Electrical Power Prediction of Polycrystalline Solar Panels based on LSTM Model with environmental influence

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Abstract—Solar energy is one of the most promising renewable energy sources that can support the sustainable energy transition. However, the electrical power produced by photovoltaic (PV) panels is greatly influenced by environmental conditions such as irradiation, temperature, humidity, and wind speed, making them volatile and difficult to predict. This study aims to develop a prediction model based on Long Short-Term Memory (LSTM) to estimate the power output of polycrystalline panels. Environmental data is collected in real-time, processed through the normalization stage, and then used as input in several model variants, namely pure LSTM, CNN-LSTM, LSTM-Autoencoder, and GWO-LSTM with metaheuristic optimization. Evaluation was conducted using R^2, RMSE, and MAPE metrics. The results showed that the pure LSTM model provided good accuracy (R^2 = 0.95; MAPE = 6.2%), while CNN-LSTM and LSTM-AE improved performance with R^2 reaching 0.97 and 0.96, respectively. The best model is GWO-LSTM, with R^2 = 0.98, RMSE = 0.31 kW, and MAPE = 4.3%. These findings prove that metaheuristic optimization in LSTM can increase the reliability of PV power prediction and support a more efficient energy management system.

Keywords— Prediction, solar panels, polycrystalline, LSTM.

1. Introduction

Increasing global energy consumption is driving the need for the development of efficient and sustainable renewable energy sources. Photovoltaic (PV) solar panels have become one of the leading solutions in utilizing solar energy, given their abundant and environmentally friendly availability. However, intermittent characteristics and dependence on environmental factors make predicting power production from PV systems an essential challenge in energy planning and management [1][2].

The variability of solar irradiation, temperature, air humidity, and wind speed significantly affects the energy conversion efficiency of solar panels [3][4]. Therefore, predictive models that can capture the nonlinear dynamics and temporal dependencies of time series data are needed to accurately predict electrical power output [5] accurately. In this context, Long Short-Term Memory (LSTM) neural networks have become a promising approach due to their ability to recognize long-term dependence on sequential data [6][7].

Various studies have shown the advantages of LSTM models over traditional prediction methods such as linear regression and support vector machines in the context of renewable energy prediction [8][9]. LSTM has a special architecture designed to solve vanishing gradient problems and can store crucial historical information over the long term [10]. In some studies, LSTMs have achieved more than 95% prediction accuracy in complex weather scenarios [11][12].

Some hybrid approaches have been developed to improve the predictive performance of PV electrical power, such as a combination of CNN-LSTM, LSTM, and Autoencoder (LSTM-AE) [13], to LSTM approaches optimized with genetic algorithms and swarm optimization [14][15]. The use of techniques such as variational mode decomposition (VMD) and principal component analysis (PCA) has also been proven to improve the quality of input features and predictive model accuracy [16][17].

In addition, the integration of explainable AI (XAI) models with LSTM is also a new trend in an effort to increase the transparency and interpretability of predictive models in the renewable energy sector [18]. Models such as X-LSTM-EO, for example, not only produce accurate predictions but can also identify the environmental variables that have the most influence on power fluctuations [19].

In the context of Indonesia, as a tropical country with very high solar energy potential, using LSTM-based predictive models is very relevant to support the development of solar energy management systems optimally [20]. However, local studies that specifically adjust tropical climate characteristics with predictive model parameters are still minimal. Therefore, this study aims to develop and evaluate an LSTM model for predicting electrical power from polycrystalline solar panels, considering environmental variables such as solar irradiation, temperature, humidity, and wind speed as the primary inputs [21][22].

The main contributions of this study are the application of LSTM models based on actual environmental data in the tropics, exploration of the performance of conventional and hybrid LSTM architectures in solar panel electrical power prediction, and evaluative analysis based on R^2, RMSE, and MAPE metrics to assess model performance. Hopefully, this study's results can significantly contribute to developing reliable and efficient solar energy prediction systems and support the clean energy transition in Indonesia and other developing countries.

