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Predicting the Stabilization of Electric Power in Solar Panel Systems using a Support Vector Machine

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ABSTRACT: Energy efficiency in the utilization of electrical energy has attracted significant attention in academia and industry for many years, efforts to develop hybrid systems, especially with solar power, continue to be developed. In this study, the support vector machine (SVM) method was used to predicting stabilization the electric power from the PLTS which was implemented for ATS switching. The data process is recorded when the angle is shifted by the servo motor according to the time of the sun's shift and the angle range of the solar panels between 60°, 90° and 120°. Based on the research that has been done, it can be concluded that the accuracy increases up to 98% in data set testing and 97% in real time testing. The SVM model is used in real time as a relay control prediction for switching between PLTS and PLN, this is evidenced by testing data taken from conditions when tested on a relay with an error prediction error of 3% during the day.

KEYWORDS:SVM, Stabilization, Solar Panel, Hybrid, Real Time.

I.INTRODUCTION

Energy efficiency in manufacturing processes has attracted significant attention in academia and industries over the years. In recent years, the development of renewable energy technologies and policy support has led to a tremendous increase in the share of renewable energy sources (RES). The power conversion efficiency of organic solar cells has increased significantly over the last decade. According to research, the highest efficiency of solar cells reported by the National Renewable Energy Laboratory (NREL), namely single junction organic solar cells, reached 17.4% in January 2020. This efficiency is two times greater than that reported 10 years ago[1].

The sun is a potential source of energy for human needs, where this energy can be obtained from heat that propagates to the earth's surface, or light that falls to the earth's surface[2]. In addition, the hybrid system recombination process must be adequately understood to maximize energy efficiency to achieve the best power conversion efficiency (PCE)[3]. With the rapid growth in terms of valid data collection and excellent improvement in the use of artificial intelligence (AI) methods, especially machine learning in the industrial and household sectors, machine learning is very good to apply. The most widely applied machine learning techniques in this field are artificial neural networks (ANN), support vector machines (SVM), regression and clustering of gaussian distributions [4].

The position of the tilt angle and tracking of the solar radiation are also needed in this study to obtain optimal power output. Solar tracking systems play an important role in solar energy applications where the advantages are not only in performance and increased efficiency compared to static/fixed systems, but also in the economic analysis of large-scale solar energy applications. The system is oriented at an optimal tilt angle towards the equator from the horizon to maximize solar radiation on the solar panels. The tracking angle depends on latitude and climatic conditions. There are two main types of solar panel tracking systems that depend on the degree of freedom of rotational movement about the axes namely single axis solar panel tracking systems and dual axis solar panel tracking systems [5].

Planning a hybrid solar panel system with PLN combined to obtain efficiency in the use of electrical energy, the use of a switching system using an automatic transfer switch (ATS) as an electric power diversion system. There are two typical methods for the power switching mechanism: manual switching which requires the operator to physically operate or switch the switch to transfer load to the secondary source, while automatic switching i.e. triggers itself after the primary source loses or regains power. ATS is an electrical/electronic switch that detects when the primary power



source is cut off and automatically switches the load to the secondary source, of course, as long as the newer parameters (voltage & frequency) are within set limits[6]

Based on the above, a prototype was created to design an optimization model for solar power resources combined with electric power from PLN using the support vector machine (SVM) method. the support vector machine (SVM) method is used because the SVM classifier offers high accuracy and works well with high dimensional spaces. Where the results of this SVM modeling are used in real time as predictions of relay control for switching between PLTS and PLN.

II.METHODOLOGY

2.1. Research Stages

The sequence of research stages/ research procedures can be observed in figure 1 below.

