International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 5, October 2024, pp. 5970~5983
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i5.pp5970-5983

Enhanced accuracy estimation model energy import in on-grid rooftop solar photovoltaic

Alfin Sahrin, Imam Abadi, Ali Musyafa
Department of Engineering Physics, Faculty of Industrial Technology and System Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

Article Info

Article history:

Received Mar 21, 2024
Revised Jul 9, 2024
Accepted Jul 17, 2024

Keywords:

Energy import
Grid search cross-validation
Estimation model
Machine learning
On-grid rooftop solar photovoltaic

ABSTRACT

Installing rooftop solar photovoltaic (PV) with an on-grid system benefits consumers because it can reduce imports of electrical energy from the grid. This study aims to model the estimation of energy imports generated from on-grid rooftop solar PV systems. This estimation model was carried out in 20 provincial capitals in Indonesia. The parameters used are weather conditions, orientation angle, and energy generated from the on-grid rooftop solar PV system. The value of imported energy is divided into three combinations based on the azimuth angle direction, which describes the type and shape of the roof of the building (one-direction, two-directions, and three-directions). Modeling was done using machine learning with neural network (NN), linear regression, and support vector machine. A comparison of the machine learning algorithm results is NN produces the smallest root mean square error (RMSE) value of the three. Model enhancement uses a grid search cross-validation (GSCV) to become the GSCV-NN model. The RMSE results were enhanced from 53.184 to 44.389 in the one-direction combination, 145.562 to 141.286 in the two-direction combination, and 81.442 to 76.313 in the three-direction combination. The imported energy estimation model on the on-grid rooftop solar PV system with GSCV-NN produces a more optimal and accurate model.

Corresponding Author:

Ali Musyafa
Department of Engineering Physics, Faculty of Industrial Technology and System Engineering, Institut Teknologi Sepuluh Nopember
ITS Campus, Surabaya 60111, Indonesia
Email: musyafa@ep.its.ac.id

1. INTRODUCTION

The increasing adoption of on-grid rooftop solar photovoltaic (PV) technology requires understanding energy imports in planning renewable energy infrastructure that can meet future growth and sustainability demands. Solar PV production produced from residential areas and commercial buildings can meet peak load needs to minimize imports from the grid [1]. Solar PV installed with various types of roofs can reduce electricity imports by between 4 and 7% and limit peak electricity export to 125% [2]. The application of rooftop solar PV combined with combined heat and power generation can reduce imports of electrical energy and increase the use of electric vehicles [3]. Various system modes, such as batteries as energy storage from solar PV when energy production is at its peak, can reduce electrical power imports and export excess to the distribution grid [4], [5]. Studies conducted [6] show that Turkey heavily depends on energy imports, with increased rooftop solar PV installations lowering power imports and saving 90,298 kWh from a system that supplies 13.2% of annual electrical energy consumption in buildings.

Estimating imported energy in on-grid rooftop solar PV systems is highly dependent on solar irradiation, weather conditions, geographical location, tilt and azimuth angles, and building type. The size of energy delivery from buildings connected to rooftop solar PV with the grid is an essential consideration in determining renewable energy generation capacity [7]. Solar PV penetration in cities can reduce pollution and carbon emissions used as an energy source for vehicles and reduce dependence on the grid from 0.809 to [8]. On-grid rooftop solar PV also has advantages in energy storage if storage is switched to the grid with hourly net measurements with an increase of 3 to 5 percentage points [9]. Solar PV in buildings can be integrated with control and monitoring systems through internet of things (IoT) for energy supply and consumption. It is to monitor internal needs and external conditions of energy supply and demand needs from the grid [10].

Therefore, a deep understanding of energy import estimation models in on-grid rooftop solar PV systems is essential for more efficient and environmentally friendly sustainable energy planning. Deep learning solar PV installation estimation modeling that optimizes the training process using a non-dominant sorting genetic algorithm (NSGA) and customized dataset with functional data analysis (FDA) produces estimates with errors of 6% and 18% in synthesis data and 6% and 12% in actual data [11]. The multi strategy gradient-based algorithm (MAGBO) to solve the problem of multimodal and non-linear characteristics combined with a modified gradient search rule (MGSR) and novel refresh operator (NRO) results in high precision and reliability [12]. The opposite-based exponential distribution optimizer (OBEDO) algorithm uses the estimation of PV systems affecting current and energy. The algorithm performs better than others to identify solar PV parameters to improve performance [13]. ISSAEDO combines a sparrow search algorithm and exponential distribution optimization (EDO) to produce effectiveness and speed in estimating PV models such as single-diode and double-diode models [14]. Rat swarm optimizer algorithm to solve complex mathematical model problems and non-linear problems. The algorithm compared to particle swarm optimization, ant lion optimizer, salp swarm algorithm, Harris Hawks optimization (HHO), and grasshopper optimization has resulted in fast and accurate PV cell estimation [15].

However, it is still difficult to find research that discusses estimating imported energy on-grid rooftop solar PV. Previous studies, such as those on different weather condition parameters, can affect the estimation results of solar PV systems with multi-criteria decisions combined with empirical formulas [16]. The estimation method to determine the potential area of rooftop solar PV can be installed using object-based image classification and digital surface models with geographical limitations [17]. Integrated 3D modeling for assessing solar potential on building roofs using light detection and ranging (LiDAR) can be used to estimate rooftop solar PV installations [18]. Turin combined the geographic information system (GIS) system with energy generation and consumption estimation models to produce energy power profiles [19]. The Werner deconvolution method, which improves the detection of geological structures from magnetic field data, has successfully determined the estimation of the depth position of geological objects [20]. In the city of Sardinia, the algorithm of calculating the shadow of the roof of the building and solar radiation in real time has resulted in a potential rooftop solar PV of 22 TWh [21]. Analyze the accuracy of the PV model to obtain optimal performance results of the maximum power point by reconstructing the characteristic curves on different PV panels [22].

Exploring machine learning algorithms more profoundly and the attributes' power can improve the accuracy of imported energy estimation models. The modeling energy consumption and differences between AH.264/AVC and VP8 encoders using linear regression in machine learning [23]. Applying machine learning with cross-group learning can make good prediction models between single-atom copper-based alloys with different alloying elements [24]. Support vector machine (SVM) and naïve Bayes algorithms for image processing, then continued using PVWatt, PVGIS, and ArcGIS, have generated solar PV potential of 21.1, 24.9, and 22.9 GWh/year [25]. Models of neural networks (NN), back propagation neural networks (BPNN), and convolution neural networks (CNN) are used to estimate solar radiation in areas with limited data. Limited meteorological and radiation data are then simulated with energy and diesel consumption so that this method can solve problems in areas with low radiation data [26]. Estimated PV production per hour using feedforward neural network (FFNN) using numerical weather data such as ambient temperature, relative humidity, and wind speed. The model resulted in an root mean square error (RMSE) of 6.4%, resulting in savings and increased self-consumed energy [27]. By comparing three random forest (RF) algorithms, gradient boost regression tree (GBRT) and AdaBoost were used for annual roof radiation estimation. The results of this random forest method provide a more accurate and faster estimation with an absolute mean error (MAE) of 22.83 kWh/m²/year [28]. Estimating energy potential generated from solar PV using high-definition map images and deep learning (DL) resulted in a power potential of 442.4 MW in rural China [29].