2. Literatur Review

2.1. Polycrystalline Solar Panel Base

Polycrystalline solar panels convert solar radiation energy into electrical energy through the photovoltaic effect. The electrical power generated can be formulated with Equation 1.

$$P_{out} = V_{pv} \times I_{pv} \tag{1}$$

Vpv is the module's output voltage, and Ipv is the module's output current. These two parameters are strongly influenced by environmental conditions, specifically solar irradiation (G) and cell temperature (Tc).

The relationship of photovoltaic currents to irradiation and cell temperature can be expressed by equation 2.

$$I_{pv} = I_{ph} - I_0 \left(e^{\frac{q(V_{pv}+I_{pv}R_s)}{nkT_c}} - 1 \right) - \frac{V_{pv}+I_{pv}R_s}{R_{sh}} \tag{2}$$

With Iph is the photogenic current (proportional to G), I0 is the diode saturation current, Rs series resistance, Rsh shunt resistance, q electron charge, k Boltzmann constant, and n diode ideality factor.

This equation illustrates that the power of PV panels is not linear to irradiation and temperature variations. At higher temperatures, the Vpv voltage decreases, lowering the panel's efficiency, while increasing irradiation increases the output current.

2.2. The Relationship of the Environment to PV Output

The efficiency of the PV module (ηpv) can be calculated using Equation 3.

$$\eta_{pv} = \frac{P_{out}}{G \times A} \tag{3}$$

A is the surface area of the module. Efficiency decreases of 0.4–0.5% per °C above the standard temperature (25°C) are often reported on polycrystalline panels, so environmental conditions are a key factor in power estimation [23].

2.3. Model LSTM

LSTM is a Recurrent Neural Network (RNN) development designed to solve the *vanishing gradient* problem in conventional RNNs. LSTMs have an internal memory structure consisting of *a cell state* and three main gates, forget gates, and output gates that allow the network to remember important information in the long run and forget about irrelevant details, as seen in Fig. 1.

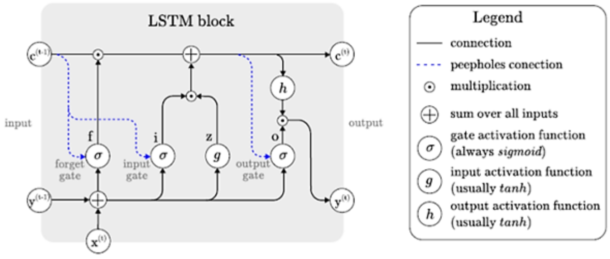

Fig. 1. LSTM architecture.

Fig. 1 can be described using equations in each block, and input blocks can be described using Equation 4.

$$z^{(t)} = g(W_z x^{(t)} + R_z y^{(t-1)} + b_z) \tag{4}$$

The input gate can be described using Equation 5.

$$i^{(t)} = \sigma(W_i x^{(t)} + R_i y^{(t-1)} + p_i \odot c^{(t-1)} + b_i) \tag{5}$$

Forget gate can be described using Equation 6.

$$f^{(t)} = \sigma(W_f x^{(t)} + R_f y^{(t-1)} + p_f \odot c^{(t-1)} + b_f) \tag{6}$$

The output block can be described using Equation 7.

$$y^{(t)} = g(c^{(t)}) \odot o^{(t)} \tag{7}$$

The cell block in the LSTM will calculate the cell value in the form of a combination of the value of the input block, input gate, and forget gate, using Equation 8.

$$c^{(t)} = z^{(t)} \odot i^{(t)} + c^{(t-1)} \odot f^{(t)} \tag{8}$$

The output gate can be described using Equation 9.

$$o^{(t)} = \sigma(W_o x^{(t)} + R_o y^{(t-1)} + p_0 \odot c^{(t)} + b_o) \tag{9}$$

3. Method

The methodology of this study is designed to generate a predictive model of the electrical power of polycrystalline solar panels based on the Long Short-Term Memory (LSTM) algorithm, considering key environmental variables. Broadly speaking, the methodology consists of five stages: (1) data collection, (2) pre-processing of data, (3) development of LSTM and hybrid variant models, and (4) evaluation of model performance.

