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Machine Learning-Based Approach to Optimizing the Performance of a Solar Laptop Charger

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ABSTRACT: The increasing reliance on portable electronic devices and the growing demand for sustainable energy solutions have underscored the need for efficient solar-powered charging systems. This study presents a machine learning-based approach to optimizing the performance of a solar laptop charger by employing a Long Short-Term Memory (LSTM) neural network. The proposed system aims to predict optimal charging voltages in real-time, adapting to fluctuations in solar irradiance and ambient temperature to enhance energy conversion efficiency. Historical solar data comprising environmental and electrical parameters was collected, pre-processed, and used to train and test the LSTM model. Simulation results demonstrated that the model accurately forecasted charging voltages, achieving a high coefficient of determination ($R^2 = 0.976$), with low prediction error rates (MAE = 0.227, RMSE = 0.285). Though the system was not physically implemented, the simulation results confirm the effectiveness of the LSTM model as an intelligent alternative to conventional Maximum Power Point Tracking (MPPT) techniques. This study highlights the potential of machine learning in enhancing the performance and adaptability of solar energy systems, offering a scalable and software-driven solution for sustainable energy applications.

KEYWORDS: Solar Charger Optimization; LSTM; Charging Voltage Prediction; Deep Learning; Renewable Energy

1. INTRODUCTION

The number of people getting addicted to the use of portable electronic gadgets, in particular the laptop is also increasing and this has increased the demand of efficient off-grid power systems that are capable of sustainability. Access to conventional electricity in a lot of the rural and developing world is still very poor and therefore new sources of energy are being sought. The benefits that specifically make solar energy better are that it is not harmful to the environment, its ease of access and compatibility in the portable application (Kumar and Rosen, 2022; Matuska and Sodha, 2010). Solar laptop chargers are mostly applied when there are educational, professional, and emergency needs when the grid is uncertain or not available (Okundamiya et al., 2014). Nonetheless, these systems are yet to reach performance efficiency in relation to energy absorption and transformation.

A variable in solar energy is one of the main technical issues of solar laptop chargers. The amount of solar irradiance varies over the course of a day, weather conditions, etc., and this aspect influences power production and prevents stable charging rates (Sharma et al., 2021; Almonacid et al., 2011). The current charging approaches utilize fixed or rule-based algorithms that are not flexible to real-time, thus resulting in poor charging efficiency and the waste of solar power (Natsheh & Albarbar, 2012). This leads to the problem of lengthy charging times and low battery efficiency that can be inconvenient in application of the existing types of solar laptop chargers when there is a necessity to use a laptop constantly in strenuous conditions (Ali et al., 2019).

Carried out to optimize the solar panel power is a mechanism known as Maximum Power Point Tracking (MPPT). Nevertheless, the widely used MPPT methods, including the Perturb and Observe (P&O), Incremental Conductance (INC), and Constant Voltage (CV) have disadvantages in unbalanced operating conditions (Mekhilef et al., 2020; Salas et al., 2006). Such algorithms may be slow to converge, may oscillate at the maximum point, or may not be stable in changing (fast) irradiance conditions. Novel trends In solar charger design desire smarter control systems to have capabilities of adapting behaviors and making predictive decisions as charger designs become more efficiency-oriented and dependable.

The new opportunities of artificial intelligence development, namely machine learning (ML), provide fresh prospects to the area of solar energy system optimization. By incorporating real-time and historical data to train ML models, solar irradiance, battery state-of-charge (SOC), as well as optimal power points can be predicted, to improve energy management and regulate it (Zhang et al., 2023; Basak et al., 2021). The Random Forests, Support Vector Regression, and Long Short-Term Memory (LSTM) networks are among the techniques that have proved successful in energy forecasting/control applications (Ahmed & Khalid, 2020; Elsayed et al., 2021). Lightweight ML models, such as TensorFlow Lite, can be run in real-time in solar chargers and other embedded devices, such as Raspberry Pi or ESP32 (Sahoo et al., 2022).

