A Smart Control of Solar Panel Mechanism with Arduino Based Data Logger for Neural Network Analysis

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Abstract

A solar panel mechanism is a system of devices that can track the sun's movement and adjust the solar panels accordingly. In this experiment, the amount of solar irradiation that can be captured and converted into electrical energy by a solar panel and pyranometer is being investigated. Preliminary study has been done to gather solar irradiance data from the pyranometer and solar panel for comparison. The data gathered was then used to perform a forecast using neural network analysis. Two configurations were used in this experiment where both labelled as "Auto-detect" and "Passive." Auto-detect refers to the placement of the solar panel on a 3D-printed base with a servo motor that regulates rotations in response to inputs from Light Dependent Resistor (LDR) sensor. This arrangement will keep an accurate orientation between solar panel and solar energy source. While in passive configuration, the solar panels are manually positioned. From this study, the maximum sun irradiance measurements made with a pyranometer were 0.9986 W/m2 in auto-detect mode and 0.9962 W/m2 in passive mode. Auto-Detect Configuration has 72.46% efficiency while Passive Configuration: 58.46%. For the neural network analysis, it has been found that the prediction has low accuracy. Therefore, additional improvement techniques can be used in future work.

Keywords: Solar, Control, Arduino, Pyranometer, Neural network

1.0 Introduction

Malaysia's adaptation to the development of renewable energy sources is still limited, and they are not being completely utilized. Due to its geographical advantages, Malaysia has been the solar industry's hub for years, as it receives adequate sunlight for 4 to 6 hours each day [1]. The average daily sun radiation is 45000 kWh m-2 due to the country's natural tropical environment [2]. Malaysia has a solar energy potential of 1,930 MW, according to the International Renewable Energy Agency (IRENA)[3]. As of 2022, Malaysia's energy mix was dominated by fossil fuels, with coal accounting for 52% of electricity generation, followed by natural gas at 44%. Renewable energy accounted for only 4% of electricity generation in 2022, with hydropower being the largest source of renewable energy [4]. The Malaysian government has set a target of increasing the share of renewable energy in the country's energy mix to 20% by 2025 [5]. The government has also set a target of achieving net-zero greenhouse gas emissions by 2050 [6].

2.0 Literature Review

A Smart control of solar panel mechanisms is a promising approach for improving the efficiency and performance of solar energy systems. Studies have shown that smart control of solar panel mechanisms using Arduino-based data loggers and neural network analysis can lead to significant improvements in the efficiency and performance of solar energy systems [7]. Benefits of using active control for solar panel mechanisms may lead to increase in power generation, reduced energy losses, extend the lifetime of solar panels and finally improved the reliability and performance of solar energy systems [8]. An Artificial Neural Network (ANN) is a method of data analysis, which imitates the human brain's way of working. It can be useful to forecast the data from the input and learn the data to perform the prediction output. To make the best use of solar energy, it is necessary to know its availability. As solar energy becomes more widely employed, there is a growing demand for more precise solar radiance modelling and forecasting [9]. It does not require precise system knowledge; instead, neural network analyze previously recorded data to learn the link between input parameters and output variables. It is perfect for modelling nonlinear, dynamic, noisy data and complicated systems [10]. This study focuses on the best way to convert solar energy into electricity using small scale solar photovoltaic panels (PV). The solar panel mechanism is controlled by an Arduino controller based on the pyranometer's measurement of irradiance. The data collected, such as the solar panel's orientation and irradiance, was processed using the neural network method.

The solar photovoltaic (PV) panel and the pyranometer are the two major pieces of equipment that has been used in this study. These two have their own set of requirements.

3.1 Photovoltaic (PV) Panel

The function of the PV panel is to measure the amount of solar energy that can be collected. As the experiment involving a small scale set up, 5cm x 3.2cm of solar panel is used. It made from polycrystalline silicon with 2V rated voltage and 100 mA rated current. A holder powered by motor and LDR is used with the solar panel.