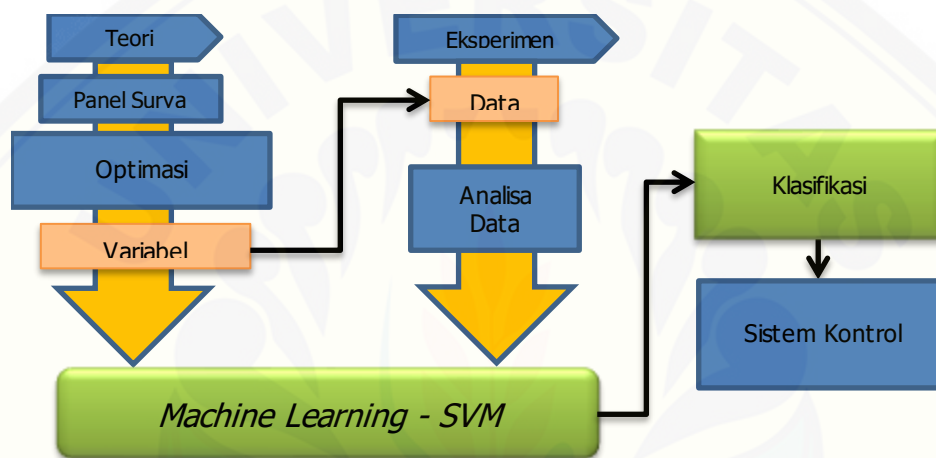


Fig 1. Research stages

Where after studying the literature then making a prototype model, designing solar panels to obtain optimal power through the sensors used to retrieve data to be processed by machine learning using the support vector machine (SVM) method. So that from the output of the SVM, a classification with stable and unstable categories is obtained which is fed in the form of a control system to drive relays for switching PLN and PLTS.

2.2. Angle Design of Solar Panels

The use of experimental methods in this study is actually used to show the extent to which the availability of solar panel energy can be implemented in a hybrid source system. This research is expected to overcome the efficiency of energy consumption in households and industries. This solar panel is one of the choices in applying a combination of electrical energy. The stages of this research include: prototype design, prototype making, prototype testing and discussion.

The first thing to do is to make a design of the solar panel to be able to capture optimal solar radiation, namely by designing the angular position of the solar panel to the sun's radiation during the day.

Figure 2 shows six types of tracking models that have been evaluated through mathematical models to predict the energy absorbed, the benefits of energy used and the heat efficiency of flat-plate solar panels [5]. The type of tracking applied in this study is as shown in figure 1 (R2) where the north-south rotation axis is horizontal with a predetermined angle and the east to west direction corresponds to the direction of the sun's movement which is clockwise.

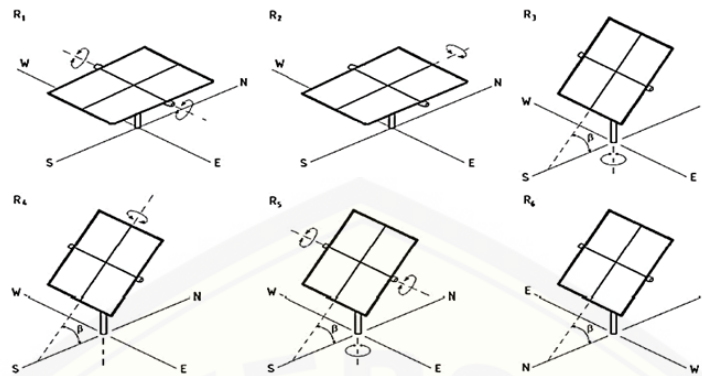


Fig 2. Types of solar tracking system models

Figure 2 shows the types of solar panel trackers, which consist of single-axis trackers and dual-axis trackers. Single axis trackers track each day of the sun from east to west and can be divided into horizontal single axis trackers and vertical single axis trackers [5].

To obtain the data in this study, the current and voltage data of the solar panels are set when the angle of the solar panels is in the angle range of 600, 900 and 1200 from the support shaft, where the weather conditions follow the conditions at that time whether cloudy, overcast or sunny. Figure 3 below is a design of the angular position of the solar panels in this study, where the direction of the sun runs from east in the morning to west in the afternoon.

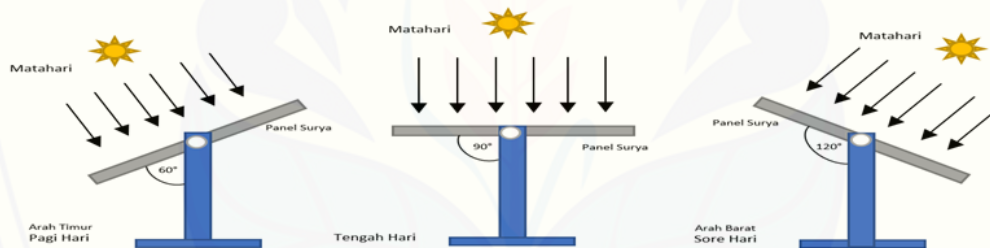


Fig 3. Direction of reception of sun rays and solar panel angle

2.3. Support Vector Machine (SVM)

Vapnik was the first to create the Support Vector Machine (SVM) method around 1992, have shown their effectiveness in many pattern recognition problems, and they can provide classification performance that is superior to many other classification techniques [7].

