



Performance Evaluation of Solar-PV Panels for Static and Sun Tracking System in Kirkuk-Iraq Using SVM

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ABSTRACT

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This paper presents an investigation using Support Vector Machine (SVM) on the power generation prediction of Photovoltaic (PV) panels for both the fixed and sun-tracking solar models. It compares the energy production for both systems using the historical irradiance data, providing superior effectiveness for the tracking panels. Both fixed and tracking systems were monitored on different days during summertime for three months from 7:00 am to 7:00 pm in Kirkuk, Iraq. The comparative and comprehensive performance of both methods, using a maximum of 40-watt solar PV panels, was evaluated. The study also emphasizes the effectiveness of SVM algorithms in predicting the performance of both systems. The findings of this study are most relevant to high-potential solar regions, where efficient use of photovoltaic technology can maximize independence and sustainability in terms of energy use. Future studies could include extending the analysis through integration with additional factors such as temperature variation, cloud cover, and wind speed, in an effort to maximize predictive accuracy and optimize use of solar energy.

1. INTRODUCTION

The performance of both the static and sun-tracking systems is studied in this regard. This is the mechanism that brought about enormous growth in effective energy from environmentally friendly sources. The combination of sun tracking systems with solar Photovoltaic (PV) panels is a most hopeful way to increase the efficiency of solar energy collection. The world has changed too much in terms of the considerable contribution of PV systems to meet global energy needs and environmental sustainability. As such, PV systems have already been established as a major supplier of environmentally friendly energy, and therefore, a feasible solution for sustainable development in the world that challenges climate change and sustainability [1].

Solar PV panels are devices that can change sunlight into electricity. However, scientists are trying to make them work better with sun-tracking systems following the movement of the sun in the sky. In this way, it shall help them to get more solar energy and hence create more power. Solar PV panels have changed the world for the good through clean and green energy that is being used and meets our ever-increasing needs. It also helps us to fight climate change and for the promotion of sustainable development because it reduces our reliance on fossil fuels and harmful emissions. Besides being good for the environment, solar PV panels are also good for the economy.

They may be coupled with other renewable sources of power including wind, concentrated solar power, hydro, and batteries among others. All these applications help in the reduction of costs and risks of power generation, and the improvement of operation and planning of the energy systems [2]. PV systems play a vital role in reducing the environmental impact of carbon dioxide and other greenhouse gases. In the performance of the PV cells, there is a consideration of the values with various parameters that include the geographical location, the amount of solar radiation received, the wind speed, and consideration of the electrical characteristics of the PV cells. Furthermore, the PV systems are being integrated with the power systems as a clean and renewable source of energy to help in reducing the environmental impacts and improving stability in a power system [3]. The PV system is the base of renewable energy systems that allow for more power to move into sustainable energy sources [4].

On the other hand, the increase of energy that does not affect the environment adversely is one of the most complicated tasks existing before the research community. Nowadays, PV solar is most widely applied as a distributed energy resource due to economic factors and many advantages. Table 1 summarizing prior Support Vector Machine (SVM)-based solar prediction studies.

Table 1. SVM-based solar prediction studies

References	Region	Inputs	Prediction Horizon	Accuracy / Metric
[5]	Taiwan	Temperature, humidity, rainfall, wind speed, irradiance	1-hour ahead	Mean Absolute Error (MAE) $\approx$ 5%; SVM outperformed Random Forest
[6]	Benchmark dataset	12 weather features (incl. heat index, wind speed)	24-hour rolling forecast	SVM > Linear Regression, competitive with Artificial Neural Network (ANN)
[7]	Algeria (6 cities)	Extraterrestrial irradiance, declination, temperature, humidity, RH	Daily solar radiation	ANN+Firefly Algorithm (FFA) best; SVM & ANN showed promising $R \sim 0.93$
[8]	Global solar radiation modeling	Meteorological + particulate matter (PM2.5, PM10)	Daily radiation	Root Mean Square Error (RMSE) $\downarrow$ 14.6%; $R^2 \uparrow$ 2.6% with PM inputs
[9]	India/Turkey context	Diffuse & direct radiation, Tmax/Tmin, humidity	Daily global radiation	SVM outperformed tree-based models; best generalization

Iraq is going to have a good growth in solar power capacity for the near future. Iraq also envisions a capacity of 2.75 GW in solar by 2025 as part of its overall objective of 12 GW of renewable energy by 2030. The increment in solar capacity is indicative of a step in achieving energy independence, decreasing costs of generation, and imports chargeable for electricity. The renewable energy projects of Iraq encompass the construction of large solar energy power plants all over the country. These follow from the intention of Iraq to up its share of renewable energy sources to 33% by 2030. It is therefore evident that Iraq will consider the utilization of renewable energy sources in the run of its business [10]. Nemah and Albarhami [11] researched the efficiency of PV systems in their operations under Iraq's environmental conditions in Al Najaf. The study used MATLAB/Simulink to develop a model and simulate it. The variables to be considered are radiation, sunlight, ambient temperature, and panel efficiency. According to the research, it has been found that with an increase in temperature, the effectiveness of this system has been the highest and hence draws the need to consider environmental temperatures during the design of a turbine especially within the environment of Iraq. Researchers at the Bukhara State University of Uzbekistan, Raxmatov et al. [12] analyzed a 300 KW grid-connected solar PV system and evaluated its economics. Economic analysis of the same, presented above, demonstrates that the time required to recover the initial investment in case the cost of energy equals 0.099 \$/kilowatt-hour, is 9.7 years. Their work suggests that it is financially feasible to build the PV systems on the same regions of interest or valuable information on what the financial outcome could be to systems at Kirkuk.

