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Application of Optimization Algorithm to Machine Learning Model for Solar Panel Output Power Prediction: A Review

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Abstract *– Solar panels have become a popular source of renewable energy due to their sustainability and environmental friendliness. Accurate predictions of solar panel output are crucial for various applications, such as energy system optimization, power grid management, and economic planning. Many important factors pose challenges in predicting the output of solar panels, such as weather conditions that can change at any time, geographical factors, data quality, and the duration of data collection. Machine learning (ML) models show promising performance in this prediction; there are many types of machine learning models, some are single models and others are hybrid models. Optimization algorithms are used to optimize parameters and improve the prediction accuracy of machine learning models. This research reviews fifteen journals that have been filtered to obtain those discussing optimization algorithms in the predictive models of solar panel output power. This journal will examine the optimization algorithms used in machine learning models for predicting solar panel output power, discussing various types of optimization algorithms, their application in machine learning models, the prediction results from these models, the input data used, and the data collection locations that significantly influence the prediction outcomes. From the results of this research, it does not conclude which machine learning model is the best, due to the many factors that influence it. However, this research is expected to provide references on the application of machine learning models in predicting the output power of solar panels, thereby encouraging the use of renewable energy sources.*

Keywords: *Optimization Algorithm, Machine Learning, Power Output Prediction, Photovoltaic*

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Abstrak *– Panel surya telah menjadi sumber energi terbarukan yang populer karena keberlanjutan dan ramah lingkungannya. Prediksi daya keluaran panel surya yang akurat sangat penting untuk berbagai penerapani, seperti optimasi sistem energi, manajemen jaringan listrik, dan perencanaan pada ranah ekonomi. Banyak faktor penting yang menjadi tantangan dalam memprediksi daya keluarna panel surya, contohnya seperti faktor cuaca yang dapat berubah kapan saja, faktor wilayah, kualitas dataset, dan durasi pengambilan data. Model machine learning (ML) menunjukkan kinerja yang menjanjikan dalam prediksi ini, model machine learning sangat banyak jenisnya, ada yang model tunggan dan ada juga model hybrid. Algoritma optimasi digunakan untuk mengoptimalkan parameter dan meningkatkan akurasi prediksi dari model machine learning. Penelitian ini mengulas lima belas jurnal yang telah dilakukan filter untuk mendapatkan jurnal yang membahas tentang algoritma optimasi pada model prediksi daya keluaran panel surya. Jurnal ini akan mengulas algoritma optimasi model machine learning yang digunakan untuk prediksi daya keluaran panel surya, membahas berbagai jenis algoritma optimasi, penerapannya pada model machine learning, dan hasil prediksi dari model prediksi, dan juga data input yang digunakan, serta lokasi pengambilan data yang cukup berpengaruh dalam hasil prediksi. Dari hasil penelitian ini, tidak menyimpulkan model machine learning mana yang terbaik, dikarenakan sangat banyak faktor yang mempengaruhinya. Namun dari penelitian ini diharapkan mendapatkan referensi tentang penerapan model machine learning dalam memprediksi daya keluaran panel surya, sehingga mendorong dalam penggunaan sumber energi terbarukan.*

Kata Kunci*: Algoritma Optimasi, Machine Learning, Prediksi Daya Keluaran, Panel Surya*

I. INTRODUCTION

The utilization of the sun as a source of electrical energy is called Solar Power Plant (PLTS), but solar panel or *photovoltaic* (PV) technology used as the main device of Solar Power Plant has a weakness, which is very dependent on uncertain weather conditions [1]. The impact is that the production of electrical power generated by PV is also erratic, because the production of PV electrical power is the result of the conversion of solar energy [2]. Because of its intermittent nature [3], making solar energy difficult to do planning and management of electric power energy for the allocation of consumer use [4]. PV power output prediction is an appropriate method to be used as a problem-solving tool in planning and management. The level of accuracy is a requirement in the prediction model, which can improve system reliability [5].