The grid search cross-validation (GSCV) process can significantly reduce the ability to produce models that perform better and improve the accuracy of imported energy estimation models. Some previous research, such as the application in determining the performance limits of RC seismic columns using machine learning methods, then optimized with grid search and cross-validation to determine hyperparameters, has resulted in excellent accuracy [30]. The application of predicting and identifying children and adolescents at risk of readmission to the hospital using GSCV method can significantly reduce the ability to produce models that perform better and improve the accuracy of imported energy estimation models. Some previous research, such as the application in determining the performance limits of RC seismic columns using machine learning methods, then optimized with grid search and cross-validation to determine hyperparameters, has resulted in excellent accuracy chine learning classification and regression tree (CART), RF, gradient boosting machine (GBM), dan extreme gradient boosting (XGBoost). 75% training data and 25% testing and applying cross-validation with five folds, then looking for hyperparameters using grid search techniques. The XGBoost algorithm has produced more accurate results than others [31]. In the health sector, to analyze gastroscopy images using the EfficientDet method, a grid search is used to optimize image resolution, and cross-validation with k=5 produces precise results [32] in the temperature test bench experiment to study the phenomenon of nucleate boiling using several machine learning methods and grid optimization search cross-validation in the training process. The support vector machine algorithm produces the best performance with R2 performance greater than 0.95 [33]. To predict the percentage of biodiesel yield using the CatBoost regressor method optimized using a search cross-validation grid to produce an effective and optimal biodiesel prediction model [34].

This study is critical because the energy imported estimation model on rooftop solar PV systems can help plan energy consumption efficiently by accurately estimating the amount of energy imported from the grid. In addition, limited studies discussing estimating energy imported are used as an indicator in planning and installing rooftop solar PV. The existence of an energy imported estimation model in the on-grid rooftop solar PV system can accelerate the implementation of rooftop solar PV technology that can reduce carbon emissions in urban areas. The purpose of this study is to model energy imported estimation using machine learning (ML) algorithms, namely neural network (NN), linear regression (LR), and support vector machine (SVM). The dataset was obtained from the simulation results on the rooftop solar PV on-grid system, and energy data that can meet the needs of electrical loads was obtained. The energy import generated from the system is divided based on the azimuth angular direction that describes the model and shape of the building's roof (one direction, two directions, and three directions). A comparison of the machine learning algorithm results shows NN produces the smallest RMSE value of the three. Then, model improvements are carried out using GSCV to obtain more accurate model results. By combining the GSCV process with NN (GSCV-NN), the model's results can enhance the RMSE results even more accurately.

Although energy import estimation modeling compares simple algorithms such as NN, LR, and SVM, adding the GSCV process can improve the highly accurate estimation model on the GSCV-NN combined. This study provides new insights into modeling energy imported estimates. Accurate modeling results can provide an overview of a compelling rooftop solar PV on-grid installation plan based on the amount of energy imported from the grid. Furthermore, the implementation between the simulation results of the energy import estimation model and the application of actual conditions is studied holistically.

2. MATERIAL AND METHOD

Comprehensively conduct a review of various things to complete this research. Initially, it will explain the collection of data used in this process. Before data processing, a pre-processing stage will be carried out to prepare the data to be modelled. Various machine learning models will be tried and compared, and optimizations will add accuracy to enhance their performance. The evaluation must be applied to measure model performance and thoroughly analyze the architecture. It discusses the resulting model for solving problems and evaluates the regression model to estimate energy imported in the on-grid rooftop solar PV system. Data accuracy is a measure of the estimation model relied on in data-based research.

In general, through three stages: data selection, evaluation, and comparison of the resulting regression model. The most accurate models are optimized to enhance performance in predicting test data. Figure 1 shows the modeling framework in this study, starting from data collection, pre-processing, modeling process, and model evaluation. The results will be discussed in the discussion. The stages of completing this study will be explained in more detail as follows.

2.1. Step 1: Data collection

Data is obtained from open sources and processed on PVsyst for an on-grid solar PV system analysis. This dataset has attributes: latitude (°), longitude (°), air pressure (kPa), temperature (°C), relative humidity (%), wind speed (m/s), precipitation (mm/day), total insulation (W/m²), tilt angle (°), azimuth angle (°), production energy in Kilowatt hour per year (kWh/year), array energy (kWh/year), and has labels: energy imports (kWh/year). Meteorological parameters are obtained from NASA Prediction of Worldwide Energy Resources. The dataset is obtained from each of the 20 provincial capitals in Indonesia, as shown in Figure 2.

This angle describes that the type and shape of the roof of a building can consist of one or more sides. The angular direction follows the eight cardinal directions: north (N), northeast (NE), east (E), southeast (SE), south (S), southwest (SW), west (W), and northwest (NW) as shown in Figure 3. The dataset is divided into three clusters based on the number of azimuth angles and the number of inverters: one-direction, two-directions, and three-directions. The number of dataset samples in the provincial capital is divided into three combinations, as shown in Table 1. Details of the location of each provincial capital is shown in Table 2.

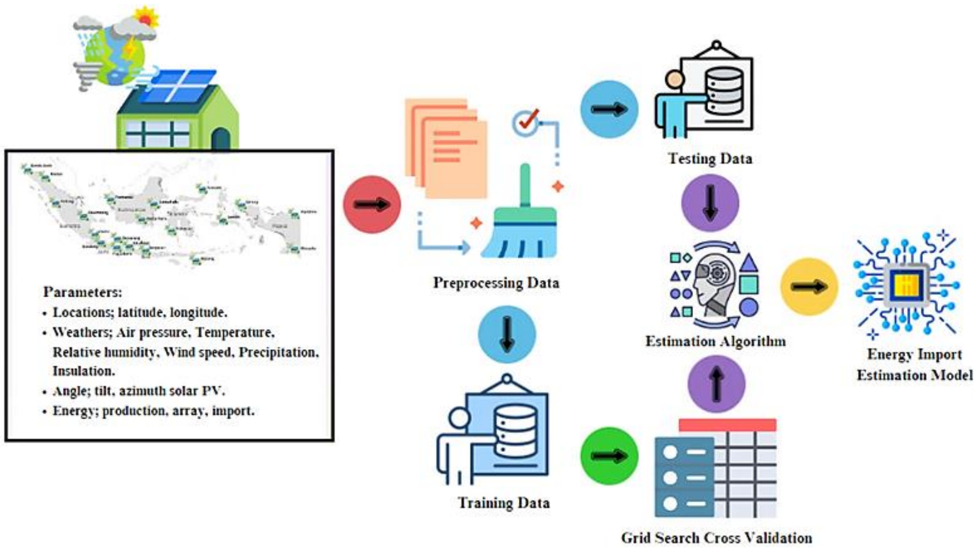

Figure 1. Modeling framework

Figure 2. Provincial capital

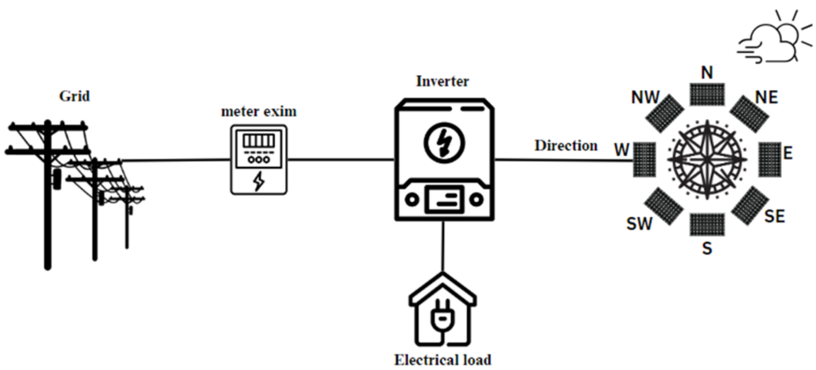

Figure 3. On-grid solar PV system

Table 1. Dataset samples

Combination	Amount of data
One-direction	2400
Two-directions	2800
Three-directions	5300