3.2 Pyranometer

A pyranometer is a device that uses a hemispheric field of view to measure sun irradiances on a flat surface. To calculate the amount of sun irradiance, the ML-01 Si pyranometer was chosen. Furthermore, it is a high-quality, industrial-grade solar sensor designed specifically for performance ratio measurements in environmental studies. With approximation 50 $\mu V/W/m^2$ of the sensitivity, the measured data is near to precision as it can collect data during the value changes. For the pyranometer, the sensitivity of the sensor has been given by approximately 50 $\mu V/W/m^2$. The data has been collected by using HIOKI LR5041 Voltage Logger in unit of mV. Then, the solar irradiance can be calculated by using formula given in the manual.

3.3 Experimental Setup

Experimental setup is the largest part of this project to obtain data measurements from PV panels and pyranometer as shown as Figure 1. Before measuring the data, the best location to setup the experiment has been identified. A running test has been performed to make sure that all the experimental components are working properly. A multimeter and data logger are used to read the values of voltages and currents that have been produced by both solar panel and pyranometer.

Figure 1: Complete setup with solar panel and pyranometer

Solar radiation is the radiant energy of the Sun incident on a surface unit area. There are formulas and equations that must be concentrated to determine the amount of solar power with precision and accuracy. This will help to make the quantity of solar irradiance received by the solar PV panel more precise and accurate before the pyranometer confirms the actual number.

3.4 Data Analysis

From the data collected, the analysis is performed by using Orange software with following configuration in Figure 2.

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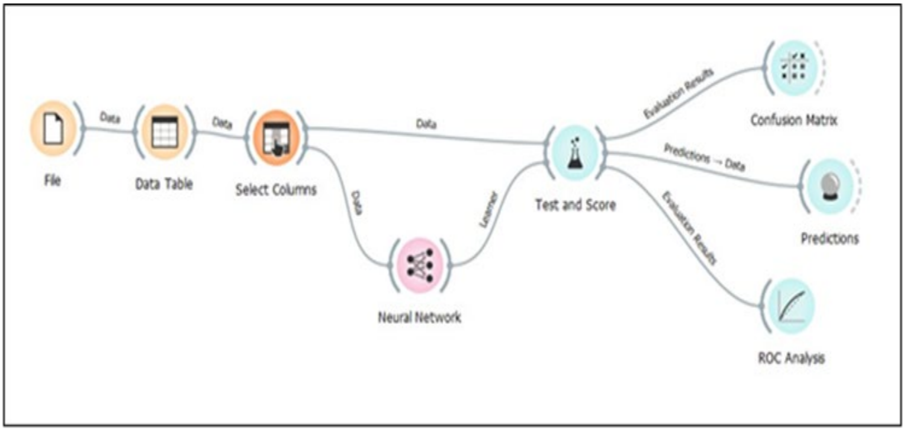

Figure 2: Orange software analysis configuration

The process will be done automatically once the configuration is done properly and it will generate the result immediately. The data generated by the software are in confusion matrix, prediction in percentages and ROC analysis.

4.0 Result and Discussion

The result obtained for this research is based on solar irradiance and solar power.

4.1 Solar Irradiance

The data was collected over the course of 5 days in two separate settings (Auto-Detect and Passive) but only day 1 and day 5 are discussed as in Figure 3 and 4. From 10 a.m. to 5 p.m., data is collected in 10-minute intervals. The measurements for the solar panel are in voltage and current and converted into irradiance energy in W/m². As obtained in Figure 3 for day 1, the incline of the graph started at 11:00 a.m. and started to decline at 1:00 p.m for all different type of solar irradiance detector which includes both pyranometer (Auto Detect and Passive) and also solar panel (auto detect and passive). The highest peak is around 0.9736 W/m² received by pyranometer (auto detect and passive) as expected. The maximum irradiance energy received by Solar panel (Auto detect and Passive) was lower which was at around 0.3378 W/m² due to the small surface area of solar PV (less than 1 m²).