Artificial intelligence techniques have a major role in the development of technology, because the system is able to learn from experience, adapt to evolving input, and perform human-like tasks [6]. Various models were created using artificial intelligence techniques, to solve more specific problems based on their expertise [7]. Artificial neural networks are a widely used artificial intelligence method, because they are able to learn complex problems. Artificial neural networks are widely used in prediction cases, because of their ability to process historical data to work on prediction cases. Historical data is used in prediction to form a pattern, which then produces a predicted value [8]. Artificial neural networks have subfields, one of which is machine learning which is used for modeling large and complex neural networks, and can make accurate decisions based on large data sets [9].

Machine learning is proven to be a powerful time series based prediction tool [10]. The complexity of the data set due to the large number of time series and the intermittent nature of solar panel output power, coock applied optimization algorithms to get the most optimal results. Optimization algorithms play a role in solving complex problems, for example, prediction cases with high complexity [11]. Various studies show that optimization algorithms can improve the performance of deep learning models. The purpose of this study is to review and analyze the characteristics of optimization algorithms applied to machine learning models for predicting solar panel output power.

II. RESEARCH METHODE

This journal review is compiled based on journals published by reputable publishers from 2019 to 2024. The search engine used is Google Schoolar using the keywords "algorithm optimization", "machine learning", "photovoltaic forecasting".

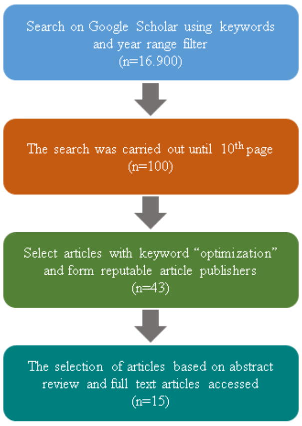

Fig 1. Article search flow for reviews

Figure 1 shows the flow of finding journals for review. An overall search with keyword filters and year range, the Google Scholar search engine presented 16,900 journals. Each page presents 10 journals, meaning there are a total of 1,690 pages, so the search is limited to 10 pages, with 100 journals presented. To sort the journals, the keyword optimization was searched from the pieces of journals displayed by Google Scholar, and 43 journals were obtained. From the relevant journals, a brief review was carried out based on the abstract and the text could be accessed in full to read the entire content of the journal, 15 journals were obtained that were suitable for review. The content of the journal that is the main highlight is in the section on how the optimization algorithm is applied in the machine learning model and the results of the application of the optimization algorithm on the quality of solar panel output power prediction.

III. RESULT AND DISCUSSION

From the collected articles, a review was conducted on the application of optimization algorithms in machine learning models used for predicting the output power of solar panels. The review journal [12] discusses the prediction of solar panel output power in Nordic regions and does not delve deeply into the application of optimization algorithms in machine learning, only mentioning the Improved Ant Colony Optimization (I-ACO) algorithm. The review journal to be presented focuses on the application of several types of optimization algorithms in machine learning models for predicting solar panel output power across different countries, where weather conditions can vary significantly in each region.

In the journal of research results presented in the journal [13], discusses the prediction of solar panel output power using the Recurrent Neural Networks (RNN) model based on the Bayesian Regularization Algorithm (BRA). The Bayesian Regression Algorithm applied to the RNN model to learn non-linear patterns in historical data, proved to be able to improve performance, with a 4-4-1 network architecture and a learning rate of 0.01. The predicted solar panel output power from this method has an accurate value with a Mean Absolute Percentage Error (MAPE) of 1.0227%.

Comparison of optimization algorithm analysis on the application of the Least Square Support Vector Machine (LSSVM) model found in the journal [14], presents a comparative analysis between Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO). From the results of the study, GWO-LSSVM has better performance in terms of optimizing the accuracy of the LSSVM model for solar radiation prediction, with a MAPE value of 7.3167%, while PSO-LSSVM is 7.3176%. GWO is inspired by the leadership hierarchy and hunting mechanism of the gray wolf. There are also LSSVMs that apply the Whale Optimization Algorithm (WOA), such as in the research of [15], WOA is proven to be able to improve LSSVM parameters in calculation speed and accuracy. The RMSE value obtained is quite low at 2.55% compared to the comparison models, namely PSO-LSSVM (3.00%), LSSVM (5.60%), LSTM (6.03%).

