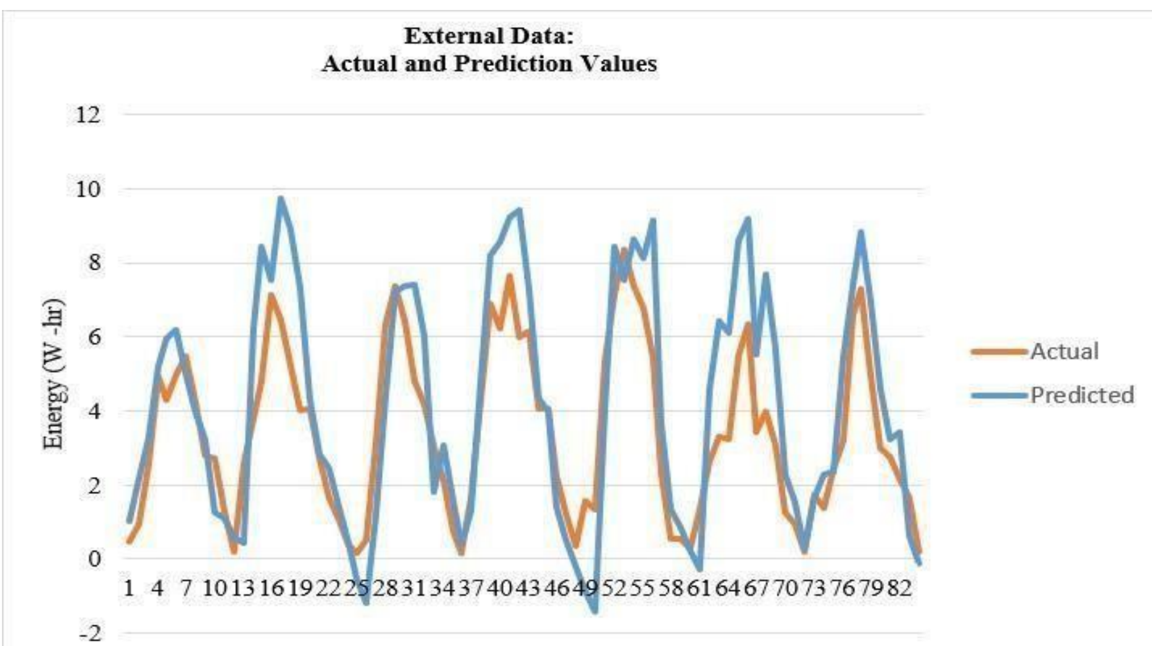

External Data:
Actual and Prediction Values
Energy (W -hr)
Actual
Predicted

Figure 3.5 Graph representation of Actual and Prediction Values of External Data

	Average MSE	Average RMSE
Internal Data	2.209325837	1.097906786
External Data	2.899934576	1.344072138

Figure 3.4 Average MSE and RMSE values for the validation of Internal and External Data

Table 3.2 Forecasted Values of Energy Generation (W-hr.) of the prototype for 6 months

	ACTUAL ENERGY GENERATION	**FORECASTED ENERGY GENERATION**					
DAY	**MONTH 1**	**MONTH 2**	**MONTH 3**	**MONTH 4**	**MONTH 5**	**MONTH 6**	**MONTH 7**
1	38.81	38.95	40.65	45.46	28.87	64.95	28.33
2	37.26	60.03	32.37	62.11	45.09	73.33	47.41
3	38.74	61.91	41.03	29.32	27.35	67.04	65.12
4	46.45	58.85	31.54	76.47	62.28	25.7	68.93
5	72.3	63.07	35.24	67.41	44.66	71.87	44.61
6	51.97	54.23	49.55	33.95	20.07	47.42	23.71
7	50.78	46.69	63.72	61.2	55.37	36.28	31.26
8	56.7	68.08	67.99	46.97	37.21	27.62	28.81
9	55.48	80.32	31.17	37.12	40.1	31.61	76.97
10	61.22	73.01	57.83	27.67	48.79	23.35	48.57
11	69.82	57.42	78.27	46.57	56.47	52.19	37.04
12	75.92	28.48	86.06	16.15	4.28	69.64	48.48
13	33.79	54.69	68.24	55.66	51.24	73.15	38.07
14	64.55	55.19	62.81	48.13	55.16	70.24	49.32
15	60.33	48.41	56.79	79.56	48.92	48.18	68
16	68.55	69.56	40.25	67.88	49.16	43.48	51.72
17	69.94	65.31	32.06	71.19	38.24	23.24	43.81
18	74.33	73.28	43.46	45.17	29.88	48.57	61.92
19	74.17	84.09	37.75	52.39	34.32	66.01	27.47
20	65.48	75.07	46.15	21.59	24.32	54.87	55.67
21	54.79	37.61	65.3	9.13	26.81	54.13	53.59
22	59.25	76.64	59	18.8	43.91	65.98	21.98
23	48.17	70.19	48.75	20.9	22.02	57.23	32.16
24	57.9	72.59	42.09	59.21	47.58	36.75	45.87
25	56.12	82.32	62.44	41.47	59.45	35.33	35.01
26	64.7	85.65	67.52	14.14	67.57	54.22	48.24
27	66.88	81.68	47.82	20.25	59.58	43.82	40.65
28	75.77	44.53	73.01	47.58	55.94	22.5	24.85
29	52.83	67.84	66.38	21.64	63.68	47.28	42.13
30	45.96	43.07	65.28	39.69	66.17	27.33	28.9

