ISSN:1533-9211
SEYBOLD Journal REPORT
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Prediction and estimation of PV and WP models based on measurement data

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Abstract
An integrated power grid can increase renewable energy sources (RES) in a decentralized power system accompanied by an increase in complex networks. RES integration is very important for estimation and prediction of future network stability and design. However, a single virtual power plant (VPP) is not suitable for large-scale renewable generation. In this paper, a hybrid (PV and WP) computational prediction and estimation model is proposed. Artificial neural networks (ANN) are used for computing. In addition to the predictions and estimates assessed based on the different investigated input features and uncertainties, also the relative mean absolute error (rMAE) on weather conditions such as cold and hot weather on the generating capacity. The results show that there is a difference between the two seasons, where in winter it reaches around 0.48% and in summer around 2.6% for PV power to installed capacity, while PV generation with an average value of around 1.68% and 4.8% for wind generators.

ISSN:1533-9211
SEYBOLD Journal REPORT
www.seybold-report.com

ISSN: 1533 - 9211

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KEYWORDS:

PV. WP, Integration, Artificial neural networks, generating capacity

Received: 05 Marcj 2024
Accepted: 22 March 2024
Published: 31 March 2024

TO CITE THIS ARTICLE:

Sukarwoto, C. I., Fauziah, N., & Suwarno. (2024). Prediction and estimation of PV and WP models based on measurement data. *Seybold Report Journal*, *19*(03), 280-297. DOI: 10.5110/77. 1134

1. Introduction

Renewable energy supplies (RES) provide part of the world's energy contribution (Gielen et al., 2019). Hybrid integration between photovoltaics and wind in RES continues to increase, followed by its development (Suwarno et al., 2023). RES target is 23% in 2025 and 31% in 2050, with a target to be achieved in 2025 of 255 MW for wind energy and solar energy of 0.87 GW or around 50MWp/year in Indonesia (David Firnandi Silalahi et al., 2021). Estimates suggest that around 45.3% of gross electricity consumption is supplied from renewable energy (Faisal Irsan Pasaribu et al., 2023). The balance between production and consumption of electrical energy becomes a model for forecasting output power between solar and wind plants to improve distribution at any time of the day (Dai et al., 2023), (Yang Li et al., 2023b). RES power production is highly dependent on weather conditions. Solar irradiation affects PV power output and wind speed has a significant impact on wind power generation. Therefore, predictions and forecasts for electricity generation from RES, especially PV and wind, are important for grid operators.

Electricity generation from a single RES power plant under different operating conditions and montage types is analyzed in (Yang Li et al., 2023b), Single devices are considered, but regional power output and predictions must be based on large-scale power generation across the region (J Jurasz et al., 2020).

Commissioning of regional renewable power supply systems occurs through non-homogeneous distribution of RES. Therefore, aggregated power output is essential for the development of regional grid planning and energy management of electricity generation and consumption as well as the stability of the power supply system (Yuan Zeng et al., 2019). However, the main challenge in estimating and forecasting regional electricity generation for RES systems is that not all RES systems are equipped with metering devices (Sulman Shahzad et al., 2023).

In addition, regional variability in weather conditions and power generation distribution should be quite large. In the context of power output prediction from RES, especially PV and wind, various prediction methods have been investigated (Kelachukwu J Iheanetu, 2022). In general, regional prediction of RES power output can be divided into two groups: physical methods and data-based methods (Joao Gari da Silva Fonseca Junior and Takashi Oozeki, 2014).

Physical methods describe the process of simulating energy conversion. Regional aggregate power can be calculated by adding up the power output of each generating location. The power output of PV and wind systems changes dynamically with its own performance characteristic curve (Marco Pierro et al., 2022). Power output can be predicted from the physical properties of the generating system combined with local weather conditions. However, the virtual power generation system (VPP)-based physical model method is not feasible for large-scale distributed RES power supply systems. The reason is, there are no complete technical details about all individual devices, such as orientation or tilt angles for solar modules, or characteristic curves for each PV and wind power generation system (M A A Mamun et al., 2022), (Touileb & Abbou, 2023).