Table 2. Location of provincial capital position

No	Provincial capital	Latitude	Longitude	No	Provincial capital	Latitude	Longitude
1	Banda Aceh	5.552846°	95.319291°	11	Banjarbaru	-2.636591°	115.114494°
2	Medan	3.589665°	98.673826°	12	Samarinda	-0.501780°	117.139309°
3	Padang	-0.924759°	100.363256°	13	Pontianak	-0.022690°	109.344749°
4	Palembang	-2.988830°	104.756857°	14	Makassar	-5.134296°	119.412428°
5	Jakarta	-6.175394°	106.827183°	15	Manado	1.490058°	124.840871°
6	Bandung	-6.934469°	107.604954°	16	Kupang	-10.163221°	123.601776°
7	Semarang	-6.990399°	110.422910°	17	Ambon	-3.695943°	128.178785°
8	Yogyakarta	-7.977838°	110.367226°	18	Sorong	-0.863410°	131.254480°
9	Surabaya	-7.245972°	112.737827°	19	Jayapura	-2.538754°	140.703739°
10	Denpasar	-8.652497°	115.219117°	20	Merauke	-7.792519°	140.018355°

Figure 3 shows the system is an on-grid system without batteries. The system is built using PVsyst and optimally simulated to achieve operational viability. Energy imports are carried out through import-export meters (exim meters). The amount of energy sent from the rooftop solar PV on-grid system and received from the grid is recorded through this measuring instrument. The load is designed for household consumers and has been constant over the years. Load operates for seven days a week and 24 hours a day. Table 3 shows the appliance of consumed load. The number of PV modules used is 24, with a capacity of 250 Wp. Module voltage 26 V with polycrystalline type. Open circuit voltage (V_{oc}) 37.84 V and short circuit current (I_{sc}) 8.710 A. series and string splicing number of modules adjusted to azimuth direction. The capacity of the inverter used is adjusted in the azimuth direction. In each direction, one inverter is installed, and all inverters have a frequency of 50 Hz monophase with a grid voltage of 230 V.

Table 3. Load consumption

Nb	Appliance	Power	Unit	Daily use (hours)	Daily energy (Wh)
10	Lamps (LED or Fluo)	10	W/lamp	12	1200
2	TV/PC/Mobile	100	W/app	7	1400
7	Domestic appliances	150	W/app	24	25200
2	Fridge/Deep-freeze	0.4	kW/day	24	802
1	Dish and cloth washer	300	W aver.	2	600
3	Air conditioner	250	W/app	10	7500
1	Heater	500	W/app	5	2500
1	Stand-by consumers	100	W	24	2400
Total daily energy 41602 Wh/day					
Monthly energy 1248.0 kWh/mth					

2.2. Step 2: Data pre-processing

Effective decisions can result from accurate estimates in data analysis. Utilizing historical data is one of the data-driven modeling methods. Effective modeling requires the ability to use the proper computational and statistical techniques. For data-driven modeling and accurate estimates to be produced, it is necessary to know the steps of the process. The data cleaning identifies and handles missing or incomplete data. It can be done by filling in or deleting missing values with an average value. In the data normalization, the process of changing dataset values so that they have uniform values. The dataset value is changed to have a minimum value of 0 and a maximum of 1. The process is performed using (1).

$$X_{norm} = \frac{\mathrm{X} - \min(x)}{\max(x) - \min(x)} \tag{1}$$

X_{norm} is the normalized value, $min(x)$ $max(x)$ is the absolute minimum and maximum value, and X is the original value. In data standardization, the process of changing the values of a dataset so that it has a mean value of zero and a standard deviation of one by using (2).

$$X_{std} = \frac{X-\mu}{\sigma} \tag{2}$$

X_{std} is the standardized value, μ is the average of all dataset values, σ is the deviation of all dataset values, and X is the original value.

2.3. Step 3: Neural network

Modeling using supervised ML to estimate is essential [35]. Model learning from the training dataset and apply the known patterns to perform estimates tested with dataset testing. The learning algorithm in this study uses a NN and is compared with LR and SVM algorithms. The neural network is shown in Figure 4 and (3)-(4).

$$t_j = f0\left(\sum_{i=1}^{M} w_{i,j} * x_i\right) \tag{3}$$

$$y^* = f1\left(\sum_{j=1}^{n} c_j * t_j\right) \tag{4}$$

NN consists of a network of layered weights with interconnected mathematical operators (neurons). Where x_i is the number of inputs, Wi, j is the weight of the input variable, t_j is the neuron that has an activation function, y is the output, c_j is the weight of y, and $f0$ and $f1$ are activation functions with sigmoid functions as in (5).

$$f(x) = \frac{1}{1+e^{-x}} \tag{5}$$

NN describes the human brain, which consists of many cells called neurons that form branched networks. Connected neurons send signals to each other to process information and are connected to the next neuron. Essentially, neurons connect three layers in an artificial neural network as follows [36].

a. Input layer connects the information received on this layer: latitude, longitude, air pressure, temperature, relative humidity, wind speed, precipitation, total insulation, tilt angle, azimuth angle, production energy, array energy, and energy imports. It is then processed, analyzed based on the nodes of this layer, and moved to the next layer.
b. Hidden layer: Hidden layers get input from other layers or hidden layers. Hidden layers in an artificial neural network can number more than one. The output from the previous layer is processed, analyzed, and continued to the next layer.
c. Output layer: All previous processes will end on this node, and then the transmission process will occur. The output value will be "1" or "0" according to the activation function.