Assessment of Future Performance of the Hybrid Solar-Wind Street Lamp:
Using the generated forecasting model, the researchers could forecast the prototype's energy generation for six months. The prototypes forecasted, and actual energy generation was then statistically treated using the One-Sample T-test to assess the significant difference between the energy consumption of the same prototype. The findings presented in Table 3.4 indicate that the One-Sample T-test analysis yielded a statistically significant difference between energy generation and energy consumption. The results of this study support the alternative hypothesis, indicating that the prototype is required to undergo an upgrade and calibration to address the observed significant differences in statistical values.

Hence, to further establish a basis for the future optimization the hybrid solar-wind energy system of the constructed street lamp, the researchers conducted a sensitivity analysis using Garson’s Algorithm to demonstrate and interpret the causal relationship between the weather parameters and energy generation. The findings indicate that Solar Irradiance and Time Factor have shown the most significant degree of relative significance, with Relative Humidity, Temperature, and Wind Speed following in descending order of importance.

Table 3.3 Parameter Weights and Biases

HN	INPUT TO HIDDEN					HIDDEN TO OUTPUT
	Windspeed	Temperature	Solar Irradiance	Humidity	Time	
1	0.622904807	0.142278936	-0.902212587	-0.859532946	-0.893241199	-1.0322183
2	0.402212131	0.532621538	1.035470993	0.278828467	-2.288038457	1.7125823
3	0.857116436	0.444489191	0.650978049	-0.633199001	-0.123579303	-1.3450374
4	-0.706187999	-0.035728352	0.409435055	-0.6262568	-0.000556244	0.3195578
5	0.1544707	-0.317943944	-1.003169833	0.811994433	0.341959744	-0.7154485
6	1.009236256	-0.52977751	-0.648713673	-1.018948551	-1.526905719	0.9944619
7	-0.724152601	-1.185203906	-1.009009402	0.766585792	0.727690171	0.6552511
8	0.358662892	0.425858421	-0.847094404	-0.494014065	-0.846312856	0.4791093
9	-0.801743074	-0.656522989	1.106402799	-0.066467138	-0.825744534	0.9954608
10	0.143579495	-0.263466117	0.160545219	-0.274857185	-2.271857531	-1.6424066
11	-0.719789571	-1.159926141	-0.381858794	0.90487942	1.058746347	-1.0426918
12	-0.559629709	0.377284908	0.07652074	-1.223786153	-0.044077409	-0.7178074
ABS SUM	28.95527323	45.362763	110.9646006	78.15325279	93.16896536	-
RELATIVE IMPORTANCE	**8.11970808**	**12.72073623**	**31.11696295**	**21.91592506**	**26.12666767**	**100**
Rank	5	4	1	3	2	-