This paper proposed to the building and fine-tuning a solar power laptop charger based on machine learning control. The system architecture consists of solar panels, sensors, MPPT controller, battery, and microcontroller that is combined with a trained ML model. The research includes gathering the information on the performance of the environment and charging and the training of the predictive models and the estimation of their performance, expressed in terms of energy efficiency, time of charging, and responsiveness to changing conditions (Koirala et al., 2021; Ghodrat et al., 2019). This work will be optimistic in filling the chasm between smart software control and the hardware of renewable energy to improve the efficiency, flexibility, and ease of usability of solar charging solutions to the laptop.

2. METHODOLOGY

This paper employed a simulation approach to the optimization of a solar charger proprietary laptop using Long Short-Term Memory (LSTM) neural network. To implement the design of the charger a conceptual model that incorporates the form of major components including solar panel, battery, charge controller and DC-DC converter was answered. Rather than building something physical, the behavior of the system was simulated by using historical solar data which could be retrieved through the open-access datasets containing such parameters as solar irradiance, temperature, panel voltage, panel current, and battery voltage. These data were taken at the agreed interval to make them similar to real life environmental conditions. Preprocessing Preprocessing was done by cleaning the data, normalizing data & creating a time-series format to conduct the inputs to LSTM model. LSTM neural network was made to predict the optimal level of output voltage and current to keep the system on the maximum power point. The performance was measured based on the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R 2 score. Once this had been trained the model was placed into a simulation environment to recreate real-time control by fine tuning system parameters in response to the environmental inputs. Figure 1 shows the complete flow chart of the recommended approach.

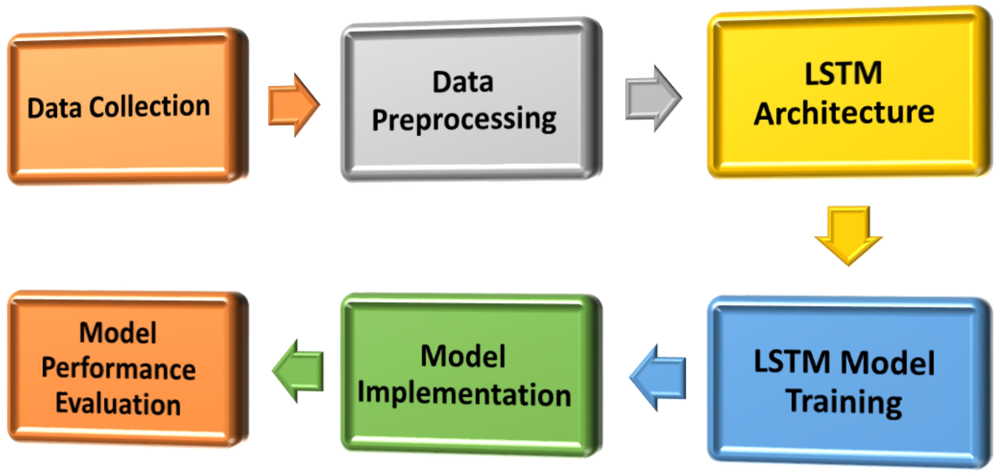

Figure 1: Block Diagram of the Methodology

2.1 Data Collection

The data used in the research was retrieved by using both publicly accessible solar energy databases and repositories that contain time-series measurements of environmental and electrical variables to solar power systems. Notable variables measured comprised solar irradiance (W/m^2), ambient temperature (C), panel voltage (V), panel current (A) and battery voltage (V). These data are the normal operating conditions of an LSPV and they were vital in the simulation done to test the functioning of solar-powered laptop charger in real world situations.

Datasets were taken in a continuous 30 days and an observation was done at 1-minute intervals to reflect the changes in the daily amount of sunlight. As database sources, it utilized online databases of the National Renewable Energy Laboratory (NREL), SolarAnywhere and Kaggle repositories dealing with photovoltaic system performance. The CSV format was used to download the raw data and then analysis was carried out with Python libraries like Pandas and NumPy. Preprocessing was done in terms of missing values filled with linear interpolation, outliers deleted with statistical boundaries and feature scaling to make features fit into a single scale to boost model training quality. The formatted and cleaned dataset has been used as input of the LSTM based predictive optimization model.