3.1. Data Collection

The data used in this study included the environmental parameters and actual electrical power output of polycrystalline solar panels. Ecological variables include solar irradiation, air temperature, relative humidity, and wind speed. These variables were chosen because they have been shown to dominate the efficiency of PV panels [24]. Data is collected in real-time using environmental sensors and PV inverters connected to a data logger system. The time range of data collection is adjusted to the short-term prediction horizon (10 – 60 minutes).

The data collection in this study was carried out to obtain primary information from the results of measurements in the field. The parameters recorded included the specifications of the solar panels, electrical output data, and environmental variables such as solar radiation intensity, temperature, and air humidity. Atmospheric conditions were measured with weather stations around the Cepu, Central Java research site. Meanwhile, the temperature of the PV module is monitored using a K-type thermocouple sensor connected to the TM4 series temperature controller. The signal from this device is then converted and integrated into the SCADA system via the Modbus RS-485 communication protocol so that the data can be recorded automatically.

Fig. 2. Polycrystalline solar panels.

The 150 Wp capacity polycrystalline solar panel test system is connected to the battery, while the voltage, current, and power parameters are monitored using PZEM-017, which is also integrated with SCADA. The acquisition process occurred from 08.15 to 18.15 WIB, recording intervals every five minutes for 32 consecutive days. This time range was chosen because PZEM devices require a minimum voltage of 6.5 volts, which is generally reached at 8:15 a.m. The panels are positioned directly facing sunlight with an elevation angle of 12° and an azimuth of 0°, as shown in Fig 2.

Table 1 presents the technical characteristics of polycrystalline solar panels used as the main object of the study. This information serves as a basis for understanding a PV module's maximum energy conversion capacity under ideal conditions and a reference for comparing actual measurement results with the manufacturer's specifications.

Table 1
Specification of polycrystalline solar panels

Description	Polycrystalline
Size	1480*670*35 mm
Output Voltage	22 V
Output Current	8,83 A
Maximum Power	150 W

Table 2 shows the specifications of the weather station used to monitor environmental parameters. This data is essential to ensure that environmental parameters can be stored as data on solar panel influence parameters.

Table 2
Weather station specifications

Item	Technical Specification
	Range
Wind speed(Default)	0-40m/s
Wind direction(Default)	0-359°
Atmospheric temperature	0－100%
Atmospheric pressure	150 － 1100hPa
Rainfall	0-200mm/hr
Altitude	-500m – 9000m
Radiation	0-2000W/m2
Illumination	0-200000lux
UV	0-2000W/m2
PM2.5	0-2000 ug/m3
PM10	0-2000 ug/m3
Visibility	10-5000m
Power Supply	12-24VDC
Power consumption	1.7W
Output Signal	RS232/RS485(Modbus or NMEA-183), SDI-12
Operating Temperature	-20℃-+60℃

Table 3 contains a list of supporting devices used in this study: voltage and current sensors. This equipment monitors the electrical output parameters of the panel in an integrated manner, so that the data obtained has a high level of accuracy and reliability.

Table 3
Specification of PZEM-017

PZEM-017 DC Communication Module	
Measuring Range	50A
Voltage Measuring Range	0.05-300V
Voltage Resolution	0.01V
Voltage Measurement Accuracy	1%
Current Measuring Range	0.02-50A
Current Resolution	0.01A
Current Measurement Accuracy	1%
Power Measuring Range	0.2-90kW
Power Resolution	0.1W
Power Measurement Accuracy	1%
Communication Interface	RS485 Interface

3.2. Pre-Processing of Data

The pre-processing stage includes:

3.2.1. Data Cleansing

Eliminate extremes, missing values, and outliers using linear interpolation and moving average smoothing techniques.