Data-driven models based on artificial intelligence (AI) or probabilistic approaches can avoid detailed information from RES generators (Rogerio Adriano da Fonseca Santiago et al., 2024). In contrast, historical measured power data and meteorological data are essential for model training, validation, and testing. In addition, to increase the scale of regional power generation, representative power curves of rated reference power plants are used (Yang Li et al., 2023a). The unknown VPP power output is estimated. Spatial interpolation such as the inverse distance weighted interpolation method is applied to generate power generation for unknown locations that do not have measurement devices (Marco Pierro et al., 2022). Indeed, reference generators must be chosen carefully.

As mentioned above, several prediction methods have been used to improve regional PV/Wind power predictions or estimates (Marco Pierro et al., 2022). However, only a few studies have discussed the influence of input parameters on the performance of RES power estimation. PV/Wind power estimates are highly dependent on regional weather conditions. Therefore, in this paper we propose an approach to estimate regional solar and wind power generation with artificial neural networks (ANN) using real measured meteorological data, PV and Wind integration data. ANN is one of the most effective and widely implemented methods for solving various problems in power estimation (Olufemi A Omitaomu and Haoran Niu, 2021).

This novelty and research use different input features. The complex relationship between weather parameters and PV/wind power needs to be studied. In particular, focus on different categories of weather data input. Combinations of input features, such as solar radiation, air temperature and wind speed, will be trained separately to compare the results and accuracy of the proposed model. Additionally, different estimation methodologies are applied to project regional aggregate PV/wind power without single device measurements.

Next, the average value of weather data is adopted for feature reduction. Due to the smoothing effect, regional power generation predictions will be further investigated based on the average values of weather data. Longer weather data will provide more precise predictions or will be redundant information for the ANN model. This study allows a complete assessment of the prediction accuracy in different aspects, such as MAE, rMAE, MAPE and deviation distribution (Catra Indra Cahyadi et al., 2024), (Suwarno et al., 2023). A comprehensive sensitivity study on different input features and their seasonal estimation errors is presented in this study.

The remainder of this paper is organized as follows: Section 2 explains how the dataset was obtained and used. Section 3 focuses on regional power prediction with ANN model development and case studies with different input features. Pre-processing and post-processing of featuresinput and output targets are presented. The simulation procedures and results are presented in Section 4. Section 5 discusses the results and discussion of research results regarding the research proposal. onclusions are given in Section 6.

2. Literature review

2.1. Generator electricity

Case study in Indonesia as a case study with a hybrid power dataset (PV and WP) collected from distribution system operators, consisting of PV and wind from low voltage (LV), medium voltage (MV) to high voltage (HV) power supply systems. Power plants connected to extra-high voltage levels are not considered in this study. This dataset covers a one-year period in 2021 with a resolution of 15 minutes.

2.2.Kinstalled capacity

Renewable energy evaluation is based on the installed capacity of PV and WP (Wind Power) generators. RES data for the annual report consisting of data from all reported RES systems is part of the annual report (Even Fallan, 2013), which shows the development of PV and WP installed capacity as data until 2025 as in Figure 1.