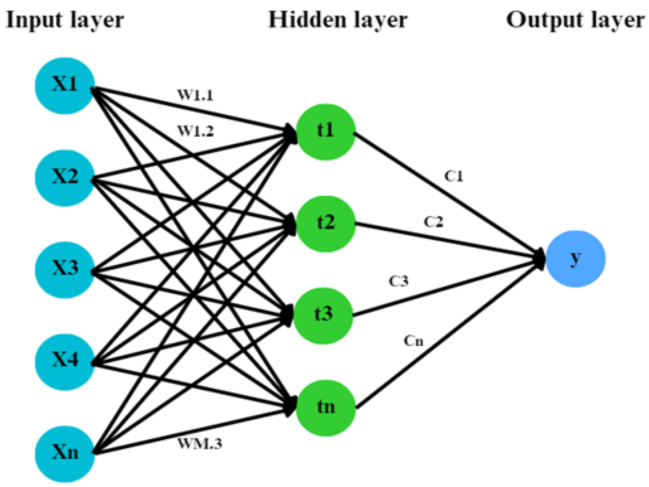

Figure 4. Neural networks

2.4. Step 4: Grid search cross-validation

Grid search cross-validation (GSCV) is a technique used to enhance model performance by finding the optimal combination of parameters. Sharing training and testing data is a step that must be determined in advance. This study divided the data based on 80% training and 20% testing data [37]. In the training process, data is divided into 10-fold, 9-fold data as training, and 1-fold data as validation of as many as ten crosses. The average validation value is the best hyperparameter search for testing for artificial neural network parameters, as illustrated in Figure 5. This cross-validation process is carried out randomly on the search grid with vulnerable numbers of 2–100.

2.5. Step 5: Model evaluation

To evaluate model performance in regression modeling using RMSE. It can indicate the model's accuracy with the actual values in the dataset. The better the accuracy prediction performance, the smaller the RMSE value. The RMSE is shown in (6),

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y1-\hat{y}1)^2}{n}} \tag{6}$$

where n is the number of sample data in the dataset, yi is the actual value of the i data, and $\hat{y}i$ is the value that the model predicts for the i data. This study compared the RMSE results of the NN, LR, and SVM models before and after the addition of GSCV in a combination of one-direction, two-directions, and three-directions.

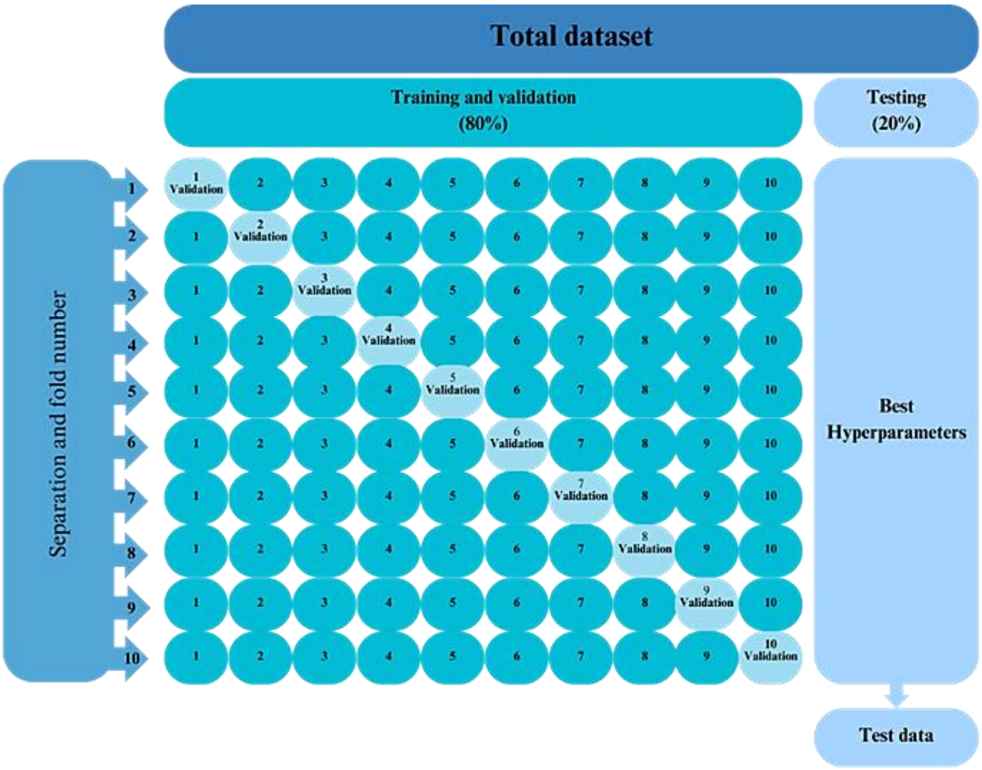

Figure 5. 10-fold cross-validation diagram

3. RESULTS AND DISCUSSION

This study aims to make an estimated model of imported energy from on-grid rooftop solar PV systems. An essential part of this research is the model generated from training data with validation that is separated independently without involving testing data. This method can enhance the accuracy of better estimation models. The results show the correlation between attribute variables in the dataset using the correlation matrix, as shown in Figure 6, as the attribute parameter of the estimation model.

The correlation matrix measures the strength and direction of the relationship between two variables corresponding to values ranging from -1 to 1. If the correlation value is close to 1, it indicates a perfect positive correlation that tends to move in the same direction. A correlation value relative to -1 indicates a perfect negative correlation. The variable tends to move in the opposite direction. However, if the correlation value is close to 0, it means the absence of correlation or weak correlation between variables. In Figure 6, the most potent positive correlations to imported energy are latitude (0.328), relative humidity (0.484), precipitations (0.484), and tilt angle (0.474). The negatively correlated are longitude (-0.429), temperature (-0.290), wind speed (-0.498), total insolation (-0.240), production energy (-0.877), and array energy (-0.555).

The discussion of imported energy on the on-grid rooftop solar PV system here goes further to using electrical energy that has reached consumers. The production of solar PV energy should be able to supply all the needs of consumer loads. However, with the fluctuating nature of solar PV due to the influence of external weather conditions, energy needs to be supplied from the grid. Imported energy on an on-grid rooftop solar PV system shows how much electrical energy is delivered from the grid system. The smaller energy provided by the grid shows a significant effect of renewable energy on reducing carbon emissions because the grid system still uses many primary materials from fossils. This study shows the estimated amount of imported energy in 20 provincial capitals in Indonesia. The potential for on-grid rooftop solar PV development in Indonesia is in big cities with many buildings and residential density. Energy imported in each town differs, even with the exact PV capacity, due to other conditions, such as tilt and azimuth angles. This study was divided into three datasets based on the number of azimuth angle directions and inverters. Each azimuth angle direction can find the smallest amount of imported energy, and the location of the provincial capitals is shown in Table 4.