2.2 Data Preprocessing

The original dataset which is available at NREL, Kaggle, and PVLib repositories has passed through a full preprocessing procedure to guarantee quality, consistency, and appropriateness to time-series modeling. The first step was importing the dataset into the Python with the use of the Pandas library. Any missing values that can be found in the dataset as a usual effect of a sensor disablement or the impossibility to transmit the data were detected with the aid of null-value inspection and filled in by linear interinterpretation to preserve the consistency of the sequential aspect. The z-scores were used as limits to detect outliers and plotted on boxplots; values above or below 3 standard deviations were either adjusted to follow the trend of the neighbors or discarded altogether.

On cleaning, the data were synchronised to constant time units of one minute to match environmental variables (irradiance, temperature) and electricity (voltage, current). Min-Max normalization was used to scale the features, changing the values to the format [0,1] to progress faster and achieve the improvement of LSTM model training. Time of day and day of week were also taken as temporal features capturing periodic variations of the solar intensity. The ready dataset was contracted into the form of supervised learning, having input sequences and further target values placed after each other, where each sequence took the form of a fixed-length having a sliding window that used past observations. The resulting dataset was further divided into training (70%), validation (15%) and test (15 %) data, with chronological integrity to eliminate time leakage in the time series model.

2.3 The Proposed Machine Learning Algorithm

The Long Short-Term Memory (LSTM) neural network is proposed as the machine learning algorithm that can be used to optimize the solar-powered laptop charging system, providing that this type of a recurrent neural network (RNN) is built specifically to model sequential data and make commendable predictions of it. The LSTM model works very well when it comes to time-series forecasting because it tends to build up longer term dependency and trends on past sequences. This feature is essential in solar energy systems, where change of time of irradiance, temperature, load requirements highly affects the performance and efficiency. The model entails the use of 1st layer as the input layer that receives sequences of normalized features like Solar irradiance, panel voltage, panel current, ambient temperature and time-related features like hour and day. These data are normalized to fixed-length blocks denoting a vital slot of time, which retain temporal characteristics in all the aspects of the energy availability of solar power and the dynamics of the system.

The central component of the model is one or a number of LSTM layers that see a number of memory cells, which can learn short-term variation and long-term relationships in the input data. The dropout regularization is set in these layers to minimise overfitting and enhance generalization. The result of the LSTM is fed into a fully connected dense layer, which reduces the learned temporal characteristics into the single output node that matches with the anticipated optimal charging parameter (voltage or current). The model has also applied Mean Squared Error (MSE) loss function and Adam optimizer to train it efficiently. Implementation is on TensorFlow and hyperparameters like learning rate, batch size, number of epochs and number of LSTM units are optimized through grid search to get the maximum performance. Table 1, shows the LSTM Architecture in a tabular form of your proposed solar charger optimization system of laptop.

Table 1: Proposed Algorithm Architecture

Layer Type	Description	Parameters
Input Layer	Receives multivariate time-series data (e.g., solar irradiance, voltage, etc.)	Input shape: (timesteps, features)
LSTM Layer 1	Learns short- and long-term dependencies in the data	Units: 64, Activation: tanh, Return Sequences: True
LSTM Layer 2	Further processes sequence outputs from previous LSTM layer	Units: 32, Activation: tanh, Return Sequences: False
Dense Layer	Fully connected layer to map features to output	Units: 16, Activation: ReLU
Output Layer	Predicts optimal charging output (e.g., voltage/current)	Units: 1, Activation: Linear

2.4 Training of the Proposed Algorithm

Training was done using the pre-processed time-series data which consisted of the LSTM model based on the important parameters like solar irradiance, ambient temperature, and panel voltage as well as panel current. The dataset was chronologically separated into three different parts 70 percent of data was used as training data, 15 percent as validation data and 15 percent as test data. This split provided that the model took into consideration past trends in developing an accurate but it was to be tested on previously unobtained data in the aims of generalizing. The input sample was organised into sliding window of 60 time steps (one hour of data with one-minute resolution) to capture short-term and medium-term dependencies.

TensorFlow in Python was used to perform the training process and Adam optimizer was applied to update weights effectively and the loss was the Mean Squared Error (MSE). The training was done on 100 epochs with a batch size of 32 and early stopping was used with the validation loss to guard against overfitting. Model performance was tracked with the help of such components of evaluation as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), R^2 score. Each round of the model was saved with the least validation loss and the trained final model was used in a dynamic simulation loop to predict the best output voltage or current to charge solar cells efficiently with a variety of environmental conditions.