The term hyperplane which is used to divide between classes is a function, whereas to find the best hyperplane line by maximizing the range of distances between classes, and this is used in SVM. Line whereas is the term used for classification between classes in 2-D functions, while 3-D uses the term plane similarly, while the function used for classification in a higher dimensional class space is called hyperplane [8]. A simple example of how the support vector machine works can be explained as shown in figure 4 below.

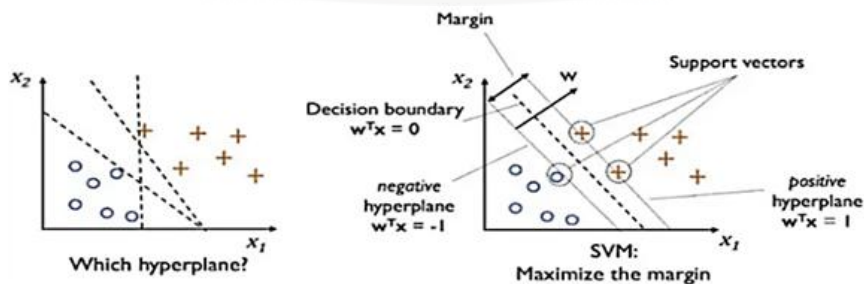


Fig 4. Support vector machine (SVM)



2.4. Confusion Matrix

The confusion matrix has matrix tables that can show the performance of a classification model on a test data set whose value is a way to infer the distribution of any performance indicators calculated from the confusion matrix. The confusion matrix provides information on the comparison of the classification results performed by the system with the actual classification results, to evaluate the variability of an indicator and to assess the significance of the differences observed between two performance indicators [9]. The image form of the confusion matrix table is shown in figure 5 below.

		Actual Values	
		1 (Positive)	0 (Negative)
Predicted Values	1 (Positive)	TP (True Positive)	FP (False Positive) <i>Type I Error</i>
	0 (Negative)	FN (False Negative) <i>Type II Error</i>	TN (True Negative)

Fig 5. Confusion Matrix

2.5. Prototype System Design

The system design in this study consists of an electronic schematic and a model design scheme. The prototype system design can be seen in figure 6 below.

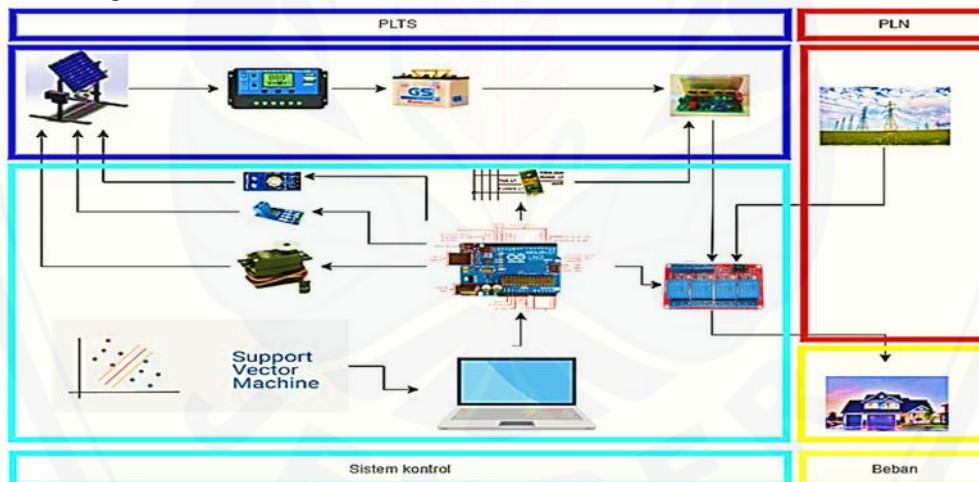


Figure 6. Prototype System Design

Hybrid source system block diagram combining PLTS and PLN. In the process data is taken from sensors of DC voltage, DC current and AC periodically through a device server with serial communication, the data is processed as an initial stage of SVM modeling. SVM modeling is obtained by processing data from the server being tested based on changes in angle and length of time taken, the next stage is the model that has been trained will be implanted on the server for relay control classification. The control system on the server will send a serial communication that functions as a trigger relay when data is streamed and predicted, as a reference for hybrid changes from PLN or PLTS power supply sources automatically.