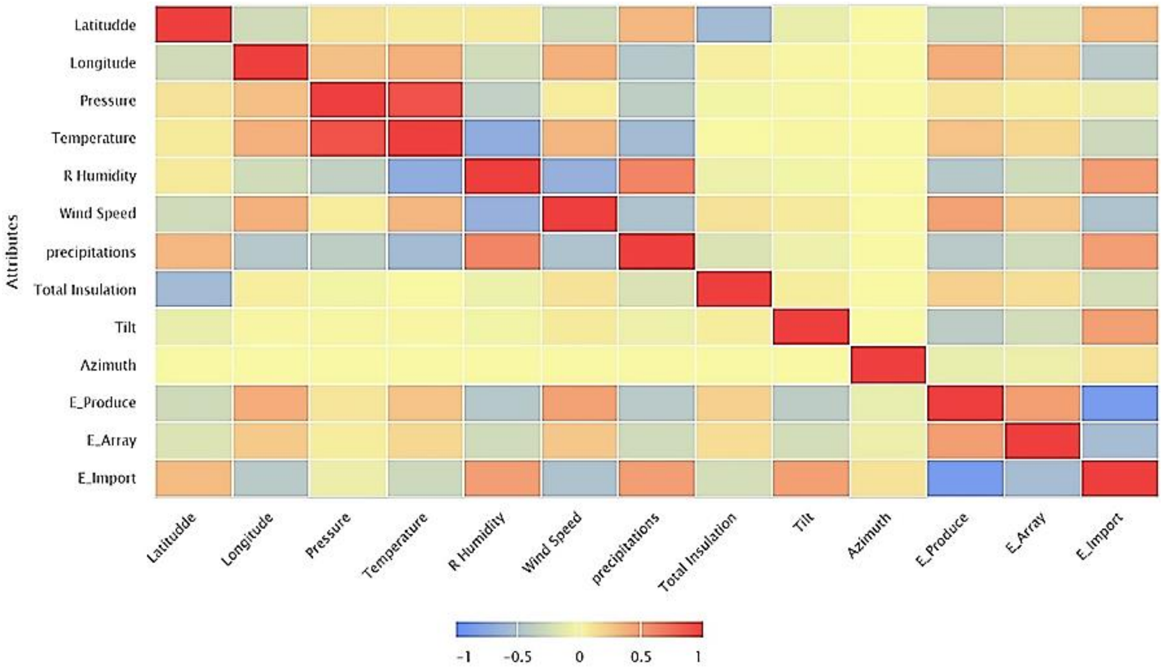

Figure 6. Correlation matrix of attribute on-grid rooftop solar PV

Table 4. The provincial capital has the lowest energy import

Combination	Angle direction	Provincial capital	Energy import
One-direction			
− one inverter	north	Denpasar	5338 kWh/year
− two inverters	north	Denpasar	5339 kWh/year
− three inverters	north	Denpasar	5441 kWh/year
Two-directions	north, northeast	Denpasar	5393 kWh/year
Three-directions	north, northeast, northwest	Denpasar	5509 kWh/year

Explore more profound machine learning algorithms to enhance the accuracy and accuracy of imported energy estimation models. Approaches such as NN, LR, and SVM algorithms can identify complex patterns in historical data and enhance the model's ability to estimate fluctuations in imported rooftop solar PV energy. NN results are enhanced for better accuracy with GSCV. The technology can also better adapt to environmental conditions that affect the performance of solar PV systems. More precise and adaptive estimation models can be produced to make smarter decisions by harnessing the power of machine learning. Figure 7 is the one-direction azimuth angle of the energy import estimation model, Figure 8 shows the two-directions azimuth angle of the energy import estimation model, and Figure 9 is the three-directions azimuth angle of the energy import estimation model. The figure explains the comparison between NN, LR, and SVM, showing that NN gets more accurate results. The NN results were enhanced to get more accurate results by adding GSCV so that it became the GSCV-NN result. All estimation model results are illustrated by comparing NN, LR, SVM, and GSCV-NN. This result applies to all images in the estimation model in one-direction azimuth angle, two-directions azimuth angle, and three-directions azimuth angle. The value of the hidden layer of each node and the threshold in the combination of directions are shown in Table 5.