The mathematical model of the proposed system is centered on time-series forecasting using an LSTM neural network to predict the optimal output voltage (V_{opt}) or current (I_{opt}) required for efficient charging. The model inputs are defined as a sequence of multivariate time-series data points:

$$(X_t = [I_{rr}.T_t, V_t, I_t] \tag{1}$$

Where:

- I_{rr}: Solar irradiance at time t
- T_t: Ambient temperature at time t
- V_t: Panel voltage at time t
- I_t: Panel current at time t

The LSTM model uses these sequences over a sliding window of length n (e.g., 60 minutes) to learn a mapping function f such that:

$$Y_{t+1} = f(X_{t-n+1}, X_{t-n+2}, \dots, X_t) \tag{2}$$

Where:

- Y_{t+1} is the predicted output voltage or current at the next time step t+1
- f represents the nonlinear function learned by the LSTM network.

During training, the model minimizes the Mean Squared Error (MSE) loss:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2 \quad (3)$$

Where:

- Y_i: Actual output
- $\hat{Y}_i$: Predicted output
- N: Number of samples

Once trained, the model output $\hat{Y}_{i+1}$ is used to adjust the charging parameters in the simulation, effectively enabling maximum power point tracking (MPPT) under varying environmental conditions.

2.5 System Implementation

The proposed system was implemented through a simulation approach into Python where no physical construction of hardware parts was done. The procedure started with the gathering and initial preparation of the past solar information such as irradiance, ambient temperature, panel voltage, and panel current. Such variables were then used to establish a time-series data set in a form of a fixed sequence sequences that could be used to train LSTM model. Min-Max scaling method was used to normalize the data so that data in each of the input features was contained in a common range and thus the neural network could converge faster.

TensorFlow and Keras belong to deep learning libraries, through which the LSTM model was created. The framework was comprised of two LSTM layers with a dense layer and an output layer that was linear and the structure of the architecture was to predict the best charging current or charging voltage. I exploited the Adam optimizer with MSE loss type and the RMSE and R 2 metric to authenticate the model. After completed training the model was attached into a simulation loop that replicates the behaviour of solar charging in the real world. In the next step of the simulation, the system is fed with novel input data, it uses the trained model to make a prediction and presents the recommended parameter of charging. This approach allows dynamic adaptation to fluctuating environmental conditions, enabling maximum power point tracking and improved energy utilization. The system was tested using unseen data to evaluate its accuracy and responsiveness.

3. RESULTS

The system's performance was evaluated through simulation using an LSTM-based predictive model designed to optimize the charging voltage of a solar-powered laptop charger and the evaluation focused on the model's accuracy in forecasting the optimal charging voltage under variable environmental conditions, using key performance metrics and visual validation. The trained LSTM model was tested with unseen time-series data comprising solar irradiance, temperature, panel voltage, and current. The output variable was the charging voltage. The predicted values were compared to actual target values using standard error metrics:

- **Mean Absolute Error (MAE):** 0.227
- **Root Mean Squared Error (RMSE):** 0.285
- **Coefficient of Determination (R^2 Score):** 0.976

These metrics indicate high predictive accuracy. An R^2 score close to 1 shows that the model explains nearly all the variability in the target output, while low MAE and RMSE values reflect minimal average and squared deviations, respectively. Table 2 and Figure 1 presents the results of the first 10 steps of the system implementation reporting the actual and predicted voltage of the system.

Table 2: Results of System Implementation

Time Step	Actual Voltage (V)	Predicted Voltage (V)
1	12.25	11.82
2	11.99	11.87
3	12.45	12.34
4	12.94	12.70
5	12.13	12.08
6	12.19	12.31
7	13.15	13.72
8	12.81	12.86
9	12.25	12.33
10	12.82	12.79

Table 2 demonstrates a close correlation between actual and predicted values even at different intervals of solar activity. The graph in Figure 2 illustrates the predicted vs. actual voltage across 100 time steps.