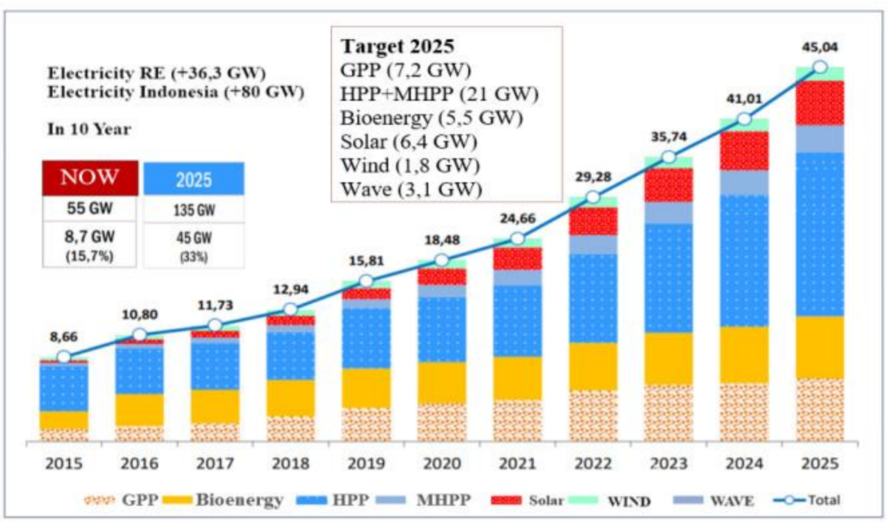

Figure 1. Renewable energy target in 2025

2.3. Weather data

Weather data is obtained from the Meteorology, Climatology and Geophysics Agency (MCGA) with various kinds of climate data in Indonesia shown in Figure 2 (Supari et al., 2016). Figure 3 shows 23 weather stationsin Indonesia which is observed by its ID number. While some weather stations provide observed weather measurements, some stations only have one parameter measurement available. For each observed weather parameter represents a distribution matrix and a data correlation matrix that includes normalized PV power (P_{pv}), normalized wind power (P_{wind}) and different meteorological parameters, solar irradiation (I_{solar}), air temperature (T_{air}), and speed. wind (V_{wind}) (Hossein Sangrody et al., 2017), (Ajith Gopi et al., 2021). The correlation coefficient between PV power and solar irradiation is about 0.98. Air temperature affects the temperature of PV panels, which in turn affects the conversion efficiency of solar cells (Taufal Hicayat, 2022). The main impact of wind speed on PV power generation is reflected in the heat dissipation conditions that influence ventilation and cooling effects for PV panels (Carlos Rossa, 2023). In addition, wind speed determines cloud movement which affects solar radiation and shadows on PV panels. The relationship between WP output and wind speed is usually more sophisticated and non-linear (Mamun et al., 2022). Wind power does not have a large linear correlation with air temperature and solar radiation, but indirectly affects wind speed, air density, and so on. These two weather parameters can be expanded as input features for wind power estimation.