Previous studies in Iraq region have employed many conventional predictive models and machine learning techniques which including ANNs and k-Nearest Neighbors. But these methodologies often need extensive datasets or may encounter difficulties in addressing the swift and intricate variations in solar irradiance characteristic like Kirkuk's geographical context. While SVMs is recognized for its proficiency in managing smaller datasets and intricate nonlinear variations and directly confront these constraints. Consequently, employing SVM to forecast PV performance in Kirkuk signifies a methodological enhancement also likely augmenting prediction precision and offering practical benefits for solar energy system planning in the area.

2. BACKGROUND

A significant achievement is the incorporation of the Maximum Power Point Tracking (MPPT) control algorithm into various converter architectures to improve the efficiency

of PV systems. Katche et al. [13] introduced a photovoltaic grid-tied system that utilizes an MPPT control algorithm and a Single-Ended Primary-Inductor Converter (SEPIC) and Luo converter. This system achieved an impressive efficiency of 96% while also reducing total harmonic distortion. In Ganguly et al.'s study [14], the work primarily focuses on the development of MPPT algorithm design. The proposed system involves the utilization of a SEPIC converter to facilitate the charging of the battery using solar energy. To achieve maximum power under any environmental conditions, it needs to optimize the resistance (load) applied to the cells and accurately measure their output. MPPT devices are typically integrated into an electric power converter system that performs voltage or current conversion, regulation, and filtering. This system is used to drive various loads, such as power grids, batteries, or motors. This work focuses on the implementation of two methodologies.

Rehman and El-Amin [15] analyzed a 5.28 KW off-grid photovoltaic power plant in Dhahran, Saudi Arabia, for its efficiency. The research investigated how dust buildup and PV surface temperature can affect the panels' ability to generate electricity. Energy production decreased with increasing surface temperature and time, suggesting that dust buildup potentially be responsible, according to the study. This is particularly important for areas like Kirkuk, where similar environmental factors like dust and temperature play a significant role.

A study by Visser [16] evaluated solar power forecasting models for both intraday predictions and day-ahead collected data. It started by utilizing various methods such as physical, regression and AI (Artificial intelligence) based models, with focusing on deep learning. It demonstrates the importance of using high-quality data to create precise forecasting models. A notable feature of this research is the utilization of probabilistic forecasting models, which have shown superior performance compared to point forecasting models. Additionally for solar forecasting performance, many methods such as tree-based models, which are part of the field of artificial intelligence, are specifically recognized for their strong technical predicting. The study is crucial for comprehending the role of AI in improving the ability to forecast and ensure the consistency of solar power generation.

Another study has introduced an approach that assesses the technical and economic feasibility of a solar PV system. Where this approach combines machine learning and optimization techniques. The study utilizes site-specific data obtained from Moi University in Kenya, encompassing temperature, solar radiation, and power demand data. The simulation findings from this study emphasize the importance of accurately determining the appropriate dimensions for solar PV installations. Neglecting this crucial aspect often results in

system malfunctions. Applying AI and machine learning in system design and optimization guarantees dependability, effectiveness, and cost-efficiency, rendering it a valuable point of reference for comparable research in diverse geographical areas like Kirkuk, Iraq [17]. Additionally, another work is concerned with designing an Adaptive Neuro-Fuzzy Inference System (ANFIS) based SEPIC Converter for MPPT of PV Modules. The method used for the system's MPPT is Perturb and Observe. The system is controlled by an Adaptive Neuro Fuzzy Inference System. The work has a hardware prototype and the performance of the controller for MPPT is tested in simulation. A comparison between the fuzzy logic controller single-ended primary inductance converter for MPPT and the adaptive neuro-fuzzy inference system single-ended primary inductance converter for MPPT was discussed, and the results showed that the ANFIS has more efficiency [18].

Rahif [19] described MPPT system design for photovoltaic energy conversion by proposing the fuzzy logic controller and it details how to create fuzzy inference rules and fine-tune membership functions to regulate the duty cycle of a DC–DC converter so that photovoltaic array attained maximum power point despite fluctuating irradiance and temperature as well as it may offers an important control oriented alternative to data-driven ones such as SVM prediction that have been employed in recent studies and provides an alternate artificial intelligence method for maximizing photovoltaic output in consideration of variable environmental conditions.

The aim of apply machine learning techniques, and more specifically the SVM models, to predict the power output performance of PV systems accurately. This specific objective is set to compare static and sun-tracking solar panel efficiencies, so that the most efficient set-up concerning solar energy control and generation of electricity may be pinpointed. The contribution of this work lies in the development and validation of a prediction model to be applicable by both power producers and grid operators to give more exact forecasts on the generation of solar power. It introduces research on Support Vector Regression (SVR) in solar energy systems as follows:

- Helps to further understand the effect of panel orientation and different tracking mechanisms on the gain of energy.
- Is part of the complete knowledge framework in alternative energies which supports the transition towards more sustainable sources of energy generally and especially in Kirkuk Iraq.
- Offers insights that could lead to cost reductions and increased efficiency in the energy sector.