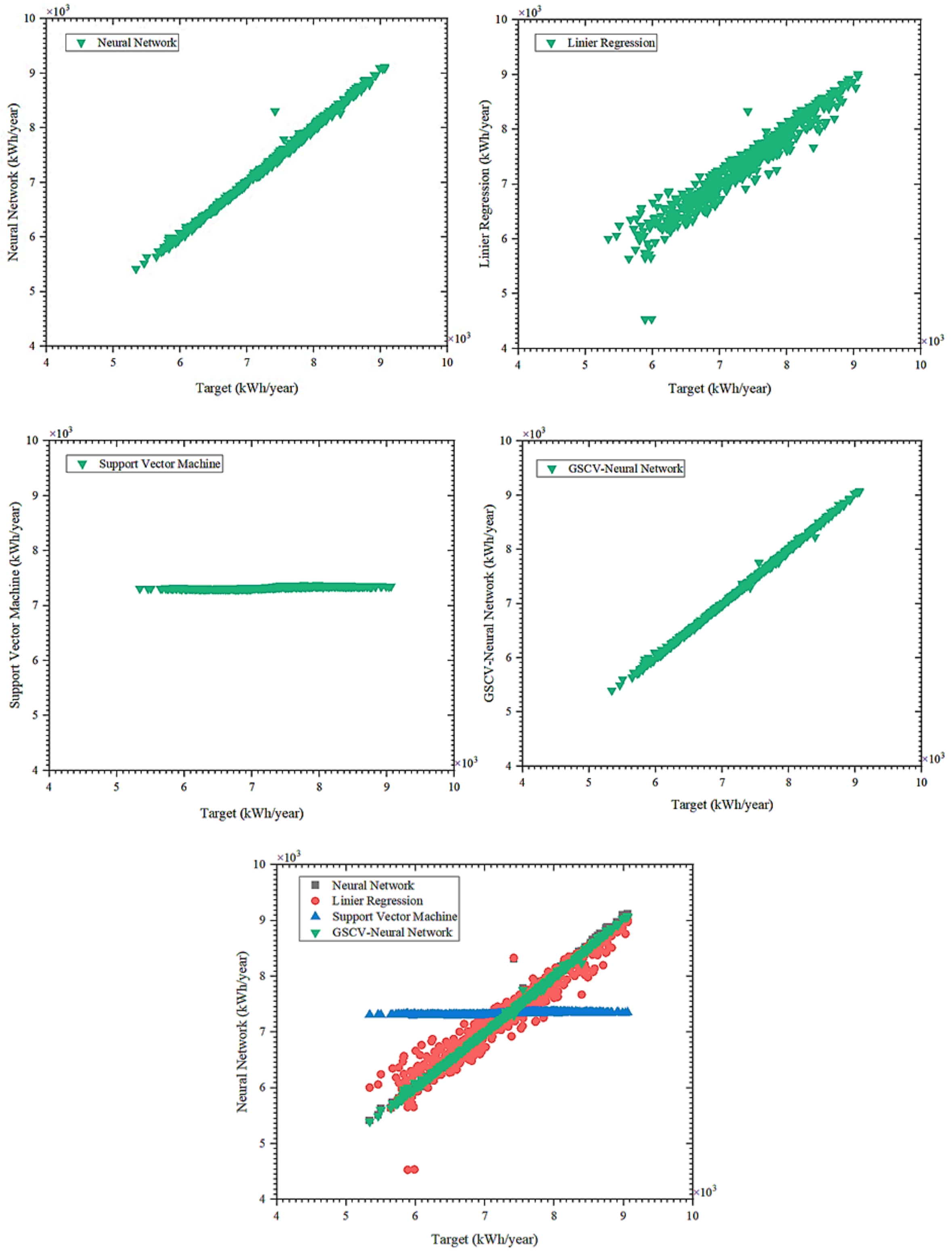

Figure 7. One-direction azimuth angle of the energy import estimation model

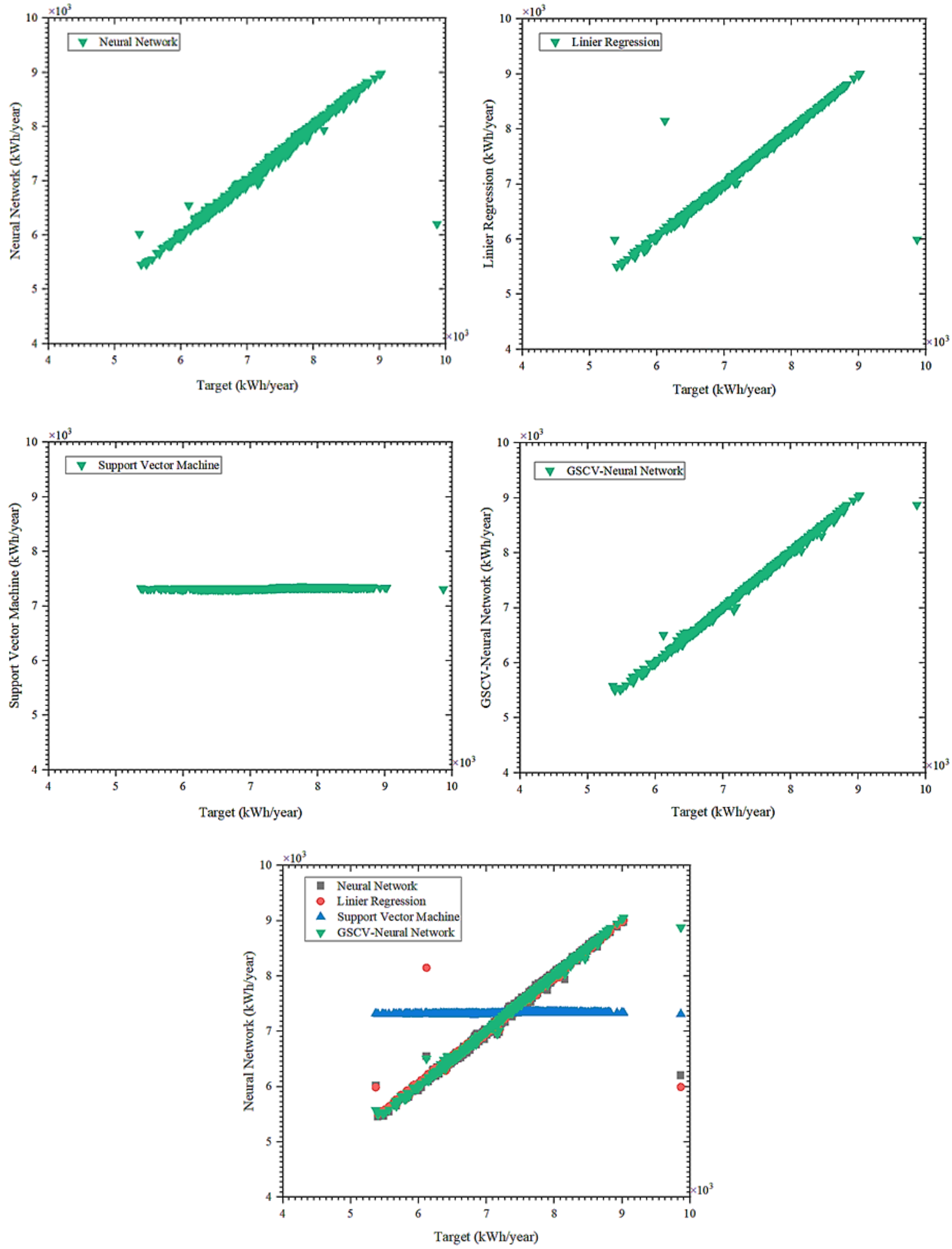

Figure 8. Two-directions azimuth angle of the energy import estimation model

The GSCV process can significantly increase the ability to produce models that perform better and enhance the accuracy of imported energy estimation models. GSCV can systematically find the optimal parameter in the estimation model by conducting a broader and more complex parameter search. GSCV can also reduce the risk of overfitting to model new data properly. Table 6 shows the results of enhancing the accuracy of the energy import estimation model with the addition of the GSCV process. In a one-direction combination, the RMSE GSCV-NN is 44.398, GSCV-LR is 177.923, and GSCV-SVM is 439.044. In a two-directional combination, the RMSE GSCV-NN is 141.286, GSCV-LR is 94.729, and GSCV-SVM is 446.176. In a three-directional combination, the RMSE GSCV-NN is 76.313, GSCV-LR is 85.367, and GSCV-SVM is 523.598.