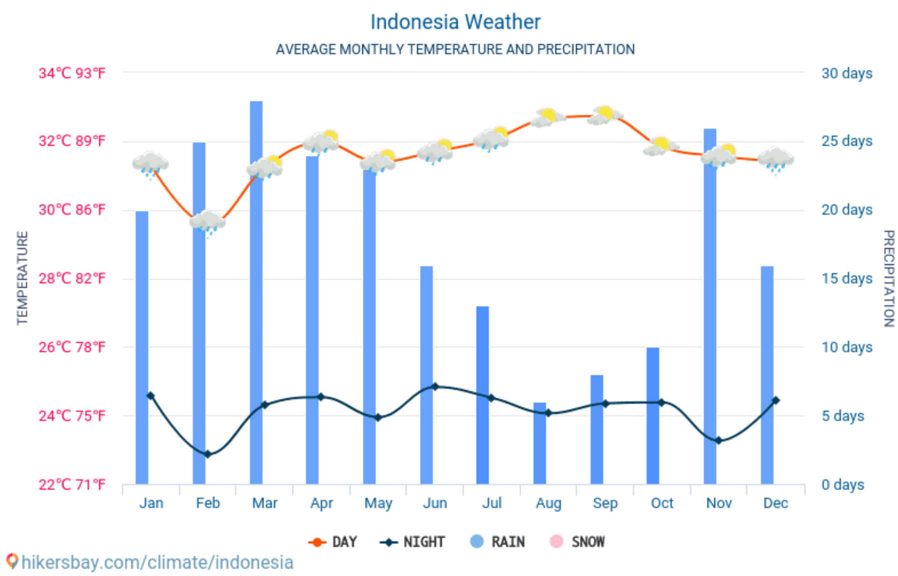

Figure 2. Weather climate and weather in Indonesia

ID	Station Name	No. of Missing Data	Location (Lat/Lon)	Location (Region)
960110	BANDA ACEH BLANG BI	1803	5.517° N, 95.417° E	Sumatra Island
960350	MEDAN POLONIA	1401	3.567° N, 98.683° E	Sumatra Island
960730	SIBOLGA PINANGSORI	1888	1.55° N, 98.883° E	Sumatra Island
961090	PEKAN BARU SIMPANGT	1783	0.467° N, 101.45° E	Sumatra Island
961710	RENGAT_JAPURA	1778	0.333° S, 102.317° E	Sumatra Island
967490	JAKARTA SOEKARNO-HA	1885	6.117° S, 106.65° E	Java Island
968050	CILACAP	1946	7.733° S, 109.017° E	Java Island
968390	SEMARANG AHMAD YANI	1900	6.983° S, 110.383° E	Java Island
969330	SURABAYA_PERAK_I	1957	7.217° S, 112.717° E	Java Island
969350	SURABAYA JUANDA	1338	7.367° S, 112.767° E	Java Island
969870	BANYUWANGI	1625	8.217° S, 114.383° E	Java Island
970140	MENADO SAM RATULAN	1944	1.533° S, 124.917° E	Sulawesi
970480	GORONTALO_JALALUDDI	1791	0.517° N, 123.067° E	Sulawesi
971800	UJUNG PANDANG HASAN	1556	5.067° S, 119.55° E	Sulawesi
972300	DENPASAR NGURAH RAI	1287	8.75° S, 115.167° E	Lesser Sunda Islands
972600	SUMBAWA BESAR BRANG	1912	8.433° S, 117.417° E	Lesser Sunda Islands
973400	WAINGAPU_MAU_HAU	1958	9.667° S, 120.333° E	Lesser Sunda Islands
965810	PONTIANAK SUPADIO	2092	0.15° S, 109.4° E	Kalimantan
966330	BALIKPAPAN SEPINGGA	2172	1.267° S, 116.9° E	Kalimantan
966450	PANGKALAN BUN ISKAN	2685	2.7° S, 111.7° E	Kalimantan
975600	BIAK_FRANS_KAISIEPO	3035	1.183° S, 136.117° E	Papua Region
977240	AMBON PATTIMURA	3016	3.7° S, 128.083° E	Maluku Islands
979000	SAUMLAKI OLILIT	2549	7.983° S, 131.3° E	Maluku Islands

Figure 3. List of 23 surface weather stations in Indonesia

3. Methodology

3.1. Prediction procedure

It is difficult and complicated to formulate different power generation mechanisms from different regions. In the context of this research, using the ANN model to predict RES power generation based on measured weather data at RES stations and power plants (Hai-Van Thi Mai et al., 2021). A number of regional allocations of PV and wind generators were identified based on postal code location and installation time (Marcus Eichhorn, Mattes Scheftelowitz et al., 2019).

3.2.Neural networksimitation

Generally, ANN is divided into three parts: one input layer, one output layer, one or more hidden layers (Sujin Pyo, Jaewook Lee, Mincheol Cha, Huisu Jang., 2017). The ANN architecture with one hidden layer is illustrated in Fig4. ANN estimates the relationship between an input feature x and an output target y by combining a large number of computing units called neurons (Carlos Rossa, 2023). The description of this relationship is reflected in the weight factor W and bias b (i.e. vector). The trainable parameters (weight W and bias b) are trained using backpropagation. The ANN parameters are adjusted and tuned based on the cost function (i.e. loss metric) obtained in the previous epoch (i.e. iteration) to minimize the error rate between the predicted target value and the actual target value and make the model more reliable.

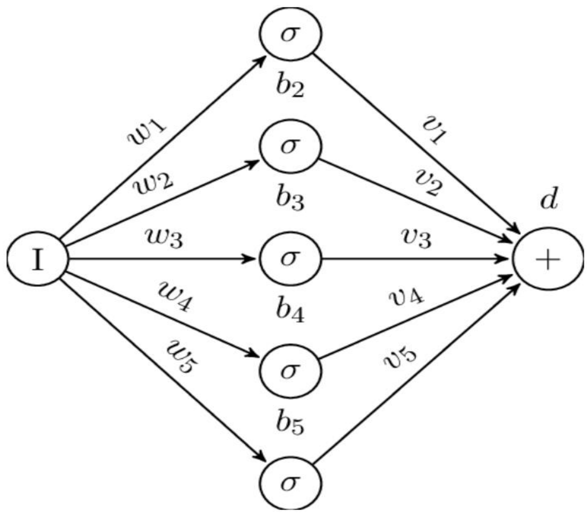

Figure 4. One-layer ANN architecture

The output of one process layer i can be described as follows:

$$\boldsymbol{y_i} = \mathrm{AF}(wi *xi + b\ )i \qquad (1)$$

where x_i, y_i are the input and output of layer *i* respectively. AF is an activation function. The purpose of using the activation function is to enable ANN deals with complex non-linear problems (Pathamuthu Suresh Kumar and Selvaraju Sivamani, 2021). The most widely used non-linear ANNs are *ReLU* and sigmoid functions.