Solar PV systems are leading the way in renewable energy since they turn sunlight into electricity. Using the energy from the sun, a device called a solar cell, which is basically a p-n junction, can produce direct current (DC) electricity. Nevertheless, because each cell produces a relatively small voltage, solar panels consist of multiple cells working together to generate higher voltages. To comprehend and optimize solar panel systems, it is essential to know the properties of the current-voltage (I-V) and power-current (P-I) relationships. When it comes to improving the efficiency of PV energy conversion systems, the notion of the MPPT algorithm is crucial. Taking Özçelik and Yilmaz as an example, they investigated the use of wireless energy transmission in conventional and MPPT PV systems, and they searched how MPPT improves conversion efficiency [20].

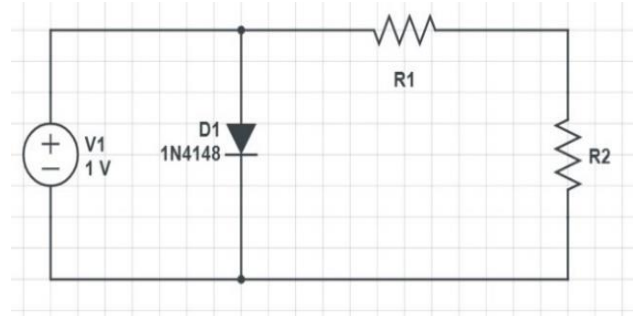


Figure 1. Photovoltaic cell model

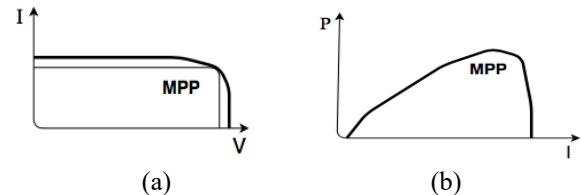


Figure 2. (a) I-V characteristics; (b) I-P characteristics current-voltage and current-power characteristics of a typical solar panel

The solar cell is a p-n junction that generates DC electricity power from the sun's radiation. Considering the resulting voltage for each single cell is small, the solar panel contains a number of these cells, that are linked together. The model has a diode, a current source, and a resistor in series, as shown in Figure 1. The effect of the resistor symbolizes the leakage resistance of the cell. The current source symbolizes the current produced by photons, the output of PV is stable under fixed temperature and fixed radiation of light. Figure 2 demonstrates the characteristics of the current voltage (I-V) and the current power (I-P) for a solar panel, respectively. MPP is the peak point of the power for a solar panel.

Earlier research has verified that the incorporation of single or double-axis tracking systems considerably enhances the energy output of photovoltaic systems; like Bazyari et al. [21] demonstrated that single-axis tracking and double-axis both has the capacity to enlarge the mean energy gathered in comparison to static panel installations on Qeshm Island in Iran. Carrying on in the same method this work assesses similar tracking systems under climatic conditions in Kirkuk in the Republic of Iraq using an SVM prediction model.

The next stage is the DC-AC inverter, which converts the DC electricity from the solar array into AC, suitable for distribution on the power grid. This conversion is necessary because the grid operates on AC, and most home and business appliances are designed to use AC power. Finally, the AC electricity is transmitted to the grid, where it is distributed to end-users.

In some systems, there may be additional steps or components, such as battery storage systems that store excess power for use when the sun is not shining, or transformers that adjust the voltage to the appropriate level for the grid.

3. SEPIC CONVERTER

A PV application requires a proper converter for coordinating between the PV output voltage and the required voltage for the load. The SEPIC converter stands for Single-Ended Primary-Inductance Converter, which is a DC-DC

converter. It can be a buck and boost converter or just a buck or just a boost converter. In this work, the SEPIC is used because it is appropriate for the PV output and the input voltage for an MPPT. Depending on the switch duty ratio D , the converter buck and boost provide the voltage of the output to be greater or lower than the input voltage.

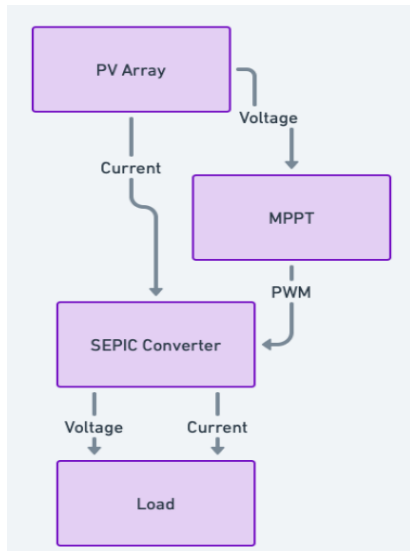


Figure 3. SEPIC converter

In recent years, a SEPIC converter in battery-powered systems has become more popular and needs to step up or down according to the charge level of the battery. Requiring the relatively ripple-free, that is drawn from the current of the input. That is why the SEPIC converter is used in many applications [22, 23]. In some converter types, the output results do not reach the maximum power. However, using SEPIC converter topology with MPPT is the most convenient technique that assures extraction of the power and the steady

output with ripple-free for the current-voltage curve and without fluctuations. Thereby, the peak current control used by the SEPIC converter with a PV voltage and the signal generated by the battery current controller that is a comparative and integral (PI) controller will be zero. That means, the voltage is generated by combining the battery charging loop and MPPT control loop. The mixture of MPPT and charging control immediately balances the power of the system to charge the battery. The voltage of the PV is determined completely by the MPPT controller. Therefore, the PV module is functioned with the MPPT point, as shown in Figure 3.