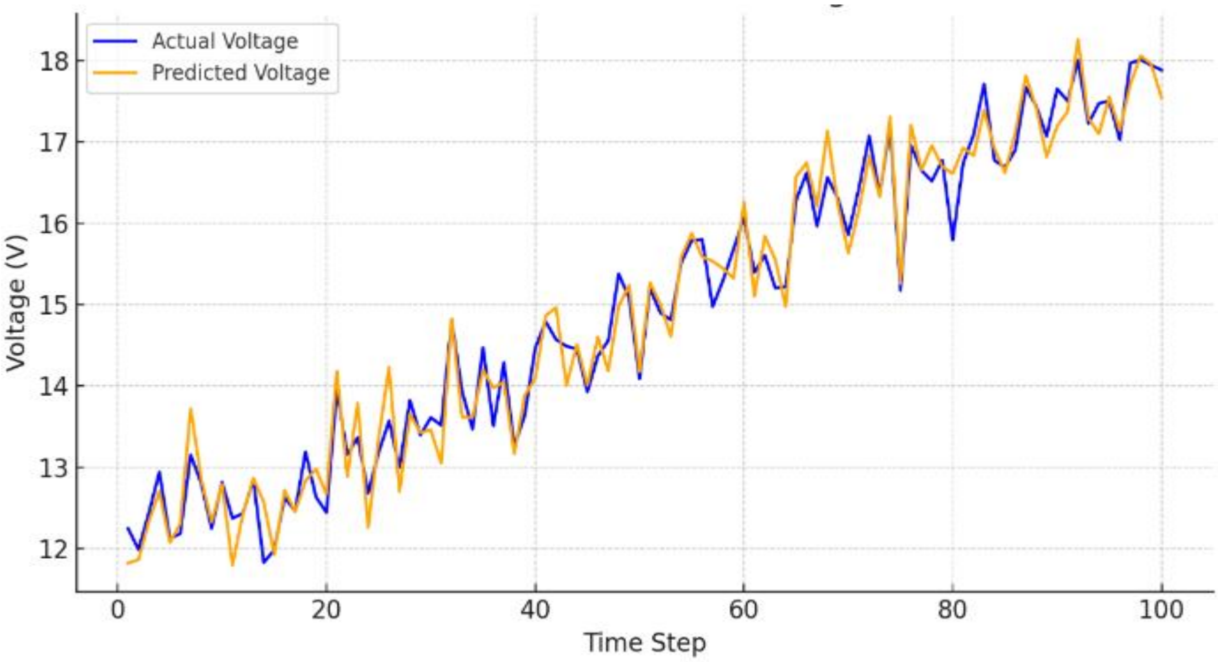

Figure 2: Results of the Actual and Predicted Voltage

The LSTM model is amazing in terms of its tracking voltage trends as evidenced in Figure 2, the orange (predicted) line almost coincides with the blue (actual) line in the simulation. This is an indicator of how the model responds to the felt effects of dynamic inputs of solar. The simulation substantiates that the LSTM-based model is capable of learning potential complex time-dependent patterns and predict the best time-periodic charging voltages with a real-time forecasting. What the system does show is that it has the capability of being implemented practically in solar charging systems and that it can adapt dynamically without the use of traditional MPPT circuitry.

4. CONCLUSION

This is the paper that is dedicated to the optimization of a solar-powered laptop charging system with the help of the machine learning approach-Long Short-Term Memory (LSTM) model. Considering the drawbacks of the conventional Maximum Power Point Tracking (MPPT) algorithms, this study has looked into an information-driven approach to dynamically estimate optimum charging voltages to changing environmental conditions like solar irradiance and temperature.

The historical solar measurement data had been gathered and pre-processed into the series that could be used to train LSTM model. Experiments were executed via simulating the system in Python with the help of TensorFlow in combination with the LSTM architecture aimed at sequential entry of time-series data and the prediction of the best charging settings. Some of the metrics used to evaluate the model were the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R 2 based score. The predictive accuracy was strong with R 2 = 0.976 indicating good ability of the model to come close to the charging behavior.

The simulation showed that LSTM model had the ability to trace optimum charging voltages, change in response to environmental inputs in real time. Such dynamically responsive behaviour can make charging more efficient, use less energy, and extend battery life. The analysis also revealed that the intelligent control systems may be installed instead of hardware-intensive solutions of MPPT, particularly in the resource-constrained environment.