GWO optimization algorithm can also be combined with Differential Evolution (DE) optimization algorithm or can be called hybrid [16]. In the journal, using a combination of Principal Component Analysis (PCA) and K-Means Clustering, which is optimized using a combination of GWO and DE optimization algorithms, it is carried out into a hybrid optimization algorithm which is given the initials Hybrid Grey Wolf Optimization (HGWO). HGWO is applied to the Random Forest (RF) model to improve the fitting ability against noise data, and increase stability and accuracy. The PCA-Kmeans-HGWO-RF model, has a low prediction error value, but not too significant with the comparison model HGWO-RF, with MAE 4.76 and 4.94. However, this means that the PCA-Kmeans-HGWO-RF model is still superior and has better prediction accuracy than the comparison model.

Prediction of solar panel output power with the Support Vector Machine (SVM) model which is improved by the accuracy of prediction using Ant Colony Algorithm (ACO) is presented in the journal l [17]. ACO can increase the regression coefficient (R2) by 6.8%, but the smoothing process is not suitable for preprocessing models with large data sets and is not good at predicting at night and during peak load conditions. To overcome this, an improvement to the algorithm, namely Improved ACO (I-ACO), was applied. I-ACO significantly improved model accuracy with a regression coefficient (R2) of 0.997% and effectiveness in prediction at night and during peak load conditions.

SVM also has good results when optimized using Moth Flame Optimization (MFO) to predict solar panel output power [18]. The study proposed improvisation on MFO, because MFO has the disadvantage of being vulnerable to being trapped at the local optimum value and limited search capability. Therefore, a nonlinear inertial weighing strategy and a cauchy mutation method were applied. Improvised MFO (IMFO) applied to SVM, proved to improve prediction accuracy results compared to MFO-SVM, PSO-SVM, and BP-ANN models. 2The IMFO-SVM model is able to reduce the RMSE and MAPE values, and make the R value close to the optimal value.

Whereas in research [19], which discusses the SVM model with the application of the Improved Whale Optimization Algorithm (IMWOA) to optimize the prediction results of solar panels. From the results presented in the study, it shows that IMWOA in the application of SVM has a better prediction value compared to other optimization algorithms that are also applied to SVM, namely Ant Lion Optimization (ALO), Moth-Flame Optimizer (MFO), Multi-Verse Optimizer (MVO), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA).

Optimization algorithms are also well used in hybrid machine learning and deep learning approaches such as in the journal [20], Whale Optimization Algorithm (WOA) is applied to a combination of Variational Mode Decomposition (VMD) and Long Short Term Memory (LSTM) models to obtain optimal solar panel output power prediction results. VMD is used to decompose the solar panel power time series into more stable components, while LSTM is built for each decomposed component and the final prediction result, which is obtained through reconstruction and superposition of the model predictions. WOA plays a role in optimizing the parameters of VMD and LSTM so as to improve the prediction accuracy. The WOA-VMD-LSTM model is shown to be far superior to the single models WOA-VMD, WOA-LSTM, and LSTM.

A hybrid approach applied to optimization algorithms is also presented in the journal [21]. In the journal, designing a global solar radiation prediction model using a hybrid approach of Convolutional-Neural-Network (CNN), Long-Short-Term-Memory Neural Network (LSTM), and Multi Layer Perceptron (MLP) optimized using Slime Mold Algorithm (SMA). The Slime Mold algorithm is used to select optimal features, extract important features from the input data, and select the most relevant and significant variables to be included in the prediction model. The CNN-LSTM-MLP model, optimized using the Slime Mold Algorithm, showed improved performance in global solar radiation prediction accuracy by 10% compared to the CNN-LSTM, Deep Neural Network (DNN), Artificial Neural Network (ANN), RadomForest, Self Adaptive Differential Evolutionary Extreme Learning-Machines (SADE-ELM) models.