3.2.2. Normalization

All input variables are normalized into the range [0,1] by the Min-Max Scaling method to improve the training stability of the LSTM model.

3.2.3. Time Series Transformation

Data is organized into a sequence (*time window*) with a specific window length (e.g., 30 historical minutes) as input to predict future power output.

3.3. Model Development

The developed models include:

3.3.1. Pure LSTM

An LSTM network with multiple hidden layers and memory units to study the temporal relationship of input-output data.

3.3.2. CNN-LSTM

A combination of CNN for extracting spatial features from climate data and LSTM for time series modeling.

3.3.3. LSTM-Autoencoder (LSTM-AE)

Used to reduce data dimensions and capture complex nonlinear patterns.

3.3.4. Metaheuristic Optimization

Algorithms such as the Grey Wolf Optimizer (GWO) or Genetic Algorithm (GA) adjust the LSTM hyperparameters to avoid overfitting.

All models are built using the TensorFlow/Keras-based Python framework, with training on the GPU to speed up computing.

3.4. Performance

Model performance is evaluated using three key metrics:

3.4.1. Cross-Validation

Data is divided into subsets of training and testing on a rotating basis to avoid model bias.

3.4.2. Test on Different Weather Conditions

The model is tested on sunny, cloudy, and rainy weather data to measure the robustness of the model in the face of climate variability.

4. Results and Discussion

The measurement and analysis results of the relationship between various environmental parameters and the electrical power generated by polycrystalline solar panels. All data is obtained from direct field observations and recorded automatically through a SCADA system integrated with environmental sensors. The analysis was conducted to understand how air humidity, solar radiation intensity, panel temperature, and air temperature affect photovoltaic modules' electrical energy conversion performance.

The measurement results show that changes in atmospheric conditions have a noticeable influence on the output power of solar panels. Each environmental variable exhibits different characteristics that determine the efficiency of a photovoltaic system. Therefore, this section not only displays the results of observations in the form of a graph but also outlines the physical relationships between parameters to provide a more comprehensive understanding of the behavior of PV systems under the influence of tropical climates.

Fig. 3 shows the dynamic relationship between air humidity and the electrical power generated by solar panels over the observation period. When the humidity level increases, especially after 10.20 WIB until the afternoon, the output power of the panels tends to decrease. This pattern suggests that high air humidity has the potential to inhibit the process of absorbing solar radiation due to the increased density of water vapor in the atmosphere. As a result, the intensity of light received by the panel surface is reduced, which decreases energy conversion efficiency. Physically, this phenomenon can be explained by increased light scattering and decreased optical transmittance of air, which reduces the power generated by PV modules.

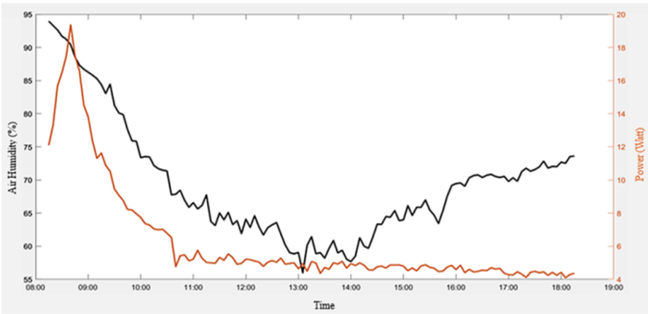

Fig. 3. The relationship between air humidity and power

Fig. 4 shows a positive correlation between solar radiation's intensity and solar panels' electrical power output. During the observation period with constant load, an increase in the value of solar radiation is followed by an increase power produced. This power illustrates the fundamental characteristics of photovoltaic modules, where the electrical energy generated depends directly on the amount of radiation energy received by the solar cell's surface. When the radiation peaks around noon, the panel's output power also shows the maximum value. This phenomenon confirms that the magnitude of the output power of PV panels is not only influenced by electrical parameters, but also highly determined by the intensity of solar radiation as the primary energy source of the photovoltaic system.