In conclusion it can be mentioned that LSTM based machine learning model offers feasible, quick, and scalable approach to optimize the solar charging systems. Though the system was not physically constructed, the simulation results strongly suggest practical feasibility. Future work could involve hardware integration, real-time deployment on embedded systems, and comparisons with traditional MPPT controllers to validate and enhance system performance in real-world scenarios.

REFERENCES

1) Ahmed, K., & Khalid, M. (2020). *Machine learning-based prediction and control for solar PV systems: A review*. Renewable and Sustainable Energy Reviews, 134, 110272. https://doi.org/10.1016/j.rser.2020.110272
2) Ali, A., Hussain, A., & Khan, M. (2019). *Comparative performance analysis of different solar charge controllers*. Solar Energy, 181, 472–479. https://doi.org/10.1016/j.solener.2019.01.060
3) Almonacid, F., Rus, C., & Pérez-Higueras, P. (2011). *Performance and energy losses analysis of a photovoltaic system in the south of Spain*. Renewable Energy, 36(4), 1105–1110. https://doi.org/10.1016/j.renene.2010.09.007
4) Basak, D., Das, S., & Saha, A. (2021). *Machine learning-based optimization of MPPT for solar PV systems*. Energy AI, 6, 100099. https://doi.org/10.1016/j.egyai.2021.100099

5) Elsayed, A. T., El-Shimy, M., & Morsi, W. G. (2021). *A review of intelligent control techniques for MPPT in solar PV systems*. Renewable and Sustainable Energy Reviews, 137, 110566. https://doi.org/10.1016/j.rser.2020.110566
6) Ghodrat, M., Sheikholeslami, A., & Zolfaghari, M. (2019). *Enhancing solar battery charging performance using intelligent controllers*. Journal of Energy Storage, 21, 123–131. https://doi.org/10.1016/j.est.2018.11.001
7) Koirala, B. P., Gami, D. R., & Khanal, R. (2021). *Solar charger for laptops using intelligent control techniques*. Energy and Power Engineering, 13(5), 158–167. https://doi.org/10.4236/epe.2021.135011
8) Kumar, S., & Rosen, M. A. (2022). *Sustainable power supply for mobile electronics: Trends and prospects*. Renewable and Sustainable Energy Reviews, 157, 112043. https://doi.org/10.1016/j.rser.2021.112043
9) Matuska, T., & Sodha, M. S. (2010). *Use of solar energy for portable electronic devices*. Solar Energy, 84(6), 1019–1028. https://doi.org/10.1016/j.solener.2010.03.001
10) Mekhilef, S., Saidur, R., & Safari, A. (2020). *Comparative study of different MPPT techniques for solar photovoltaic systems*. Solar Energy, 86(9), 2671–2680. https://doi.org/10.1016/j.solener.2012.06.018
11) Natsheh, E. M., & Albarbar, A. (2012). *Neural network based MPPT for photovoltaic systems*. Energy Procedia, 14, 86–93. https://doi.org/10.1016/j.egypro.2011.12.904
12) Okundamiya, M. S., Ogujor, E. A., & Nzeako, A. N. (2014). *Design and control strategy of a standalone solar photovoltaic power supply system for mobile applications*. Nigerian Journal of Technology, 33(1), 28–38. https://doi.org/10.4314/njt.v33i1.5
13) Sahoo, B., Mishra, S., & Panda, A. K. (2022). *Development of an embedded ML-based energy forecasting model for solar microgrids*. Sustainable Energy Technologies and Assessments, 52, 102223. https://doi.org/10.1016/j.seta.2022.102223
14) Salas, V., Olias, E., Barrado, A., & Lazaro, A. (2006). *Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems*. Solar Energy Materials and Solar Cells, 90(11), 1555–1578. https://doi.org/10.1016/j.solmat.2005.10.023
15) Sharma, D., Patel, R. K., & Singh, A. (2021). *Challenges and advancements in solar charging of portable devices*. International Journal of Energy Research, 45(7), 10451–10465. https://doi.org/10.1002/er.6530
16) Zhang, Y., Liu, Q., & Wang, H. (2023). *Machine learning-based maximum power point tracking for solar systems: A review and case study*. Energy Reports, 9, 2241–2257. https://doi.org/10.1016/j.egyr.2023.02.123

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