4. MPPT ALGORITHM

After getting the current and voltage from the photovoltaic arrays, the MMPT system algorithm controls it by a method called hill climbing. The flow chart given in Figure 4 and the block diagram in Figure 5 shows the mentioned method. In the last cycle of the algorithm, the direction of the output voltage will continue in the same direction even if there are increments in the output power from the last measurement. If the output power has decreased since the last measurement, the voltage is inverted in the opposite direction. In each MPPT cycle, the voltage of PV will be set according to the algorithm. In addition, it will fluctuate around the voltage of MPP voltage when the MPP has reached, which will lead to the loss of power that depends on the step width calculated power of one adjustment. In case the width is large, any change in operating conditions that could slow or stabilize the algorithm of MPPT will quickly respond to that sudden change. In the other case when the width is very small; any change occurs slowly or stabling the system, it will respond very slowly to solve changes in insulation or temperature. For this, it is clear that all system works depending on the value of the width [24].

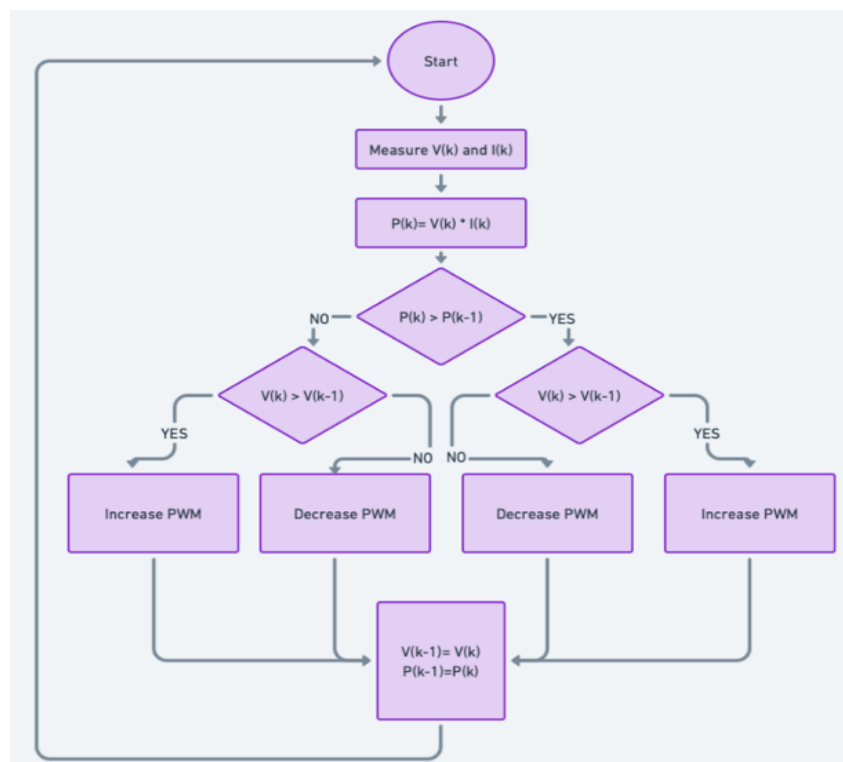


Figure 4. MPPT algorithm

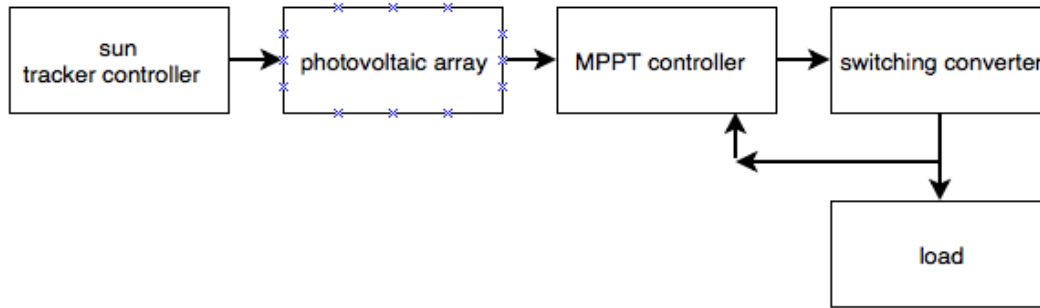


Figure 5. A PV-based MPPT control and sun tracker equipment system

5. SUN TRACKING SYSTEM

It is the device that controls the solar panel to keep it directed towards the sun. Especially in solar cells require a high degree of accuracy to ensure that the sun's waves are focused specifically on the energy system and directed.

Both systems the dual-axis tracker and the static panel are evaluated and data is gathered hourly between 7:00 a.m. and 7:00 p.m. for every day. To ensure consistent irradiance conditions for example no significant cloud cover or precipitation during the measurements and data were collected on sunny clear summer days in Kirkuk.