There are also individual CNN models that apply the Salp Swarm Algorithm (SSA) as an optimization algorithm such as in research [22]. The SSA-CNN method is able to simplify input variables and training datasets for accurate forecast results, and also produces customized CNN models with a short trial time. SSA-CNN has a low error value compared to its comparison models such as LSTM-SSA, SVM-SSA, CNN, LSTM, SVM.

In the research presented in the journal [23], the optimization algorithm used is Wavelet Genetic Algorithm (Wavelet-GA). Wavelet-GA is applied to the LSTM-DNN model to optimize window and unit sizes, so that the model is able to learn more complex long-term patterns and increase the amount of past data considered by each unit.

Wavelet-GA was shown to optimize parameters and improve prediction accuracy, compared to its comparison prediction models, such as Persistent (naive), State Vector Regression (SVR), and GA-LSTM-DNN.

Hyperparameters in artificial intelligence models are an important factor, because they are used in determining the structure and function of the model, for example determining the number of neurons in an artificial neural network, the speed of the model in learning data, batch size, activation function used by neurons to process input. Optuna library is a hyperparameter optimization tool available in Python [24]. Although it is not a single optimization algorithm, but an open-source Python framework, the Optuna Library has the ability to make the Deep Neural Network (DNN) model superior in prediction accuracy compared to its comparison models, such as RNN, LSTM, GRU.

Optimization algorithms that aim to adjust hyperparameters to become more optimal are also presented in research [25], who applied a deep stacked ensembles (DSE) approach that combines ANN and LSTM models as the base model with Extreme Gradient Boosting (XGB) as the optimization algorithm. 2 The DSE-XGB model showed good consistency and stability, was not affected by weather variations, and was shown to increase the R-value by 10%-12% compared to the comparison model.

In research [26] discusses the application of the Multiobjective Genetic Algorithm (MOGA) optimization algorithm applied to several machine learning models, to obtain Concentrated Photovoltaic Thermoelectric (CPV-TE) prediction results. MOGA can generate many system designs that meet the optimization criteria, by creating a set of solutions, evaluating the solutions, and generating new and better solutions through iteration. From the solutions generated by MOGA, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is applied, to get the best solution. The combination of MOGA and TOPSIS optimization algorithms becomes complementary to improve the CPV-TE system. Of the several machine learning models applied by MOGA-TOPSIS, Gaussian Process Regression (GPR) is the model that has a high accuracy value, with RMSE and MAE error values of $2.64\times10^{-1}0$ and 0.085×10^{-10}.

Optimization algorithms whose performance is further improved using a technique, there is also research in [27]. In that study, predicting the output power of solar panels using the Deep Extreme Learning Machine (DELM) model, the model was optimized using Enhanced Colliding Bodies Optimization (ECBO) to find the optimal parameters in the prediction model that match the characteristics of the data set. Variational Mode Decomposition (VMD) is also applied to extract data set patterns relevant to the prediction, so that the prediction model can better learn these patterns. The combination of ECBO-VMD, successfully improves the prediction accuracy of the DELM model compared to the comparison model.

A. Machine Learning Model

Machine learning is a part of artificial intelligence that is used to solve problems with a high level of complexity. Based on the literature that has been reviewed, from the various types of machine learning models, there are several machine learning models that have been researched, including RNN, LSTM, CNN, DNN, DELM, LSSVM, SVM, RF, GPR, Hybrid VMD-LSTM, Hybrid CNN-LSTM-MLP, Hybrid LSTM-DNN, Hybrid ANN-LSTM.

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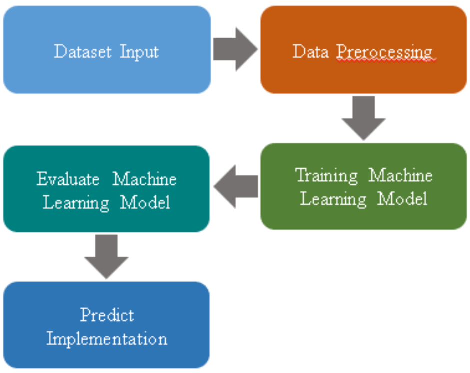