3.3.*Support Vector Machines*

Support Vector Machine (SVM) is a supervised learning method used for classification and regression (Jair Cervantes et al., 2020). The main idea of SVM is to determine a function or hyper-plane (i.e. surface) from one or more feature vectors and try to minimize the error in training (deviation to the surface).

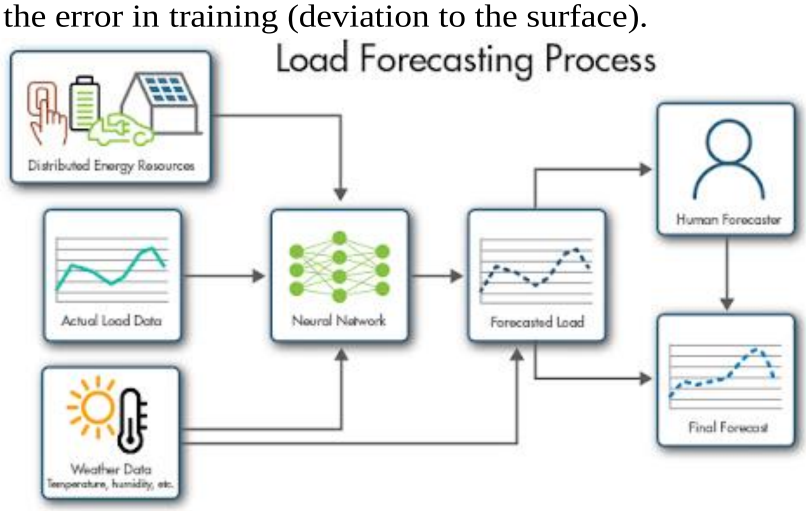

Figure. 5. Regional power prediction procedure

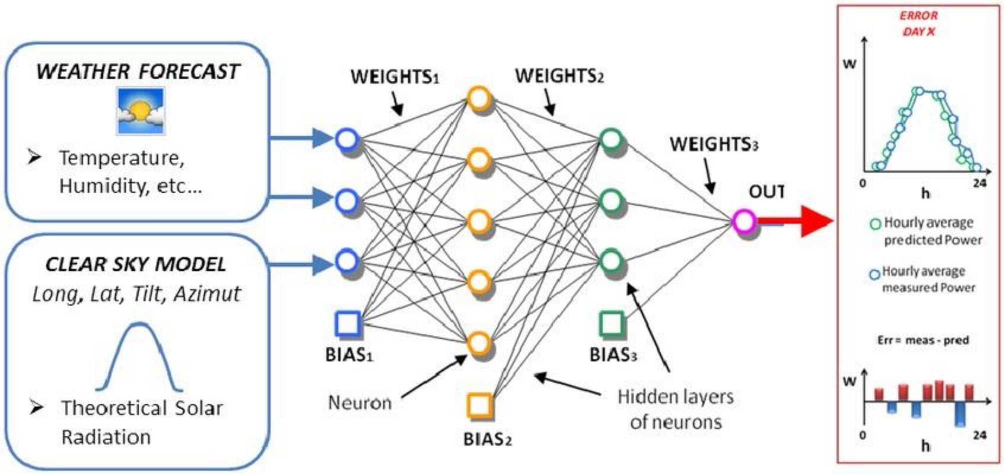

Figure. 6. ANN model architecture

In fact, most problems are non-linear, and the hyper-plane, which satisfies such conditions, does not exist at all. For the nonlinear case, the corresponding kernel function is imported into the SVM method, by mapping the data to a high-dimensional space to solve problems that are not linearly separable in the original space (Renato De Leone, 2022). In this study, the default kernel function of the Gaussian radial basis function is used for regression.