The performance assessment procedure of the tracking systems follows the general analysis procedure that was done by Bazyari et al. [21] in an adaptation to suit climatic data in Kirkuk city and using SVM-based prediction models.

6. SVM-BASED ENERGY MODELING

The data obtained from the designed system serve as inputs to the SVM model in our approach. The voltage and current measurements from the static and tracking panels are acquired through the SEPIC converter and MPPT configuration and were utilized to calculate power output. Those data points together with their related timestamps were subsequently input into the SVM for training and prediction. And an integrating hardware-collected data into the SVM ensures that the machine learning model is immediately informed by the actual performance of the system.

SVM is a supervised machine learning technique, and it identifies the decision boundaries to categorize data points based on prior classification. It thrives on complex data, transforming it into higher dimensions for clearer distinction. Focusing on key data points close to the boundary, it excels in prediction accuracy, making it valuable in domains like face recognition, bioinformatics, and image processing [25]. SVM stands out as a sophisticated algorithm designed for both classification and regression tasks, Figure 6 illustrates in detail how the SVM works in the realm of machine learning. The essence of SVM's functionality can be distilled into a sequential process that transforms raw input data into a predictive output, offering valuable insights across various domains. This paper delineates the operational framework of SVM, encapsulating its workflow into a cohesive narrative [26].

This study used a radial basis function as kernel in a SVR model. The given size of dataset and SVM hyperparameters were set to standard values like regularization parameters $C =$

1 and $\epsilon = 0.1$ while the RBF kernel parameter γ using the default heuristic. And the hour of the day serves as the SVR model's input feature also the recorded PV power at that time is the model's intended output. Since the sun's position primarily affects solar irradiance and in turn power output the hour of the day was chosen as the predictor. Also, the data did not include any other climatic variables such as temperature or irradiance sensors. This work has made sure that scale differences wouldn't affect the SVM training by normalizing the input and output data and it was determined that this design and feature selection would adequately capture the daily power generation trend.

The initial data ingestion journey begins with the ingestion of input data into the SVM model. This foundational step involves collecting and feeding the dataset into the algorithm, setting the stage for the subsequent analytical processes. The data, comprising features and labels, serves as the raw material from which the model will extract patterns and relationships [27]. Feature space transformation is the heart of SVM's efficacy as its ability to project input data into a higher-dimensional feature space through a process known as feature mapping. This transformation is pivotal, as it enables the algorithm to discern complex patterns that are not readily apparent in the original input space. By elevating the data into a higher-dimensional realm, SVM facilitates the identification of a separable hyperplane, even in cases where the data is not linearly separable in its initial form. Optimization is the core algorithmic challenge that SVM addresses is the identification and optimization of a hyperplane that optimally separates the data into distinct classes for classification tasks or closely fits the data points for regression tasks. The optimal hyperplane is the one that maximizes the margin between the nearest points of the classes it divides, known as support vectors. This step is crucial, as the chosen hyperplane directly influences the model's generalization ability and its performance on unseen data [28].

Task-specific modeling depends on the nature of the problem at hand, classification, or regression. SVM adapts its strategy, in classification tasks, the model endeavors to categorize data into predefined groups, whereas, in regression tasks, it aims to predict continuous values. This versatility allows SVM to be applied across a wide spectrum of research areas and practical applications, from image recognition to financial forecasting [29].

Model Performance Evaluation where a critical phase in the SVM workflow is the evaluation of the model's performance. Through the application of various metrics such as accuracy, precision, recall, and mean squared error, researchers can assess the efficacy of the SVM model. This evaluation not only

validates the model's predictive capabilities but also guides the fine-tuning of parameters and the selection of kernel functions to enhance model performance. Predictive outcome generation, a culmination of the SVM process, is the generation of predictions based on the input data. At this juncture, the model applies the learned patterns and the optimized hyperplane to make predictions on new, unseen data, providing actionable insights or decision support [30].

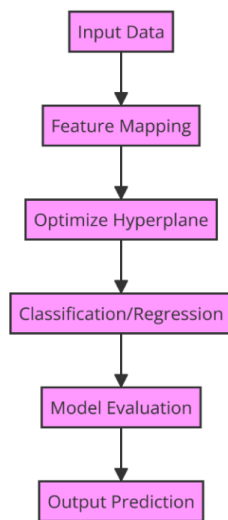


Figure 6. SVM algorithm workflow

7. PV DESIGN AND SVM MODELING

In this work, the dual-axis system is used to track the sunlight from north to south and east to west using motors, a controller, and four Light Dependent Resistors (LDRs). The LDRs are placed in four different directions, two sensors with motors are used to tilt the panel in the east-west of the sun's direction. While the other two sensors with a motor tilt the panel in the north-south of the sun's direction. The controller detects the light from the LDRs. The tracking system has been implemented using the hardware parts: diodes of 1N5407, transistors of TIP41C and TIP42C, operational amplifiers of LM324N, resistors, capacitors, and LDRs according to the values of the LDR the mode of operation changes. The LDR consists of semiconductor material with 2 electrodes on its surface. In the dark or soft light, the disc of the semiconductor has a comparatively small number of free electrons in it. A few free electrons carry an electric charge. Which is a poor conductor of electric current, meaning that the resistance is high. In the case of light, an escape from more electrons happens from the atoms of the semiconductor. That means more electrons are free to carry electric charge and become a good conductor. According to the light, the system distributes a voltage to one of its outputs, which performs a movement of the motor.