Fig. 2 The flow of machine learning model for forecasting

Figure 2 shows the general flow that is done to predict by applying the intelligence model. The Input Dataset is a collection of data that will later become the material processed by the model, the data can be in the form of weather information, temperature, humidity, solar radiation intensity, time, season, and so on that can affect solar panel power production. Data preprocessing stage, is an important initial stage to ensure the data is ready to be processed by machine learning models, such as cleaning data from missing values, detecting outliers, scaling data, parsing time series, and so on [12]. After the data is processed, the dataset is then divided into two groups (training data and testing data), in some studies the training data stage uses 70% to 80% of the dataset. From the training results, testing is carried out using 20% to 30% of the dataset, to evaluate the level of accuracy using various metrics, such as RMSE, MAE, MSE, R2 , and so on, and also comparisons are made with other machine learning models as proof that the selected model is the most appropriate prediction model applied to the conditions or cases that occur. If the results are satisfactory, the prediction model can be applied to predict future values to meet the needs.

B. Optimization Algorithm

Optimization algorithms aim to improve or maximize the potential of artificial intelligence models. Optimization algorithms that can be applied to artificial intelligence models, for now metaheuristic optimization algorithms are very popular, because they can provide high accuracy in solving problems with a wide range, and faster processing[28]. However, optimization algorithms other than metaheuristic can also be applied well as long as they match the prediction model. Optimization algorithms have differences in the placement of stages in the prediction model, in the literature reviewed there are those that use prediction algorithms at the data preprocessing stage, the stage of determining hyperparameters, and the stage of determining the optimal model weights. Optimization algorithms can be placed at any desired stage depending on the problem to be solved, but with the same goal of maximizing or increasing the potential of the prediction model.

C. Application of Optimization Algorithm ti Prediction Model

The application of optimization algorithms in prediction models is not a must, but optimization algorithms will be very useful when wanting to improve the results of prediction models. Optimization algorithms can be used to optimize parameters in neural networks, such as weights, network architecture, learning rules, neurons, activation functions, and biases [28]. Improving the performance of parameter handling to get the best pattern in solving problems with a high level of accuracy and quickly, can be done by optimization algorithms. The application of optimization algorithms based on the reviewed literature will be displayed in a metric table. The metric table aims to compare the prediction results of machine learning models applied by optimization algorithms.

TABLE 1
COMPARISON OF PREDICTION ERROR VALUES

Lit.	Machine Learning	Algorithm	RMSE	MAE	MAPE	R^2	Inputs	Duration Collected Data	Location
[13]	RNN	BRA	-	-	2.2784	-	Solar irradiance, solar panel temperature, ambient temperature, humidity, wind speed	Hourly 1 – 15 June 2019	Tangerang, Indonesia
[14]	LSSVM	GWO	-	-	7.3167	-	Air temperature, relative humidity, wind speed, time	Hourly During the summer 2017	Malaysia
[15]	LSSVM	WOA	2.55	-	-	-	Numerical weather prediction (NWP), SCADA data.	15 minutes 1 January 2016 – 31 December 2016	Southern Provinces of China
[16]	PCA-KMeans	GWO-DE	8.88	4.76	-	-	Using data from the 2014 Global Energy Forecasting Competition (GEFCom2014).	Hourly 1 April 2012 – 29 June 2012	Australia
[17]	SVM	I-ACO	-	-	-	0.997	Temperature, relative humidity, global horizontal radiation, diffuse horizontal radiation, wind direction, and sampling time.	5 minutes Spans all of 2018 and the first 11 months of 2019	Desert Knowledge Solar Centre, Australia
[18]	SVM	I-MFO	Sunny 3.33 Rainy 5.22		Sunny 2.8559 Rainy 6.9274	Sunny 0.9962 Rainy 0.9908	light intensity, wind speed, atmospheric temperature, and relative humidity	30 minutes 8 AM to 6 PM Sunny: January 2016 Rainy: March 2016	Desert Knowledge Solar Centre, Australia
[19]	SVM	I-WOA	Sunny 0.263 Cloudy 0.507	Sunny 0.212 Cloudy 0.331	-	Sunny 0.995 Cloudy 0.979	Light intensity, Ambient temperature, relative humidity	6 Month	Tianjin, China