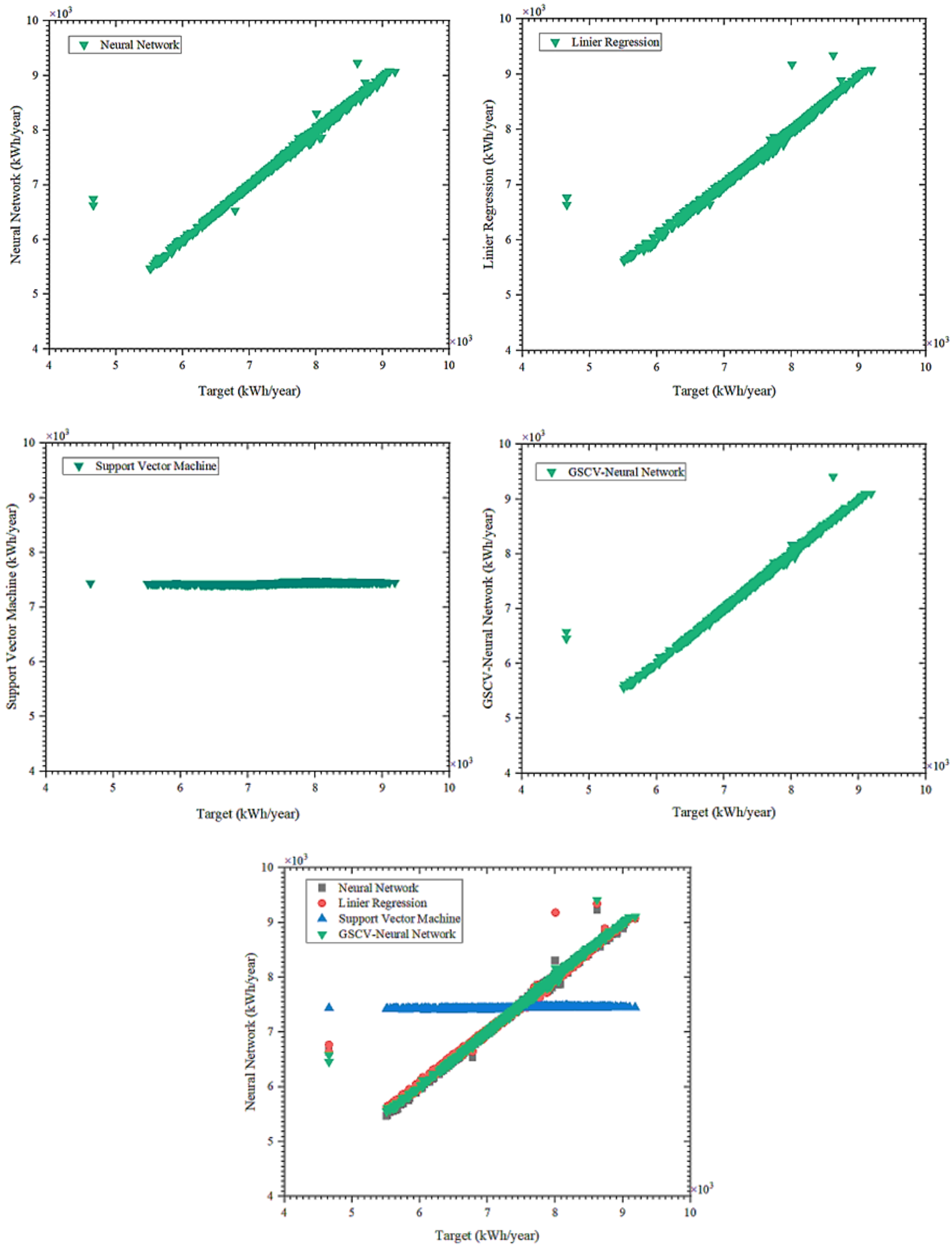

Figure 9. Three-directions azimuth angle of the energy import estimation model

Table 5. Neural network node values

Model	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	Node 8	Threshold
One-direction	1.522	-1.273	-0.363	0.428	-1.588	0.361	1.059	-1.250	-0.133
Two-directions	0.271	0.502	1.324	-1037	-1.484	0.644	-0.446	-0.227	-0.263
Three-directions	0.047	0.600	-0342	-0.830	1.694	-0.484	0.491	-0993	-0.777

Table 6. ML Evaluation of model based on RMSE measurement

Direction combination	Model ML	RMSE	GSCV addition	RMSE	Enhanced
One-direction	NN	53.184	NN	44.389	8.795
	LR	311.367	LR	177.923	133.444
	SVM	748.875	SVM	439.044	309.831
Two-directions	NN	145.562	NN	141.286	4.276
	LR	160.196	LR	94.729	65.467
	SVM	749.846	SVM	446.176	303.670
Three-directions	NN	81.442	NN	76.313	5.129
	LR	90.678	LR	85.367	5.311
	SVM	767.108	SVM	523.598	243.510

4. CONCLUSION

The on-grid rooftop solar photovoltaic estimation model impacts the development of the implementation of solar photovoltaic installation on the roof of the building with various azimuth angle directions. Estimation models using machine learning need enhancement to become more accurate. A comparison of modeling results between NN, LR, and SVM resulted in the best estimation model using NN. The enhancement model uses GSCV, which has proven to enhance results more accurately. The result of the difference between NN–GSCV-NN in the combination of one direction is 8.795, two directions 4.276, and three directions 5.129. The results of this study can impact the development of on-grid rooftop solar photovoltaic because it can provide estimated value to users in 20 provincial capitals in Indonesia. This estimation model needs further development for more optimal and accurate results with enhanced feature engineering.

REFERENCES

[1] A. Shaher, S. Alqahtani, A. Garada, and L. Cipcigan, "Rooftop solar photovoltaic in Saudi Arabia to supply electricity demand in localised urban areas: a study of the city of Abha," *Energies*, vol. 16, no. 11, 2023, doi: 10.3390/en16114310.

[2] T. V. Christiaanse, R. C. G. M. Loonen, and R. Evins, "Techno-economic optimization for grid-friendly rooftop PV systems – A case study of commercial buildings in British Columbia," *Sustainable Energy Technologies and Assessments*, vol. 47, 2021, doi: 10.1016/j.seta.2021.101320.

[3] M. Daraei, A. Avelin, and E. Thorin, "Optimization of a regional energy system including CHP plants and local PV system and hydropower: Scenarios for the County of Västmanland in Sweden," *Journal of Cleaner Production*, vol. 230, pp. 1111–1127, 2019, doi: 10.1016/j.jclepro.2019.05.086.

[4] R. Reddivari and D. Jena, "Improved Gamma type Y-source inverter for rooftop PV based V-G applications," *International Journal of Electrical Power and Energy Systems*, vol. 142, 2022, doi: 10.1016/j.ijepes.2022.108261.

[5] M. U. Hassan, S. Saha, and M. E. Haque, "PVAnalytX: A MATLAB toolkit for techno-economic analysis and performance evaluation of rooftop PV systems," *Energy*, vol. 223, 2021, doi: 10.1016/j.energy.2021.120074.

[6] A. N. Akpolat, E. Dursun, A. E. Kuzucuoğlu, Y. Yang, F. Blaabjerg, and A. F. Baba, "Performance analysis of a grid-connected rooftop solar photovoltaic system," *Electronics*, vol. 8, no. 8, Aug. 2019, doi: 10.3390/electronics8080905.

[7] N. Niveditha and M. M. Rajan Singaravel, "Optimal sizing of hybrid PV–wind–battery storage system for Net Zero Energy Buildings to reduce grid burden," *Applied Energy*, vol. 324, 2022, doi: 10.1016/j.apenergy.2022.119713.

[8] H. Ren, Z. Ma, C. Fai Norman Tse, and Y. Sun, "Optimal control of solar-powered electric bus networks with improved renewable energy on-site consumption and reduced grid dependence," *Applied Energy*, vol. 323, 2022, doi: 10.1016/j.apenergy.2022.119643.

[9] P. Puranen, A. Kosonen, and J. Ahola, "Techno-economic viability of energy storage concepts combined with a residential solar photovoltaic system: A case study from Finland," *Applied Energy*, vol. 298, 2021, doi: 10.1016/j.apenergy.2021.117199.

[10] N. H. Motlagh, A. Khatibi, and A. Aslani, "Toward sustainable energy-independent buildings using internet of things," *Energies*, vol. 13, no. 22, pp. 1–17, 2020, doi: 10.3390/en13225954.

[11] M. Martínez-Comesaña, J. Martínez-Torres, and P. Eguía-Oller, "Optimisation of LSTM neural networks with NSGA-II and FDA for PV installations characterisation," *Engineering Applications of Artificial Intelligence*, vol. 126, 2023, doi: 10.1016/j.engappai.2023.106770.

[12] B. S. Mahmood, N. K. Hussein, M. Aljohani, and M. Qaraad, "A modified gradient search rule based on the quasi-Newton method and a new local search technique to improve the gradient-based algorithm: Solar photovoltaic parameter extraction," *Mathematics*, vol. 11, no. 19, 2023, doi: 10.3390/math11194200.

[13] N. Kullampalayam Murugaiyan, K. Chandrasekaran, P. Manoharan, and B. Derebew, *Leveraging opposition-based learning for solar photovoltaic model parameter estimation with exponential distribution optimization algorithm*, vol. 14, no. 1. Nature Publishing Group UK, 2024.

[14] A. A. Abd El-Mageed, A. Al-Hamadi, S. Bakheet, and A. H. Abd El-Rahiem, "Hybrid sparrow search-exponential distribution optimization with differential evolution for parameter prediction of solar photovoltaic models," *Algorithms*, vol. 17, no. 1, 2024, doi: 10.3390/a17010026.