The design Figure 7 of a solar-PV energy generation system with a sun tracking system, MPPT controller, and SEPIC DC-DC converter has been implemented. The performance of the system has been analyzed and presented with variations in solar radiation with the device currents and voltages. The system performance is accepted under any change in loads for a sudden change in solar radiation. The MPPT controller is performing satisfactorily for tracking the operating point.

Data preparation formulation of the required data for

analysis: by defining the hours of data collection, which start at 7:00 a.m. Therefore, it gives power output data within the hours and presents the ability of the panel types to produce energy under different conditions. This raw data is organized into tabular data for ease of manipulation and presentation. The tables are designed to contain hours and their corresponding power outputs as columns hence explicit in viewing the data. Thereafter, the data is divided into the testing set and the training set, which is pivotal for testing the accuracy and efficacy of the predictive model. This partition will be useful to ensure that the model will be trained on part of the data while other data will be in reserve for testing if that predictive model is good. It helps to avoid overfitting, and in addition to this, the developed predictive model would generalize very well in making predictions on the new unseen data.

The output power for each hour was calculated by multiplying the voltage and current readings in order to prepare the dataset for SVM training. A pair time_of_day and power make up each data sample for example the static panel has 23.78 W at 12:00 p.m. and the tracking panel has 31.816 W at the same time. So as the input feature the system used the hour of the day in decimal format and the intended output was the corresponding computed power. Also, to allow the SVM to be trained on dimensionless and normalized data by the temporal feature was normalized to a 0–1 range before training assigning a value of 0 at 7:00 am and a value of 1 at 7:00 pm. Power values were then scaled by dividing by 40 W, the panel's rated peak. These steps ensured that appropriately processed data from the voltage/current measurements was used to train the SVM model.

Model for the static panel: The features (hours during the day) and targets (power outputs) are both selected from the training set for training the static solar panel, guiding the model to understand how the solar panel reacts to the time of day for energy production. The final step is developing and training the SVM model for this dataset. The SVM model is moderated to standardize the data because it is well known for its power in regression tasks, hence, to avoid the training process getting dominated by the scale of the data. After training, the model is used to make predictions of power output for the test set, and the values of the predictions are compared with the actual values, which results in the MSE. This will be useful in proving the model performance to demonstrate the matching of the predicted values to the actual power outputs, as can be shown in Table 2.

The straightforward linear regression model and utilizing hour as the exclusive input which was built for each panel's dataset. The SVM model performed significantly better than the linear model and the linear fit on the static panel data for instance the produced a significantly high error as the MSE of about 1.5 in normalized units and an R^2 value close to 0 which indicating that it explained almost none of the variance. In some cases, the tracking data produced a negative R^2 . On the other hand, the designed SVM model achieved a slightly positive R^2 about ~ 0.0035 for static and a lower MSE. In contrast to a traditional linear model which ignores the midday peak and the nonlinear features of the PV output and this comparison shows that the nonlinear SVM approach better captures the daily power-production pattern.

Table 2 shows that mean-squared error is 0.9571 was computed on power values normalised $P_{\text{norm}} = P/40$ W. Which matching root-mean-square error is $\text{RMSE} = \sqrt{0.9571} \approx 0.978$. In physical terms this corresponds to 0.978×40 W is

equal to almost 39.1 W or 97.8% of the whole 0–40 W range or about 3.5 times the mean static-panel output 11.09 W.

That's why the prediction error is rather high and has to be seen as unsatisfactory.

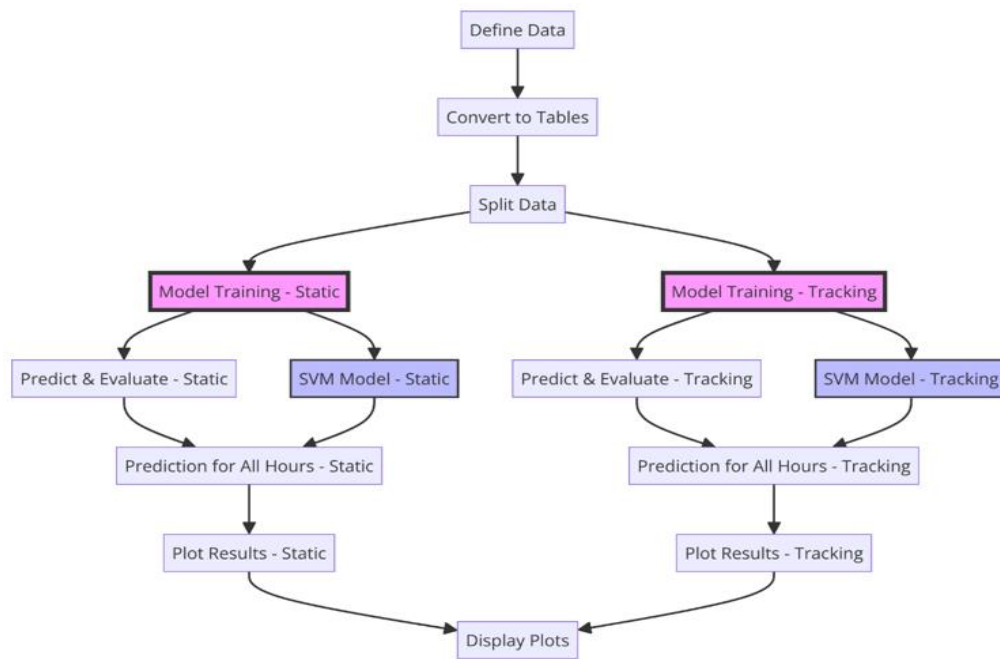


Figure 7. SVM flow of the designed system

Table 2. Evaluation metrics

Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R-Squared (R ²)
0.9571	0.0632	0.0035