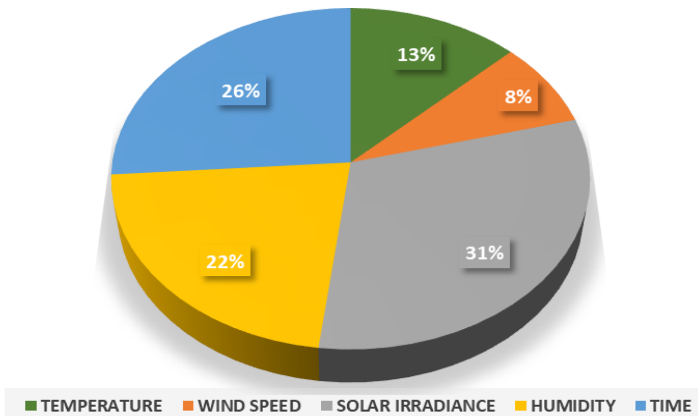


Figure 3.5 Relative Importance of Input Parameters

Table 3.4 One-Sample Test Table

ONE-SAMPLE T-TEST									
TEST VALUE = 50									
	t	df	Mean	Std. Deviation	Sig (2 - tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Month 1	3.747	29	58.2988	12.1308	0.001	8.29883	2.21477	3.7691	12.8285
Month 2	4.566	29	62.6253	15.1452	0.0001	12.62533	2.76512	6.9700	18.2806
Month 3	1.201	29	53.3508	15.2817	0.239	3.35082	2.79004	-2.3554	9.0571
Month 4	-1.971	29	42.8266	19.9295	0.058	-7.17344	3.63862	-14.6153	0.2684
Month 5	-2.157	29	43.8164	15.7022	0.039	-6.18359	2.86682	-12.0469	-0.3203
Month 6	-0.397	29	48.7766	16.8723	0.694	-1.22343	3.08044	-7.5236	5.0768
Month 7	-2.271	29	43.9546	14.5801	0.031	-6.04536	2.66194	-11.4896	-0.6011

The analysis of the p-values derived from one-sample t-tests, as presented in Table 3.4, provides substantial evidence for rejecting the null hypothesis in favor of the alternative hypothesis. The low p-values for Months 1 and 2 (0.001 and 0.0001, respectively) indicate a significant difference between energy generation and consumption, emphasizing the need for an upgrade to accommodate the excess energy. Month 3 demonstrates no statistically significant difference (p-value = 0.239), indicating that the prototype meets energy needs adequately. However, Months 4, 5, and 7 display significant differences (p-values less than 0.05) with negative mean differences, indicating an energy deficit and emphasizing the need for an upgrade. The lack of a statistically significant difference between months 5 and 6 (p-value = 0.694) indicates that operational effectiveness is satisfactory.

Conclusion:

After following and completing the methodological approaches of this study, the researchers have successfully developed a forecasting model capable of forecasting the energy generation of the hybrid solar-wind street lamp energy system. To ensure that the said forecasting model is accurate, various statistical analyses were applied to calculate the error of the simulated network. To determine if the achieved result is optimal, there is a range of values that should be met to declare that the results are acceptable, which is obtaining a Rall and MSE value of 90% and approaching to 0, respectively. The selection of optimal hidden neurons is a crucial factor that significantly impacts the target output. The present study's findings suggest that the utilization of 12 hidden neurons yielded the most satisfactory outcome compared to other quantities of hidden neurons. The assessment of weights and biases of input parameters was conducted by the researchers to facilitate a clear interpretation of the potential causal relationships between input and output data. The findings presented in Table 4.9 indicate that Solar Irradiance holds the highest relative importance, accounting for 31.12% of energy generation. It is followed by the Time factor, which reveals a numerical value of 26.13%. Furthermore, Relative Humidity, Temperature, and Wind Speed exhibit a value of 21.92%, 12.72%, and 8.12%, respectively. Thus, by doing the said parameter weight assessment, the researchers had established a fundamental basis and was able to establish an approach regarding the optimization of the energy system of the hybrid solar-wind street lamp. Moreover, the findings regarding the wind speed parameter exhibiting the lowest relative importance to the energy generation of the hybrid solar-wind street lamp contradict the findings in the reviewed literature, which suggested that wind power generation will likely improve the energy generation and performance of the hybrid solar-wind energy system. The researchers conclude that the results may still vary depending on the research locale and that the findings of this study are solely based on the weather conditions at Brgy. Tagalag, Valenzuela City.

Consequently, after performing the One-Sample T-test analysis to statistically assess the significant difference between the energy generation and energy consumption of the hybrid solar-wind energy system of the street lamp, the researchers came up with a conclusion that the p-values and mean differences back up the alternative hypothesis of this study, which denotes that there is a significant difference between the energy generation and consumption, hence, an upgrade is necessary for the prototype to improve its performance.

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