[20]	VMD-LSTM	WOA	19.745	15.247	4.45	0.997	Temperature, relative humidity, and solar radiation.	1 hour 7 AM to 7 PM 1 January 2018 – 31 December 2018	1.8 MW Solar System, Yulara, Australia
[21]	CNN-LSTM-MLP	SMA	11.66	10.71	-	-	Meteorological data sourced from Global Climate Models (GCM) and the Scientific Information for Landowners (SILO) database	Daily 1 January 1950 – 1 January 2006	Queensland, Australia
[22]	CNN	SSA	-	-	Cloudy 12.25 Sunny 5.5	-	PV power output, average temperature, relative humidity, clear-sky radiation, wind speed, and timestamps.	Hourly January – December 2017	South of Taiwan
[23]	LSTM-DNN	Wavelet-GA	0.074	0.037	-	0.922	PV power output from National Renewable Energy Laboratory (NREL), temperature and relative humidity.	30 minutes 1 January – 31 December 2006	Floridina, United States
[24]	DNN	Library Optuna	-	-	Build 1 14.67 Build 2 12.74	-	timestamps, weather, and historical load information.	Hourly 2 January 2009 - 31 December 2011	Richland, Washington, United States
[25]	ANN-LSTM	DSE-XGB	15 min 0.78 1 day 1.10	15 min 0.59 1 day 0.98	-	15 min 0.96 1 day 0.90	Global horizontal irradiance (GHI), temperature, and relative humidity.	November 2018 – January 2020	Bunnik, Netherlands
[26]	GPR	MOGA-TOPSIS	2.64×10^{-10}	0.085×10^{-10}	-	-	Solar irradiance and temperature.	-	-
[27]	DELM	ECBO-VMD	Sunny 0.4228 Cloudy 1.5771	Sunny 0.2796 Cloudy 1.1445	Sunny 0.2493 Cloudy 5.7187	Sunny 0.999 Cloudy 0.9953	Solar irradiance and PV power output.	Daily May 2018 – Juy 2019 Summer: 7:45 AM – 21:45 PM Winter: 10:00 AM – 19:00 PM	Xinjiang, China

The results of this research indicate that the application of optimization algorithms in machine learning models significantly improves the accuracy of solar panel output predictions. By using the appropriate optimization algorithms, machine learning models can be more effective in capturing complex patterns in historical data, including variables such as weather, temperature, humidity, and solar radiation intensity. With more accurate predictions, the reliability of energy planning and management can be improved, allowing energy system managers to allocate resources more efficiently, reduce waste, and enhance the integration of renewable energy into the power grid. For example, if a model can accurately predict when and how much energy will be generated by solar panels, grid operators can adjust energy supply from other sources to meet demand. Among all types of machine learning models and optimization algorithms, each has its own characteristics, and it cannot be determined which model is the best, as many factors influence this, including region, weather, climate, and the duration of data collection. The results of this research provide a reference on how various types of optimization algorithms can be applied in the context of predicting the output power of solar panels. This opens up opportunities for further research in developing and testing new algorithms that may be more efficient or better suited for specific conditions. The research results can provide references for the development of renewable and efficient energy systems in the future. By optimizing the models and algorithms used, it is hoped that a higher level of accuracy can be achieved, which in turn can enhance the broader use of renewable energy.

IV. CONCLUSION

Based on the reviewed journal, it can be concluded that optimization algorithms play a significant role in improving the quality of machine learning models. Their role in selecting the most optimal parameters is crucial for achieving good predictions of solar panel output. From the comparison results, it cannot be used as an absolute parameter to determine which optimization algorithm or machine learning model is the best, as there are many other factors that influence the prediction results, such as weather conditions or seasons at the research location, the quality of the input data set, the duration of data collection, the region, and so on. The future research agenda includes the development of more efficient algorithms, large-scale implementation, and integration with other techniques such as transfer learning and data augmentation. With the application of appropriate optimization algorithms, the prediction of solar panel output can be significantly improved to support the sustainability of renewable energy.

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