2.6. Prototype System Mechanism

The flow chart of the process of the mechanism for the running of the data processing process by SVM, can be seen in Figure 7 below.

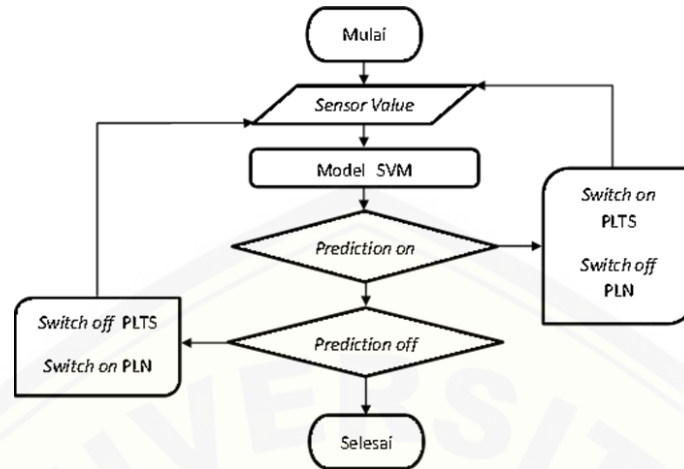


Fig 7. Prototype system mechanism flow chart

The first is to read the sensor values as input to the SVM modeling. Where the sensor input is taken from the PZEM 004t sensor as an AC power sensor as shown in figure 7 which connected to arduino[10], and the model sensor will issue a prediction to execute commands connected to the PLTS or PLN relay and finish for the control stage.

2.7. Stages of Testing Using Data Sets

In Benjamin Schafer's 2015 study entitled, "Decentral Smart Grid Control", states that the data set used was initially simulated to explore whether network stability can be maintained under DSGC, assuming a 4-node architecture: one producer provides electricity for three consumers. There are 10,000 examples and 12 attributes with electricity consumers. There are also two target variables [11].

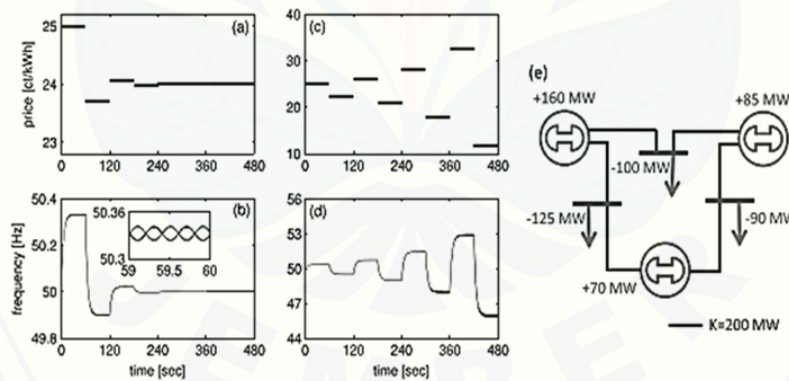


Fig 8. Grid model dynamics with DSGC

Figure 8 above is an image of the dynamics of a grid model with decentral smart grid control in a discrete time period $T = 60$ seconds. System stability depends crucially on the slope of the price curve, being stable for (a, b)

$$\epsilon = \frac{1(ct kWh^{-1})}{2\pi Hz} < \epsilon_{cr} \quad (1)$$

and unstable for (c, d)

$$\epsilon = \frac{5(ct kWh^{-1})}{2\pi Hz} > \epsilon_{cr} \quad (2)$$

We plot the dynamics of (a, c) the local prices p_j and (b, d) the local frequencies

$$(\Omega + \omega_j)/2\pi \quad (3)$$



starting from an initial price ρ_f

$$\rho_0 = 25 \text{ ct kWh}^{-1} \tag{4}$$

above the equilibrium price

$$\rho_\Omega = 24 \text{ ct kWh}^{-1} \tag{5}$$

The angular frequency deviations ω_f vary only very little from node to node as shown in the inset in panel. (b) These residual oscillations relax on longer time scales such that the system in (a, b) converges to a fixed point with

$$\omega_f = \langle \omega \rangle \tag{6}$$

and

$$\omega_f = \rho(\langle \omega \rangle) \tag{7}$$

The model grid is depicted in panel (e).