4. Multi-linear regression

Multiple linear regression (MLR) method to build a linear relationship between independent variables (input features) and response variables (output targets) (Sarat Kumar Allu et al., 2020). MLR performs model adjustmentslinear with coefficients to minimize the sum of squared residuals between the predicted value and the actually observed target value. The MLR model for time series data can be explained as follows:

$$y(t) = \beta_0 + \beta_1 * X_1(t) + \ldots \beta_k * X_k(t) + \in(t) \quad (2)$$

where $y(t)$ is the predicted value, $X_k(t)$ contributed input features, β_k is the slope coefficient of each input feature, β_0 is a constant and $\epsilon(t)$ is the residual error.

a. k-Neighbornearest

The *k*-nearest neighbors (*kNN*) method is applied to solve classification and regression tasks based on n-dimensional space representing n sample features (Elife Ozturk Kiyak et al., 2023). To predict the label of an unknown sample, the *kNN* algorithm finds a set of k closest examples based on distance calculations, such as Euclidean distance (Khalid Alkhatib et al., 2013). Examples with the same properties will be close to each other in n-dimensional space depending on the feature vector. The new instance will be assigned to the majority class of its closest instances. In this research, the *k* value is set as 3.

b. Decision tree

Decision trees are also a favorite technique in supervised learning. The principle of the decision tree method is to create a tree structure model like a flow diagram by learning simple decision rules inferred from sample features to model target values. This method can take the form of not being able to go any further. However, the complex and deep tree structures generated in this way can lead to overfitting. Therefore, the maximum tree depth was set at 5 in this study.

c. Arrangement ANN architecture

In this paper we use a simple ANN architecture, 3 hidden layers and each with 10 neuron units. The size of the input layer neurons depends on the number of corresponding input features, which can be found in the Model collection section. The parameter settings for the neural network are summarized as a reference. For time series data, a time consistent model is used for input features and output target values. All available *x* and *y* datasets are linked by time and divided into two parts, namely training and validation.

d. Pre-processing and post-processing

First check the possibility and availability of measured data from available stations. Outliers from the measured weather data will be filtered out and temporarily treated as NULL values. Next, for each station and 3 nearby valid stations will be found. Station locations can be exported from the station and nearest neighbor analysis performed in the software (David V Ogunkan et al., 2023). Due to the close spatial distance and similarity of situations, it is understandable that weather data are highly correlated. So NULL values can be filled in using the multiple linear regression method (Xinyue Wang et al., 2022).

The time resolution of the weather data and RES data is registered over 10 minutes and days, with the data resampled at 15 minute resolution to have the same time resolution as the power data. To obtain input features independently, one min-max scaler is used. Input parameters (features) are assessed in the range interval [0, 1], because different distributions and scales of input data may cause large weight values and poor training results. Scaled values in a small range are better for training neural network models. The transformation process for an input feature is given by:

$$X_{scaled}(t) = \frac{X(t) - X_{\min}}{X_{\max} - X_{\min}} \qquad 3$$

Normalized power P_{norn}^{PV} set as parameters, namely:

$$P_{notm}^{PV}(t) = \frac{X(t) - X_{\min}}{X_{\max} - X_{\min}} \qquad 4$$

Considered asi gathering rule if then, orasiprobabilitys conditional distribution according to the characteristics of the sample features. Similarly, wind power is converted into normalized power. The electricity generation time series is normalized based on installed capacity, to compare power output curves that are independent of the installed capacity of the scale of each distributed energy resource. Finally, the predicted power output will be transformed inversely with regional installed capacity into power values based on Equation (4).

e. ANN model on RSE

The correlation matrix for weather parameters has different impacts on RES power generation as shown in Figure 7. Prediction of weather strength is used as the case study selection here. As input, the input layer neurons recognize information on environmental differences.