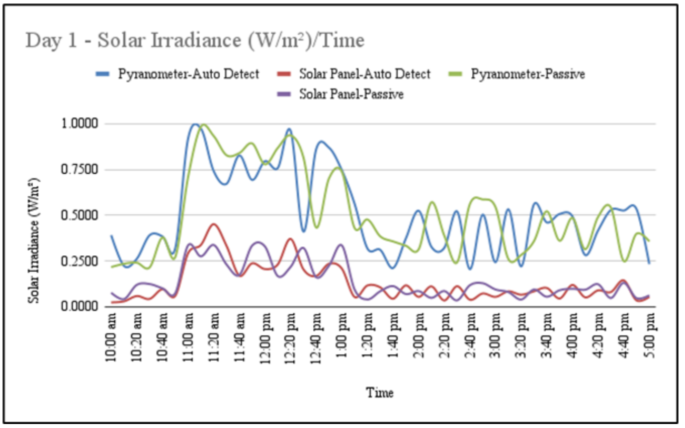

Figure 3: Solar irradiance for day 1

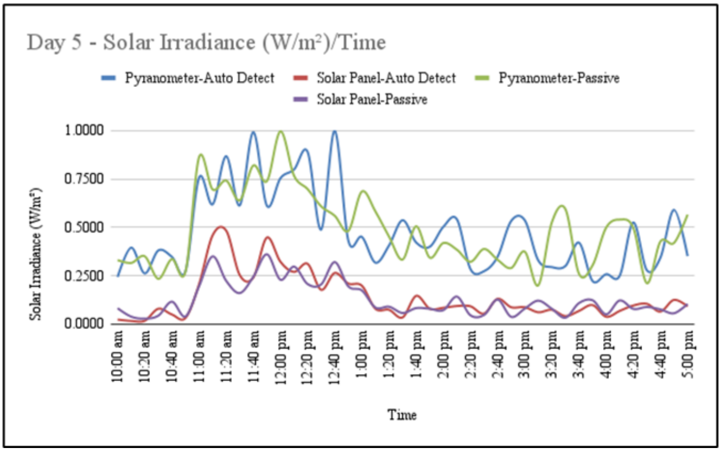

Figure 4: Solar irradiance for day 5

The same trend can be found in the results shown in Figure 4 for day 5, where the incline of the graph started at 11:00 a.m. and started to decline at 1:00 p.m for all different type of solar irradiance detector. The highest peak produced by pyranometer (auto detect and passive) at 0.9986 W/m² and 0.9962 W/m² received by pyranometer. The maximum irradiance energy received by solar panel (auto detect and passive) was lower which was at 0.2644 W/m². Therefore, from both Figure 3 and 4, it can be stated that the highest irradiance energy can be found between 11 am to 1 pm for any solar energy device measurement during sunny days. There is a slight increase for auto detect solar panel as compared to passive solar panel at 11.00 am for both day 1 and day 5 and not much increase for pyranometer with different configuration as shown in Figure 3 and 4.

4.2 Solar Power

Figure 5 and 6 below indicated the solar power for day 1 and day 5 measured in miliWatt (mW). In Figure 5, the incline of the graph started at 10:50 a.m. and decline after 1:00 p.m. The graph shows that the measured power in between of 0 to 0.73 mW and keep on alternating in range. Solar Panel Auto Detect produced the highest power at 0.7225 mW, followed by passive solar power at 0.5407 mW, passive pyranometer at 0.3736 mW and pyranometer auto detect at 0.37 mW. The graph shows some spike that happened (in purple) might possibly come from a slight error.