III. RESULTS AND DISCUSSION

In figure 9 below is the PLTS prototype model that has been made which is used to test data using the SVM algorithm in real time



Fig 9. PLTS Prototype Model

3.1. Data Set Test Results

The form of the data grid for testing this data set has the characteristics of 14 columns in the data set obtained from the journal "Decentral Smart Grid Control", with a total of 10,000 rows of data along with their labels, the shape of the signal that represents changes in data distribution, defines data changes every time interval with a value $t = 0.5$ seconds.

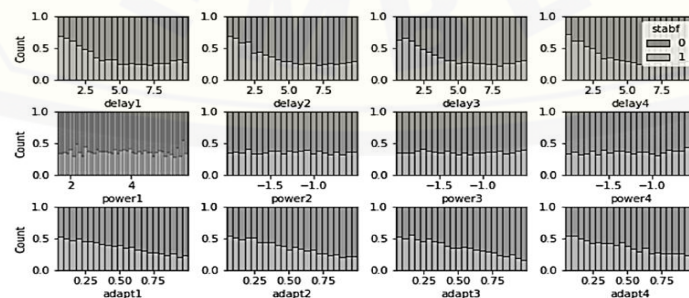


Fig 10. Latency in a grid control system

Figure 10 above shows the stability time of a control spanning 0.5 seconds. While the stages of data distribution analysis are visualized using a scatter plot, visualized as shown in Figure 11 below.

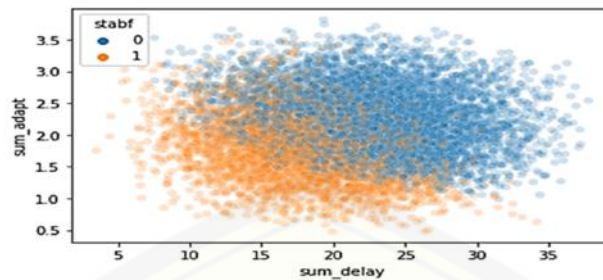


Fig 11. Form of grid data distribution Stable and Unstable conditions

From the form of the distribution data above, it shows that this structure can be classified based on the group of stable and unstable conditions, where code 1 indicates a stable condition and code 0 indicates an unstable condition.

3.2. Data Model Comparison Test Results

Testing the machine learning model aims to get the best model based on the accuracy score which can be shown in table 1 below.

Table 1. Model Comparison Test

<i>Model</i>	<i>Time Training Model</i>	<i>Data Training Score</i>	<i>Data Test Score</i>	<i>Model Description</i>
<i>svc</i>	0.586549	98.00%	96.80%	<i>Good</i>
<i>lgbc</i>	0.2485	100.00%	94.10%	<i>Over fitting</i>
<i>Rfc</i>	1.373336	100.00%	92.00%	<i>Over fitting</i>
<i>Knc</i>	0.010516	94.00%	89.20%	<i>Over fitting</i>
<i>Log_reg</i>	0.028519	81.40%	81.40%	<i>Good, but low accuracy</i>

From table 1 above it can be concluded that the SVM model has the best accuracy with a training data score of 98.00%, and a test data score of 96.80%. These results indicate that the SVM model can be categorized as the best model compared to other models such as the random forest classifier (RFC) shows the results of data over fitting, or other models in the table above.

Table 2. F1 Score data set

<i>Class</i>	<i>Precision</i>	<i>Recall</i>	<i>f1-Score</i>	<i>Support</i>
0	0.99	0.99	0.99	1276
1	0.98	0.98	0.98	724
<i>accuracy</i>			0.98	2000
<i>macro avg</i>	0.98	0.98	0.98	2000
<i>weighted avg</i>	0.98	0.98	0.98	2000

Table 2 above explains that the f1 score shows the highest value of 0.99 which is taken from all the test data, namely 2000 data with a composition of 1276 unstable and 724 stable data.

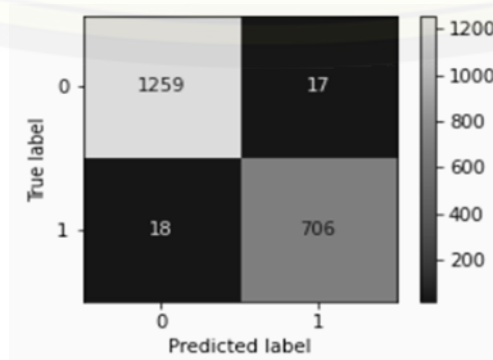


Fig 12. Confusion matrix dataset



From figure 12 above, the results of the true positive confusion matrix are indicated by the number 706 for class 1 (stable). True negatives are indicated by the number 1259 for class 0 (unstable) . For class false positive 18 data and false negative 17 data.