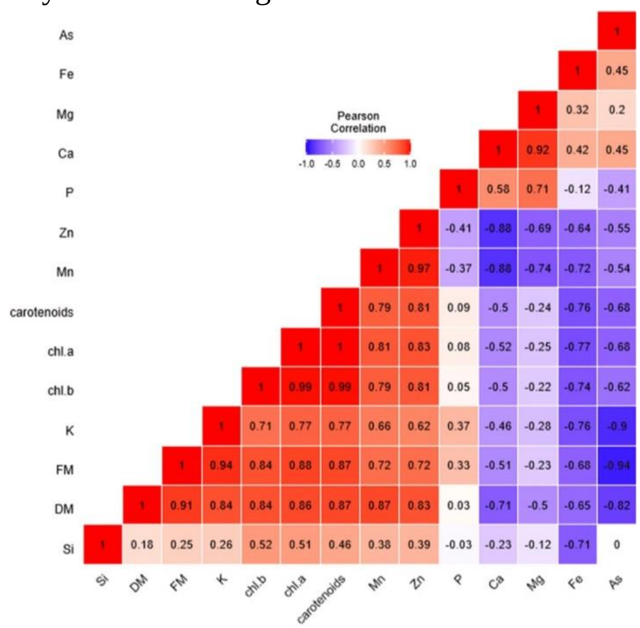

Figure 7. Correlation of weather parameters with RES

ANN modeling takes as input features as a category of weather data, while PV and WP prediction modeling, with solar irradiation and wind speed. To expand the input feature with two weather parameters in addition to other parameters. The design of the ANN model with the addition of other parameters aims to reduce the impact of one weather station's measurements on the overall power prediction to reduce computation on the average model.

d. Evaluation metrics

The *MAE* and *MAPE* analysis models are general predictive indicators. Comparison of prediction characteristics to calculate the normalized error *ε(t)*. However, the *rMAE* model used for installed capacity is also imported. The analysis model used is as follows:

$$\varepsilon(t) = \frac{P_{pred}(t) - P_{true}(t)}{P_{inst}(t)} \qquad 5$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_{pred}(t) - P_{true}(t)\right| \qquad 6$$

$$rMAE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_{pred}(t) - P_{true}(t)}{P_{inst}(t)}\right| \qquad 7$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_{pred}(t) - P_{true}(t)}{P_{inst}(t)}\right| \qquad 8$$

where N is the sample size of the prediction data set; P_{pred}(t) is the predicted power output; P_{true}(t) is the measured value of electricity generation; P_{inst}(t) is the regional installed capacity of the observed RES.

5. Results and Discussion

In practice, we divide valid historical data into two data sets, 70% as training data set and 30% as validation data set. ANN simulations, first, investigate various input categories for power prediction and run simulations on different random data sets for each training period with parameters and pre-processing set in such a way to get the expected results.

The predicted and actual measured PV power profiles are compared for two selected periods in the study, as shown in Figure 8 below:

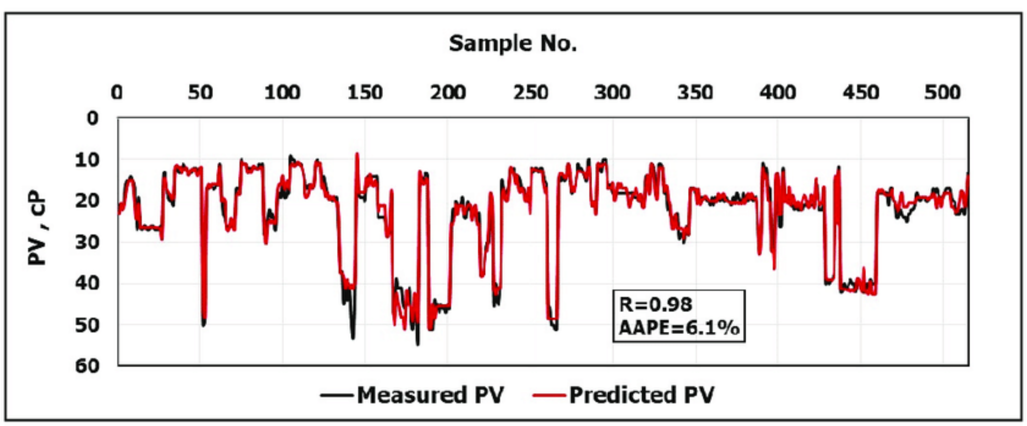

Figure 8. Comparison of measured and predicted data

ANN model with average category data to track changes in PV power generation in different weather as shown in Figure 9. The results of ANN modeling with different input features work very well in both windy and calm periods.