Similarly, the $R^2 = 0.0035$ is practically zero which meaning the model essentially lacks predictive ability to explain 1% of the variation in the measurements and stated differently the SVM as it is now set performs just somewhat better than a naive constant-mean predictor.

Model for solar tracking panel: The process in the solar tracking panel is similar to that of the static one. On the other hand, with the changeable nature of the tracking panels where they vary their position following the sun, the power output data thus reflects dynamic behavior. The model is then further trained on a subset of the data, to learn the relationship between the hour of the day and power generation with efficiency improvements that tracking technology allows. The procedure remains identical, feature and target selection, training of an SVM model, and testing its performance with MSE in predictions against the test set.

Prediction and plotting of both models trained and evaluated: predictions can be extracted for every hour within the period of the dataset. This prediction generalizes the ability to do model comparisons for performance across the whole day. Then these predictions against the actual data are plotted for visual comparison of the predicted against the actual power outputs for the static and tracking panels. These plots help visualize not only the alignment of models with data but also the performance differences and quantities of energy produced in the case of static and tracking solar panels throughout the day.

8. RESULTS

The test is performed for both static panel and dual-axis

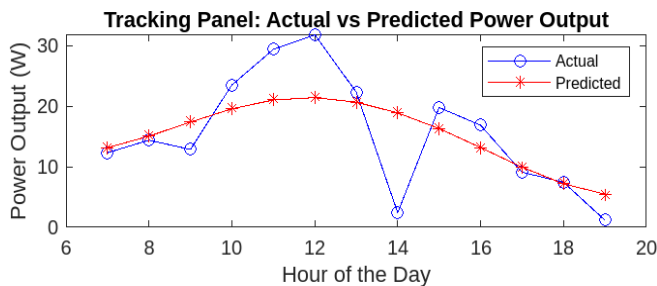
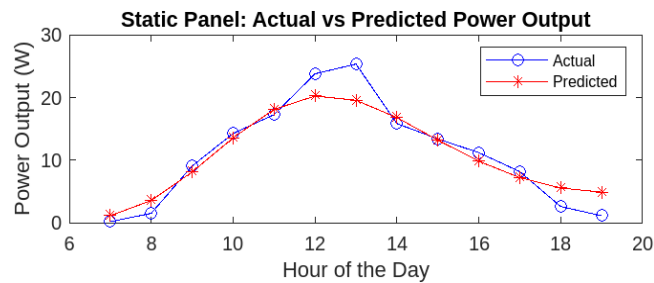
tracker, the results are recorded from 7:00 a.m. to 7:00 p.m. The results are calculated and show the difference between the static panel and tracker system, as shown in Table 3. The second approach has shown more efficiency with an increase in the average power produced from both systems; the first static system produced 11.086 Watts on average per day while the system with sun tracking produced 17.037 Watts on average.

To predict the daily power output of both static and tracking solar panels, the offered graphs show the results of an evaluation of an SVM regression model. The tracking panel's graph reveals that the SVM model tracks the real power output trend very closely, capturing the midday production peaks. A sharp peak in the tracking system's power output lines up with the sun's path, allowing the panels to get the most sunlight possible. A reasonable correlation between the predicted and actual values indicates that the SVM model has learned the pattern of the tracking panel's energy production effectively. However, there are clear differences at specific times of day, especially in the morning and afternoon. Several factors, like changes in solar irradiance, weather, or shadows that the model doesn't fully account for, could be responsible for these deviations.

Using a paired t-test is statistically significant difference t-statistic = -4.381 and p-value = 0.0009 was obtained from the observed increase in average power output 17.037 W for tracking against 11.086 W for static panels. And the standard deviations were computed to show the variation of observed outputs as the tracking system produced 8.73 W while the stationary system obtained 8.33 W. These results are validating statistically significant advantages given by the dual-axis tracking system.