3.3. Real Time Testing Results

Real-time testing uses the best framework structure from previous data set tests. In this test, the data set will be taken directly from capturing data records directly on the prototype, this test involves making a real-time UDP (user data protocol) communication line interface. Testing on the PLTS prototype is expected that the results carried out in stages can show that SVM can be used in ATS control for switching from PLN to PLTS or vice versa.

The data form resulting from realtime data retrieval for AC Power, Frequency, DC Current and DC Voltage, can be seen in the image below.

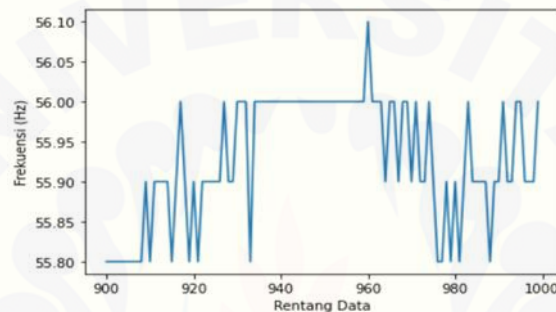


Fig 13. Graph of frequency data

From figure 13 above is a graphical image of the AC frequency value from the inverter output throughout the data collection range, it can be seen that the frequency value changes, this is because the amount of voltage and current entering the inverter changes.

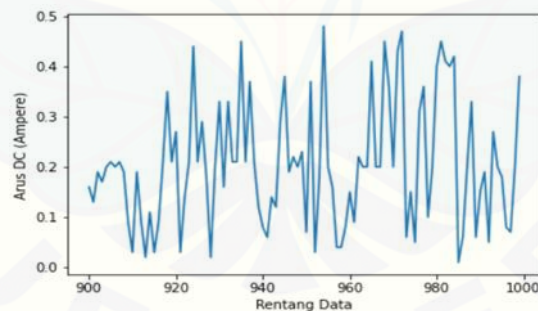


Fig 14. Solar panel DC current graph

Figure 14 above is a graphical form of the DC current value throughout the data collection range, where the current is affected by changes in the intensity of sunlight hitting the electric panel.

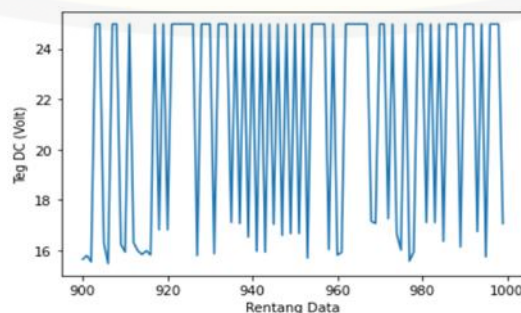


Fig 15. Solar panel DC voltage graph



Figure 15 above shows a graph of the solar panel DC voltage value throughout the data collection range, it can be seen that the voltage is unstable, this is also due to fluctuations in the intensity of sunlight.

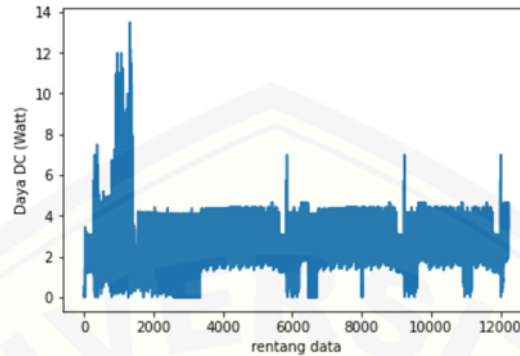


Fig 16. Solar panel DC power graph

Figure 16 above shows a graph of the value of the DC power from the solar panel.

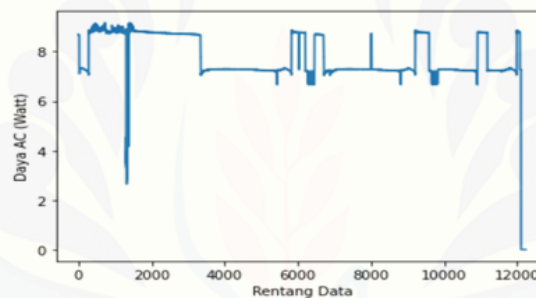


Fig 17. Inverter AC power chart

Figure 17 above is a graph of the AC power coming out of the inverter, it can be seen that the valley is formed due to the instantaneous process of switching from PLN to PLTS due to a change in load, then the longer it decreases according to the value of the voltage the battery / battery capacity decreases due to charging from solar panels also decreased.