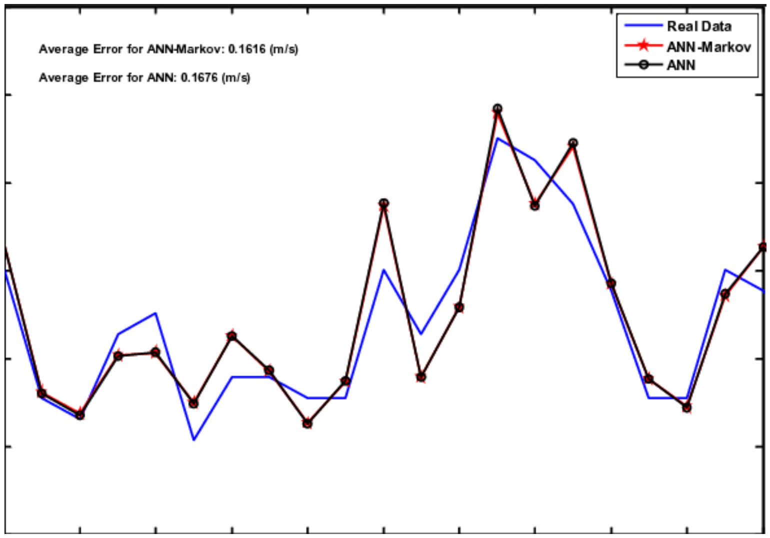

Figure 9. ANN models for different weather

The trained test model is a validated data set, and the power prediction error results with different input features for the training and validation data sets.

Based on the analysis with *MAE* and *rMAE* for the training and validation datasets the PV and wind predictions are almost close, which means each model was trained very well and no over-fitting occurred. The minimum *rMAE* of the PV model trained can reach 1.47% compared to the installed capacity, while the WP model with ANN using measured weather data as input has the best performance with an *rMAE* of 3.474%. Using all measured weather data with the ANN model with input features works better than other models. Improved input features for better predictions and providing more information on weather data conditions can be recognized by neurons in the ANN model. Extended weather parameters can improve prediction performance. However, reducing the input data to an average value will be in accordance with the input features. The model trained with input with two input features produces a smaller *rMAE* compared to the others.

The ANN PV model with input air temperature and average solar irradiance has better performance than models that only use solar radiation as input data, both in the form of raw measured data and average values. After the initial analysis above, the distribution of prediction deviations over the year-long period was also calculated. The cumulative distribution of normalized errors is plotted in Figure 10, which shows that increasing input features with different categories affects the global prediction performance.

Almost all (>95%) predicted samples are within ±10% tolerance. This illustrates that the ANN model can be well accepted for predictions and estimates for PV and WP in the future, while weather differences will influence PV, because there is a larger deviation for the *rMAE* analysis, whereas for the WP prediction model it is more stable throughout year for each input. The results of a combination of several weather parameters will provide better PV predictions and WP predictions in different seasons.

Several researchers have carried out support vector machine (*SVM*) and multi-linear regression (*MLR*), k-earest neighbor (*kNN*) and decision tree regression (*DTR*) machine learning methods. This method uses the same training data set as the ANN model to match the relationship between input features and output targets. The proposed ANN model for the best WP prediction and VP prediction with weather change input features.

6. Conclusion

This paper provides an overview of the challenges of estimating and predicting PV and WP based on real measured data. As an input feature, weather data that is consistent over time is used. As the development of installed capacity is observed over a certain period, the normalized power output can be predicted independently of the installed capacity. Even though for a few days or months, the regional installed capacity is not much different, it is likely that it will be different for a long period of time, up to years.

Based on measured weather data and average weather data as model input features for estimating PV/WP power. A simple ANN architecture is adopted using different weather input features. The ANN model can extract information from parameters related to weather changes. The research results show that with increasing input features the ANN model works better than just one highly related category of weather data. Analysis with *rMAE* can reach approximately 1.45% and 3.45% for PV power and WP prediction, respectively, while for *rMAE* sensitivity, the ANN model provides stable WP prediction accuracy throughout the year for different seasons. Higher estimation accuracy for PV power can be obtained in winter. ANN modeling provides the best prediction performance with measurement data as input features with reduced mean values. Changes in strength and trend in different weather conditions contribute to PV and WP prediction. As future research it is possible that models with reduced mean value data as input features may have wide use for the development of PV and WP models.

COMPETING INTERESTS

The authors have no competing interest to declare.

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HOW TO CITE THIS ARTICLE:

Sukarwoto, C. I., Fauziah, N., & Suwarno. (2024). Prediction and estimation of PV and WP models based on measurement data. *Seybold Report Journal, 19*(03), 280-297. DOI: 10.5110/77. 1134

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