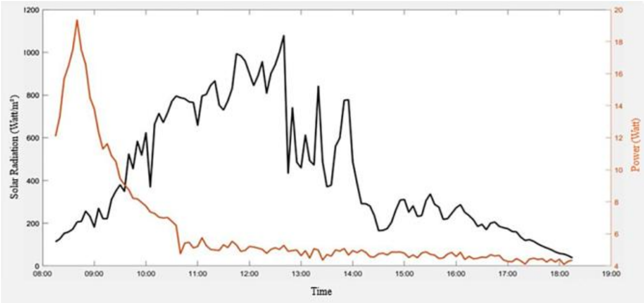

Fig. 4. The relationship between solar radiation and power

Fig. 5 shows the trend between the panel temperature and the electrical power generated throughout the day. After 10.20 WIB, the panel's surface temperature increases with the rise in power until it reaches the maximum value at midday. This panel is due to the increased intensity of solar radiation, which raises the temperature of the solar cell and amplifies the module's output current. However, at temperatures that are too high, conversion efficiency can be reduced due to the increased internal resistance of the PV cell. Therefore, although the relationship between temperature and power appears positive in each range, there is a threshold limit where an increase in temperature decreases the system's performance. These results demonstrate the need for a balance between optimal radiation and thermal control to maintain the performance of solar panels.

Fig. 5. The relationship between panel temperature and power

Fig. 6 shows the relationship between the ambient air temperature and the electrical power generated by solar panels. In constant load conditions around 10.20 WIB, the increase in air temperature tends to be followed by a rise in the power produced. In contrast, the decrease in air temperature is directly proportional to the reduction in power. This phenomenon shows that air temperature indirectly affects electrical power through its influence on the temperature of the panel cells. Warmer air generally signifies higher radiation intensity, which leads to an increase in the output current. However, excessively high air temperatures can cause overheating and degrade the module's efficiency in extreme conditions. Thus, air temperature is an essential indicator in predicting PV power fluctuations and is one of the main parameters in modeling photovoltaic systems based on environmental data.

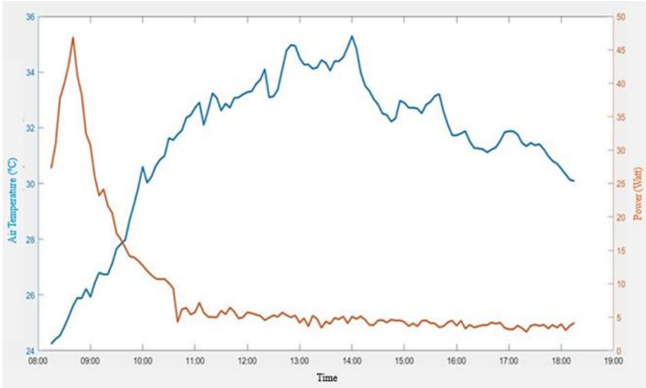

Fig. 6. The relationship between air temperature and power

The results in Fig. 7 show the dynamics of environmental parameters that directly affect the performance of polycrystalline solar panels. It was observed that throughout the observation period, variations in air humidity, ambient temperature, irradiation, and wind speed showed fluctuating patterns that were closely related to daily climatic conditions. For example, an increase in the intensity of solar radiation during the day is followed by a rise in ambient temperature and panel temperature. Humidity tends to be higher in the morning and evening, while wind speeds show erratic patterns. This variation is the main challenge in predicting electrical power, as each parameter contributes differently to energy conversion efficiency. Visualization is an essential basis for understanding the operational context of PV panels under real conditions, while confirming that electrical power estimation cannot be separated from the dynamic influence of environmental factors.