Table 3. Solar tracking for static panel and dual-axis

Hours	Static Panel			Solar Tracking (Dual Axis)		
	V	A	W	V	A	W
07.00 a.m.	2.3	0.1	0.23	11.2	1.1	12.32
08.00 a.m.	5.2	0.3	1.56	12.1	1.19	14.399
09.00 a.m.	10.12	0.9	9.108	14.3	0.9	12.87
10.00 a.m.	11.9	1.2	14.28	15.9	1.48	23.532
11.00 a.m.	13.4	1.29	17.286	17.4	1.69	29.406
12.00 p.m.	16.4	1.45	23.78	16.4	1.94	31.816
01.00 p.m.	16.9	1.5	25.35	14.9	1.5	22.35
02.00 p.m.	13	1.22	15.86	11.86	1.72	20.408
03.00 p.m.	12.2	1.1	13.42	13.2	1.5	19.8
04.00 p.m.	10.9	1.03	11.227	12.98	1.3	16.874
05.00 p.m.	9.12	0.9	8.208	10.12	0.9	9.108
06.00 p.m.	5.3	0.5	2.65	9.3	0.8	7.44
07.00 p.m.	3.9	0.3	1.17	3.9	0.3	1.17
Average Power			11.086	17.037		

**Figure 8.** Predicted data of tracking panels**Figure 9.** Predicted data of both static

For the static panel, the SVM model was able to approximate the panel's behavior by producing predictions that were analogous to the actual data. Because these panels do not change their orientation in response to the sun's movement, the graph displays a smoother curve than the tracking panel. At the same time as the tracking panel anticipates that the sun will reach its highest point, the static panel also predicts that its power output will peak. However, the static panel's performance isn't as peaky as the tracking panels, so it produces less power in the end. The tracking system is better at capturing solar energy because its peak power output is lower than that of the static panels.

Assessing the efficiency of the model, one way to quantitatively evaluate the performance of the SVM model is to calculate metrics like MSE, which measures the prediction error. The more accurate the model, the lower the MSE value. The accuracy of a model can be assessed by comparing the predicted curve with the actual data points in plotted graphs, which offers a qualitative evaluation. Figures 8 and 9 demonstrate the predicted power output.

The tracking panel's highest recorded output is about 31.8 W at noon time which fell short of its stated 40 W rating. The 40 W rating is determined under normal test conditions like

STC: 1000 W/m² irradiation and 25°C cell temperature and thus this variance is expected. While the panel's temperature much exceeds 25°C and both factors reducing its instantaneous power output the actual irradiation may be somewhat below 1000 W/m² at any given point even in direct sunlight during the field experiments. That why during midday hot conditions in Kirkuk is reaching roughly 31.8 W about 79% of the specified power indicates normal performance of the panel and hardware configuration and under real conditions the panel was running close to its operational constraints.

This work has found that dual-axis tracking increases energy production by approximately 54%, which is comparable to but higher than the values reported in the literature but in mid-latitude areas the dual-axis trackers are generally said to produce between 33 and 41 percent more energy than stationary panels. Ideal circumstances improvements could be higher, for instance, Khan et al. [29] found improvements of 39% to 54% using a dual-axis tracker depending on daily and meteorological fluctuations. And this range includes a roughly 54% increase observed in Kirkuk. Which shows significant gain that can be attributed to the clear sky conditions that are had during the summer measurements and the fixed panel's constant orientation throughout the day also gave the tracker a significant edge in the early and late afternoon. Therefore, taking into account local factors and experimental configurations the results are in agreement with previous studies. So those results which found in current work is consistent with the performance improvements reported by Bazyari et al. [21] where single-axis tracking increased average energy by 35% and the double-axis has increased by 41%.

9. CONCLUSION

Nowadays, PV solar is widely utilized to distribute energy resources as a significant sustainable and renewable source of power across various sectors, including residential, commercial, and industrial applications. However, one of the drawbacks of PV solar is the low energy conversion efficiency. Therefore, the integration of sun trackers, commonly referred to as MPPT controllers, becomes essential as they efficiently monitor and adjust solar panels to maintain alignment with the optimal angle for capturing maximum solar energy, thereby enhancing overall energy yield.

This paper offers several major contributions: The first application of SVM regression for forecasting solar

photovoltaic performance in Kirkuk, Iraq and evaluating a stationary panel and a dual-axis tracking panel as well as it offers empirical proof of the significant performance gains under Kirkuk's conditions made possible by a dual-axis tracking system.

In this paper, the evaluation of the performance of the maximum power point tracker for solar PV panels using a SEPIC converter has been demonstrated to be more efficient than using fixed static panels. A PV system has been implemented in Kirkuk city and a very corresponding predicted and actual power generated data proves that the SVM model is the highly effective method for both tracking and static solar panels. The work is based on day-to-day comparisons of the two systems' power output characteristics, the study concluded that tracking solar panel systems generates energy more efficiently than static ones in Kirkuk city.

The model can be more precise if could benefit from including additional time-related variables like weather and ambient temperature. This is planned as future work for better and more dynamic modeling with the addition of real-time data streams and the pursuit of cutting-edge machine learning techniques. The study's outcomes also support using tracking technology in solar energy systems, since they show that tracking systems produce significantly more power than static systems. This is especially the case on very sunny days, such as the one where the study took place.

To understand the limitations of the current SVM model is crucial and incredibly low R^2 value indicates that this model as implemented was far to adequately capture the complexity of the system's behavior. This is likely due using only time-of-day as input limited the model's ability to understand all important variables. In the future work this would be address by adding additional input features like recorded temperature, irradiance or dust concentration to strengthen the informational foundation of the model and also expanding the size and variety of the training data to covering a wider range of days and weather and applying hyperparameter optimization and exploring other machine learning algorithms like neural networks or ensemble methods to improve prediction accuracy. This expects a significantly better performance in PV production forecasting by implementing these improvements.

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