3.4. Real Time Data Processing Process

In this process is the stage where the signal obtained is processed into data and classified, the initial process is to retrieve data using the method of changing the angle of the solar panels in the angle range between 60°, 90° and 120°, to obtain optimal solar radiation exposure. Figure 18 below is the actual model of the PLTS prototype made in the study with the angular direction according to the design plan.

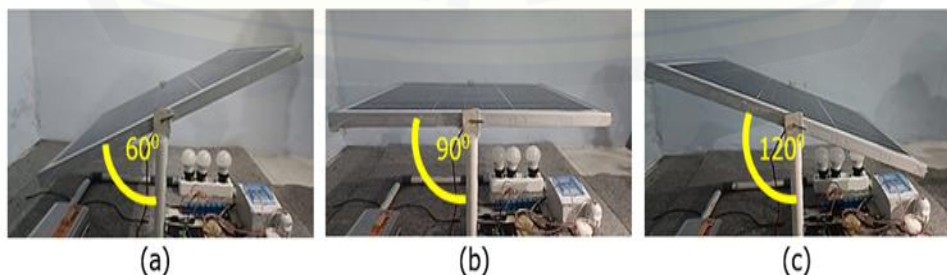


Figure 18. Solar Panel Angle Direction (a) 600 angle, (b) 900 angle, (c) 1200 angle

3.5. SVM Model Test Results

From the results of processing the real time data obtained, which is processed with google colab / google server, it produces a model testing table shown in table 3 below.



Table 3. Model Testing Table

<i>Model</i>	<i>Training Accuracy</i>	<i>Test Accuracy</i>	<i>Loss Training</i>	<i>Loss Validation test</i>	<i>Fit Time</i>	<i>Validation Time</i>
<i>SVM</i>	0.9778	0.9755	0.0221	0.0244	0.7585	0.0429

In the SVM testing table above, it is found that this model is categorized as a good model with a training accuracy of 0.97 and a test accuracy of 0.97 with an average training time of 0.7 seconds and a prediction time of 0.04 seconds.

Table 4. Real Time F1 Scores

<i>Class</i>	<i>Precision</i>	<i>Recall</i>	<i>F1-Score</i>	<i>Support</i>
0	0.97	0.99	0.98	11696
1	0.99	0.96	0.98	10000
<i>accuracy</i>			0.98	21696
<i>macro avg</i>	0.98	0.98	0.98	21696
<i>weighted avg</i>	0.98	0.98	0.98	21696

Table 4 above explains that the F1 score shows the highest value of 0.98 which is taken from all the test data, namely 21696 data with a composition of 11696 unstable and 10000 stable data.

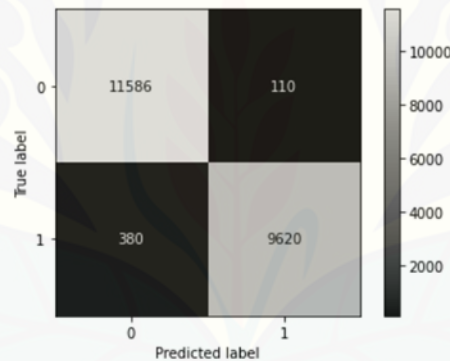


Fig19. Prediction matrix real time

From Figure 19, the true positive confusion matrix is shown as the true positive confusion matrix is indicated by the number 9620 for class 1 (stable). True negatives are indicated by the number 11586 for class 0 (unstable) . For false positive class with 380 data and false negative class 110 data.

IV.CONCLUSION

Based on research that has been done on hybrid solar panel systems using the support vector machine (SVM) method to optimize the stability of electrical energy, it can be concluded that.

1. The SVM system makes predictions obtained from voltage and current sensor data when conditions are closed loop, loading is filled with 3 variable 5 Watt LED lights, SVM predictions in the form of stable and unstable state conditions are described using numbers 0 and 1, then these numbers are executed by the microcontroller in the form of a state relay output that is connected in a hybrid way to PLN and PLTS. The hybrid system connects phase and null networks to two relays to avoid short circuits that occur at two PLN and PLTS sources.
2. The PLTS system shows an increase in accuracy of up to 98% in data set tests and 97% when conditions vary at the angle of the solar panels, namely at an angle range of 60°, 90°, and 120°. The SVM model can be used in real time as a relay control prediction by switching between PLN and PLTS, this is proven by testing data taken from conditions when tested on a relay with a 3% error prediction error in daytime conditions.