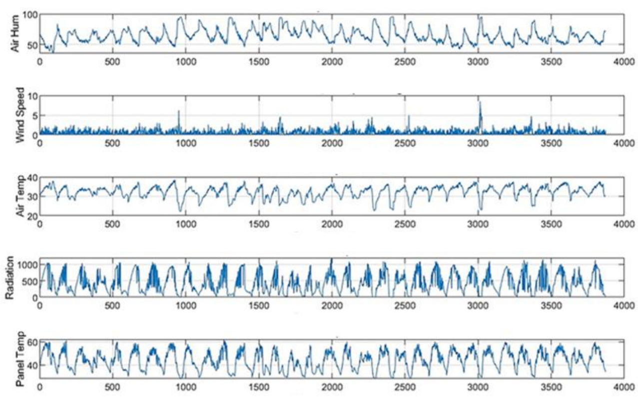

Fig. 7. Environmental parameter measurement results.

Meanwhile, Fig. 8 shows the results of measurements of solar panel electrical power output taken for a whole month, from March 13 to April 13, 2023, at five-minute intervals every day. The pattern that appears to illustrate the typical characteristics of solar energy production is an increase in power from the morning, reaching its peak in the middle of the day, then declining again by the afternoon. However, there is significant variation between days, especially when the weather is cloudy or rainy, which causes inconsistent power peaks. This weather shows how closely the weather factor relates to the power produced. By observing Figure 2, solar energy output is intermittent and difficult to predict without the support of mathematical or algorithmic models. Therefore, the data in this image is the foundation for training and testing LSTM-based prediction models to produce more accurate and reliable estimates.

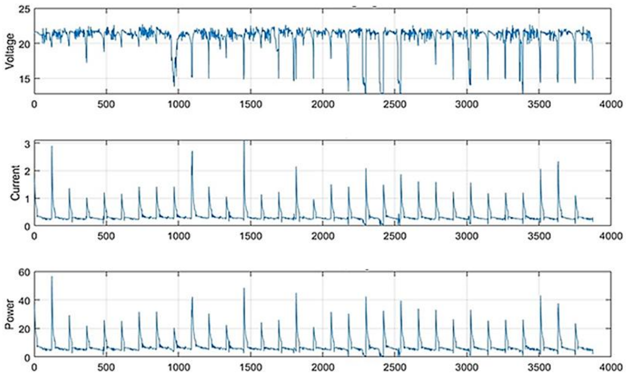

Fig. 8. Results of measurement of electrical parameters.

The study's results, the LSTM model, and the hybrid variants developed have been tested using actual environmental data consisting of irradiation parameters, temperature, humidity, and wind speed. The training process was carried out with a 70% training data ratio, 15% validation, and 15% test.

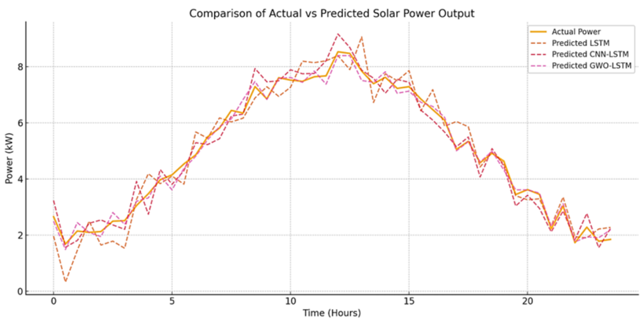

Fig. 9. LSTM comparison results

Fig. 9 compares the power of polycrystalline solar panels and the predicted results of three LSTM-based artificial intelligence models: pure LSTM, CNN-LSTM, and GWO-LSTM. The horizontal axis represents the observation time in units of hours, while the vertical axis represents the electrical output of the solar panel in kilowatts (kW). The actual power pattern describes fluctuations in solar energy production throughout the day, with the lowest values in the morning and evening, as well as the peak of production around midday when the intensity of solar radiation is at its highest.