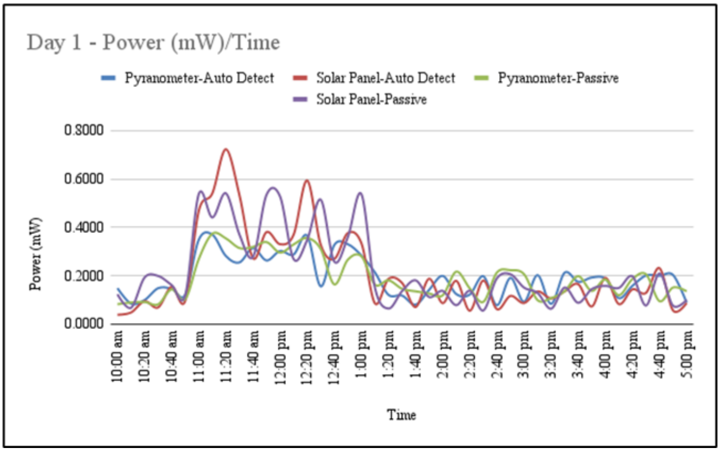

Figure 5: Solar power for day 1

While in Figure 6 for day 5, the maximum power produced again by Solar Panel Auto Detect with 0.7157 mW, followed by solar panel passive at 0.5775 mW, pyranometer auto detect at 0.3794 mW and pyranometer passive at 0.3786 mW. Therefore, the smart mechanism by using auto detect solar power has shown significant improvement in the solar energy harvesting.

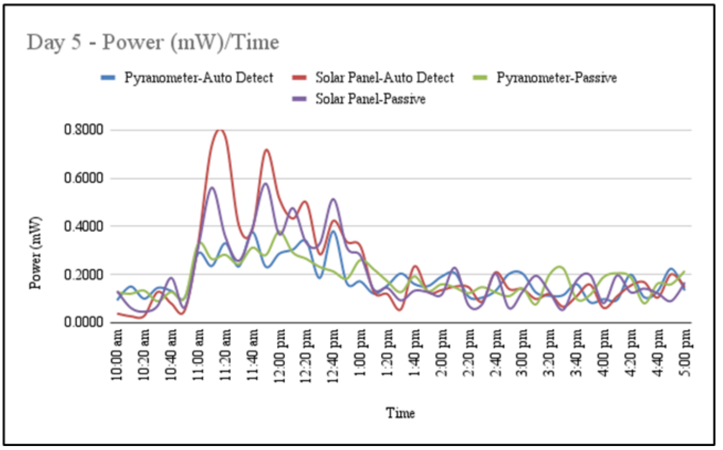

Figure 6: Solar power for day 5

The graph in Figure 7 shows that pyranometer passive has the highest irradiance than the solar panel as expected for both irradiance and power output. This is due to the pyranometer function to measure the irradiance while solar panel primary function is to produce electricity. It may also be used to measure solar irradiance with limited accuracy.

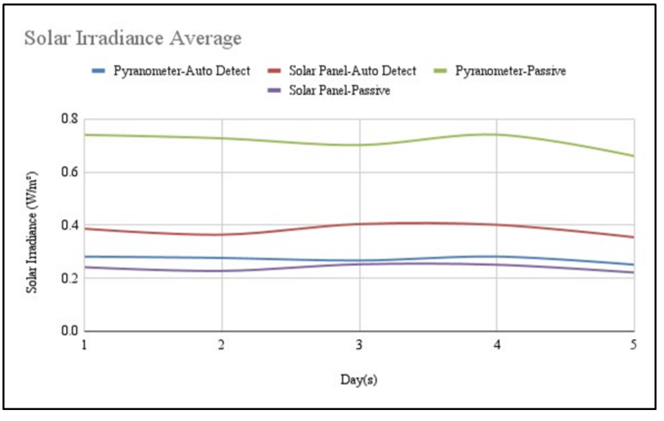

Figure 7: Average solar irradiance

From the results in Figure 6, the efficiency of the solar panel can be calculated based on the ratio between the energy converted by the solar panel over the incident energy or irradiance received by the pyranometer.