Based on the conclusions, suggestions that need to be considered for further researchers are:

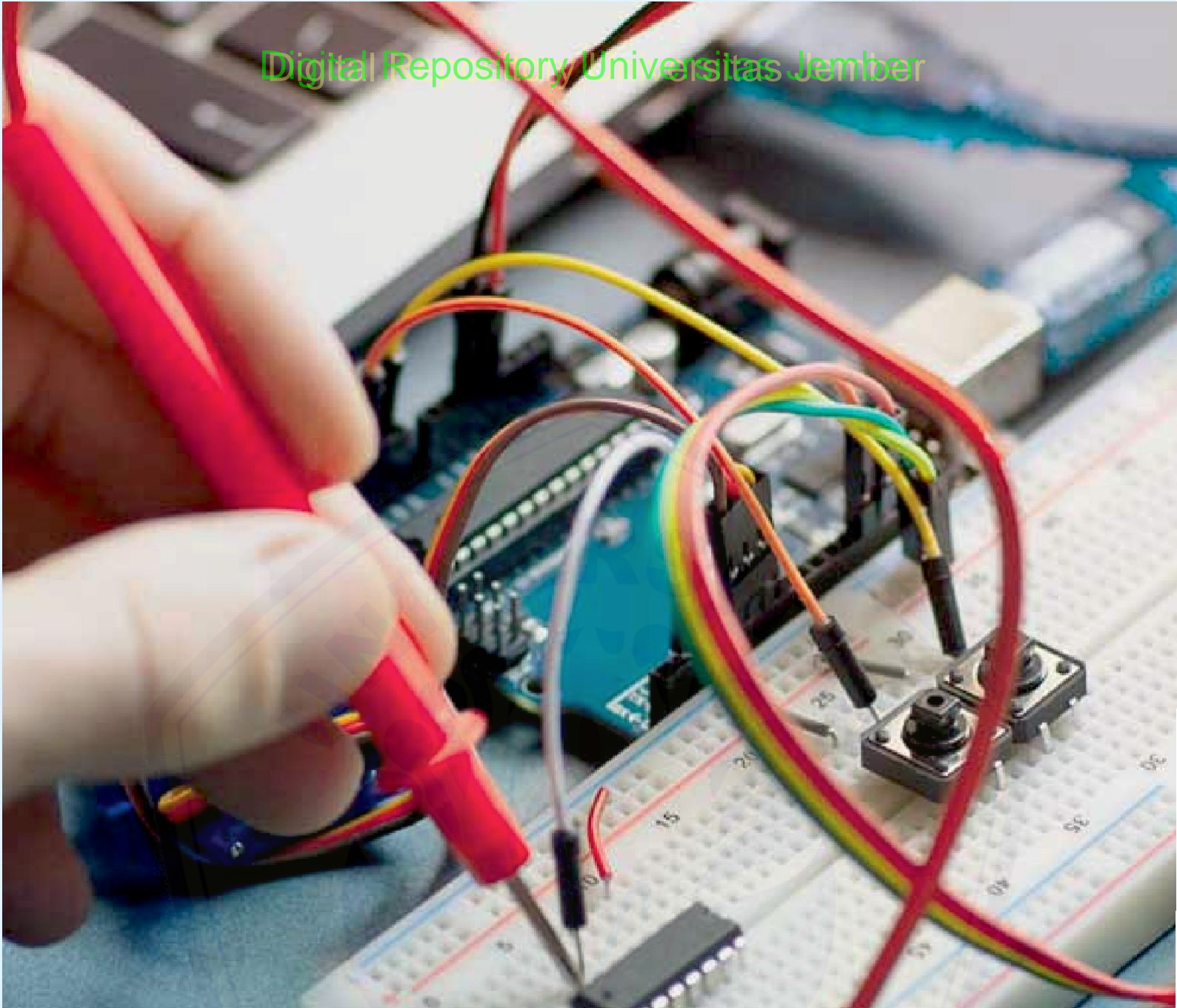
1. Research should add a device that can reduce flickering during the switching time lag, this is intended to prevent damage to electrical equipment due to momentary voltage drops.
2. Addition of single board computing to reduce power consumption and increase the flexibility of device placement.



3. Use of stepper motors or dynamixels to improve control performance because stepper motors have a more precise rotation angle than servo motors.

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