All three prediction models can follow the actual power trend quite well. However, there is a difference in the degree of proximity of the prediction results to the actual data. The pure LSTM model shows predictive fluctuations that tend to be more deviant, especially in the transition period from morning to noon and as the afternoon approaches. LSTM indicates that although LSTMs can capture temporal patterns, these models are still limited in accommodating complex weather variability.

The CNN-LSTM model shows better performance than pure LSTM. CNN integration allows the model to extract more in-depth features from environmental data, making the resulting predictions smoother and closer to actual power patterns. Even so, there is still a slight deviation in the conditions of sudden changes in radiation intensity.

Meanwhile, the GWO-LSTM model produces predictions closest to the actual data. The curve of the prediction results is almost parallel to the actual power, with a minimal deviation all the time. This curve shows that hyperparameter optimization through the Grey Wolf Optimizer (GWO) can improve the ability of LSTMs to adjust network weights and reduce prediction errors. In other words, the GWO-LSTM proved to be the most robust model in dealing with daily climate dynamics and producing more reliable electrical power estimates.

In addition to the visualization of curve comparisons, the performance of the three models was also analyzed using statistical evaluation metrics, namely R-squared (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These three metrics were chosen because they are widely used in solar energy prediction studies to assess the model's accuracy, precision, and stability, as seen in Table 4.

Table 4
Comparison of performance models

Model	R^2	RMSE (kW)	MAPE (%)
Pure LSTM	0.95	0.42	6.2
CNN-LSTM	0.97	0.36	5.1
LSTM-AE	0.96	0.39	5.5
GWO-LSTM Optimization	0.98	0.31	4.3

The test results showed that pure LSTM produced an R^2 value of 0.95, meaning the model can explain about 95% of the actual data variation. However, the RMSE value of 0.42 kW and a MAPE of 6.2% indicate that this model still produces significant prediction errors, especially in rapidly changing weather conditions.

The CNN-LSTM model significantly improves, with the R^2 increasing to 0.97, the RMSE value dropping to 0.36 kW, and the MAPE decreasing to 5.1%. These results indicate that adding the CNN layer helps the model capture nonlinear and spatial patterns in environmental data, resulting in more accurate predictions.

Meanwhile, the GWO-LSTM model proved to be the most superior, with an R^2 value of 0.98, an RMSE of only 0.31 kW, and a MAPE as low as 4.3%. The very high R^2 value confirms that the model can explain almost all the variations in actual power. At the same time, the low RMSE and MAPE indicate that the resulting predictions are accurate and consistent across a wide range of weather conditions.

Thus, the GWO-LSTM model statistically provides the best predictive performance compared to pure LSTM and CNN-LSTM. It confirms that hyperparameter optimization through the Grey Wolf Optimizer metaheuristic algorithm makes a real contribution to improving the accuracy and reliability of the predictive power of polycrystalline solar panels.

5. Conclusion

This study has developed and evaluated a model of electrical power prediction of polycrystalline solar panels based on the Long Short-Term Memory (LSTM) algorithm and its variants. The results showed that all LSTM models could follow the temporal pattern of actual power with a high level of accuracy, but there were significant performance differences between variants.

The pure LSTM model produces reasonably accurate predictions ($R^2 = 0.95$) but still faces difficulties in extreme weather conditions with relatively greater errors. The CNN-LSTM model shows an improvement in performance with the ability to extract spatial features from environmental data, so that the R^2 value increases to 0.97 and the MAPE decreases to 5.1%. Meanwhile, the GWO-LSTM model showed the best results, with R^2 reaching 0.98, RMSE only 0.31 kW, and MAPE 4.3%. It proves that integrating the Grey Wolf Optimizer metaheuristic algorithm can improve the reliability of the LSTM through hyperparameter optimization, resulting in more accurate and stable predictions in various weather conditions.

The study confirms that the use of optimization-based LSTM models is not only relevant for improving the predictability of polycrystalline PV electrical power but also has the potential to be applied in intelligent energy management systems to improve the efficiency of renewable energy-based power grids.

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