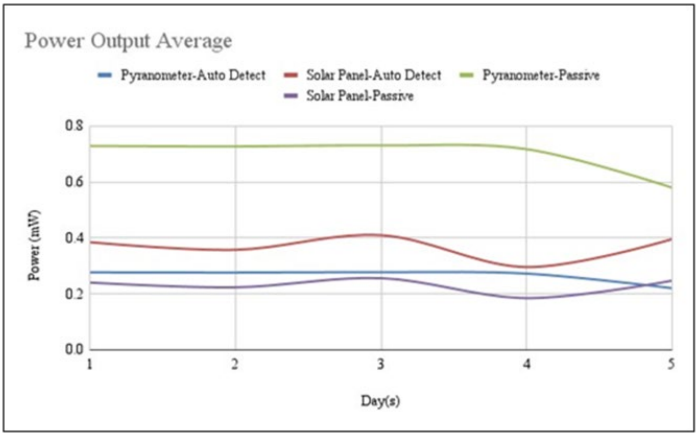

Figure 8: Average solar power output

Graph shows the average of the solar irradiance measured during the peak hours between 11:00a.m. to 1:00p.m. auto-detect configuration has 72.46% efficiency while Passive Configuration: 58.46% measured from the data collected. Figure 9 shows the different percentage value obtained from neural network between actual data and prediction.

		Predicted					
		Day 1	Day 2	Day 3	Day 4	Day 5	Σ
Actual	Day 1	23.3 %	25.6 %	16.3 %	0.0 %	34.9 %	43
	Day 2	44.2 %	11.6 %	7.0 %	2.3 %	34.9 %	43
	Day 3	25.6 %	7.0 %	23.3 %	7.0 %	37.2 %	43
	Day 4	41.9 %	16.3 %	11.6 %	0.0 %	30.2 %	43
	Day 5	37.2 %	14.0 %	30.2 %	0.0 %	18.6 %	43
	Σ	74	32	38	4	67	215

Figure 9: Average solar irradiance prediction

It shows red and blue colours with varying degrees of opacity. The higher the opacity, the more likely the data is to be very genuine (true positive) or highly false (true negative) (false negative). The colour blue denotes positivity, while the colour red denotes negativity. It indicates a forecast of whether it will happen or not based on the data collected and compare it to the actual data. For example, the matrix projected that solar irradiance would be measured by 13% of the time on day 1, however the solar irradiance was recorded by more than 13 % percent of the time. As a result, the table will be blue, which is very close to the forecast. Meanwhile, if the prediction is wrong, the colour will be red. Figure 10 shows the receiver operating characteristic curve (ROC Curve) for the analysis. The ROC curve displays precision and compares ratings. It also displays a matrix of uncertainty. True positives are shown by vertical lines on the ROC graph, whereas false positives are represented by horizontal lines. The closest the curve towards the Y-axis, the better the model predictions. The results in Figure 10 shows that the prediction need to be improved since more false negative compared to true negative.

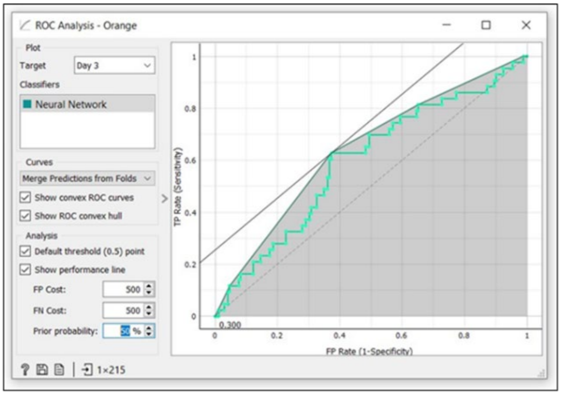

Figure 10: ROC analysis

5.0 Conclusion

It can be concluded from the results that the output power of the PV panel can be much improved by using the smart control mechanism as compared to the results gained from the pyranometer readings. A neural network analysis on the data collected has shown some improvement in the capability of predicting solar irradiance. However, the analysis is limited to forecasting a case by case scenario. As a result of the neural network's findings, data processing has to be improved with additional techniques and data input optimization.

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Author Contributions
N.H. Ibrahim: Supervision, Conceptualization, Methodology, Software, Preparation**; B.H. Baharuddin:** Writing- Original Draft, Data Curation, Validation; **A. K. Ismail:** Validation, Writing-Reviewing and Editing. **K. A. Shamsuddin:** Research Grant and Proofreading.

Conflicts of Interest
The manuscript has not been published elsewhere and is Not under consideration by other journals. All authors have approved the review, agree with its submission, and declare no conflict of interest in the manuscript.

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