[15] M. K. Singla *et al.*, "Parameter estimation techniques for photovoltaic system modeling," *Energies*, vol. 16, no. 17, 2023, doi: 10.3390/en16176280.
[16] E. M. Abo-Zahhad *et al.*, "Evaluation of solar PV-based microgrids viability utilizing single and multi-criteria decision analysis," *Renewable Energy*, vol. 221, 2024, doi: 10.1016/j.renene.2023.119713.
[17] M. Hu, Z. Liu, Y. Huang, M. Wei, and B. Yuan, "Estimation of rooftop solar photovoltaic potential based on high-resolution images and digital surface models," *Buildings*, vol. 13, no. 11, 2023, doi: 10.3390/buildings13112686.
[18] H. Waqas, Y. Jiang, J. Shang, I. Munir, and F. U. Khan, "An integrated approach for 3D solar potential assessment at the city scale," *Remote Sensing*, vol. 15, no. 23, Dec. 2023, doi: 10.3390/rs15235616.
[19] M. Massano, E. Macii, A. Lanzini, E. Patti, and L. Bottaccioli, "A GIS open-data co-simulation platform for photovoltaic integration in residential urban areas," *Engineering*, vol. 26, pp. 198–213, 2023, doi: 10.1016/j.eng.2022.06.020.
[20] D. Eshimiakhe, R. Jimoh, M. Suleiman, and K. Lawal, "Improved cluster analysis of Werner solutions for geologic depth estimation using unsupervised machine learning," *Kuwait Journal of Science*, vol. 51, no. 1, 2024, doi: 10.1016/j.kjs.2023.10.011.
[21] A. Pinna and L. Massidda, "A complete and high-resolution estimate of Sardinia's rooftop photovoltaic potential," *Applied Sciences (Switzerland)*, vol. 13, no. 1, 2023, doi: 10.3390/app13010007.
[22] T. N. Olayiwola, S.-H. Hyun, and S.-J. Choi, "Photovoltaic modeling: a comprehensive analysis of the I–V characteristic curve," *Sustainability*, vol. 16, no. 1, Jan. 2024, doi: 10.3390/su16010432.
[23] Y. O. Sharrab, M. Alsmirat, B. Hawashin, and N. Sarhan, "Machine learning-based energy consumption modeling and comparing of H.264 and Google VP8 encoders," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 2, pp. 1303–1310, 2021, doi: 10.11591/ijece.v11i2.pp1303-1310.
[24] D. Wang *et al.*, "Accelerated prediction of Cu-based single-atom alloy catalysts for CO2 reduction by machine learning," *Green Energy and Environment*, vol. 8, no. 3, pp. 820–830, 2023, doi: 10.1016/j.gee.2021.10.003.
[25] E. Muhammed, A. El-Shazly, and S. Morsy, "Building rooftop extraction using machine learning algorithms for solar photovoltaic potential estimation," *Sustainability*, vol. 15, no. 14, Jul. 2023, doi: 10.3390/su151411004.
[26] H. Li, X. He, Y. Hu, W. Lv, and L. Yang, "Research on the generation method of missing hourly solar radiation data based on multiple neural network algorithm," *Energy*, vol. 287, 2024, doi: 10.1016/j.energy.2023.129650.
[27] F. Nicoletti and P. Bevilacqua, "Hourly photovoltaic production prediction using numerical weather data and neural networks for solar energy decision support," *Energies*, vol. 17, no. 2, 2024, doi: 10.3390/en17020466.
[28] X. Liao, R. Zhu, M. S. Wong, J. Heo, P. W. Chan, and C. Y. T. Kwok, "Fast and accurate estimation of solar irradiation on building rooftops in Hong Kong: A machine learning-based parameterization approach," *Renewable Energy*, vol. 216, 2023, doi: 10.1016/j.renene.2023.119034.
[29] W. Cui, X. Peng, J. Yang, H. Yuan, and L. L. Lai, "Evaluation of rooftop photovoltaic power generation potential based on deep learning and high-definition map image," *Energies*, vol. 16, no. 18, 2023, doi: 10.3390/en16186563.
[30] C. Ma, J. wei Chi, F. chao Kong, S. hui Zhou, D. chun Lu, and W. zhang Liao, "Prediction on the seismic performance limits of reinforced concrete columns based on machine learning method," *Soil Dynamics and Earthquake Engineering*, vol. 177, 2024, doi: 10.1016/j.soildyn.2023.108423.
[31] N. C. da Silva, M. K. Albertini, A. R. Backes, and G. das G. Pena, "Machine learning for hospital readmission prediction in pediatric population," *Computer Methods and Programs in Biomedicine*, vol. 244, 2024, doi: 10.1016/j.cmpb.2023.107980.
[32] P. R. S. dos Santos, V. de Carvalho Brito, A. O. de Carvalho Filho, and J. O. B. Diniz, "KochDet: BiFPN-based deep architecture for tuberculosis diagnosis," *Biomedical Signal Processing and Control*, vol. 91, 2024, doi: 10.1016/j.bspc.2024.106056.
[33] A. Cabarcos, C. Paz, E. Suarez, and J. Vence, "Application of supervised learning algorithms for temperature prediction in nucleate flow boiling," *Applied Thermal Engineering*, vol. 240, 2024, doi: 10.1016/j.applthermaleng.2023.122155.
[34] P. Agrawal, R. Gnanaprakash, and S. H. Dhawane, "Prediction of biodiesel yield employing machine learning: interpretability analysis via shapley additive explanations," *Fuel*, vol. 359, 2024, doi: 10.1016/j.fuel.2023.130516.
[35] K. M. Mendez, D. I. Broadhurst, and S. N. Reinke, "Migrating from partial least squares discriminant analysis to artificial neural networks: a comparison of functionally equivalent visualisation and feature contribution tools using Jupyter notebooks," *Metabolomics*, vol. 16, no. 2, 2020, doi: 10.1007/s11306-020-1640-0.
[36] K. A. Bisenovna *et al.*, "Improving the efficiency of food supplies for a trading company based on an artificial neural network," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 4, pp. 4407–4417, 2024, doi: 10.11591/ijece.v14i4.pp4407-4417.
[37] W. Huo, Z. Zhu, H. Sun, B. Ma, and L. Yang, "Development of machine learning models for the prediction of the compressive strength of calcium-based geopolymers," *Journal of Cleaner Production*, vol. 380, no. P2, 2022, doi: 10.1016/j.jclepro.2022.135159.

BIOGRAPHIES OF AUTHORS

Alfin Sahrin received a Bachelor of Engineering (S.T.) degree in electrical engineering from Universitas Kristen Indonesia, Jakarta, in 2012 and a master of engineering (M.T) in electric power system engineering from Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia, in 2018. He is currently pursuing a Ph.D. at the Department of Engineering Physics, Institut Teknologi Sepuluh Nopember. His research interests include renewable energy, power generation, power grids, solar photovoltaic systems, and machine learning. He can be contacted at email: alfin.sahrin@esdm.go.id.

Imam Abadi received a bachelor of engineering (S.T.) degree in engineering physics from Institut Teknologi Sepuluh Nopember, Surabaya, in 1998 and a master of engineering (M.T.) in instrumentation and control engineering from Institut Teknologi Bandung, Bandung, Indonesia, in 2005 and the Ph.D. degree in electrical engineering from Institut Teknologi Sepuluh Nopember. He is currently working as a director of student affairs at Institut Teknologi Sepuluh Nopember. He is interested in grid-connected photovoltaic systems, PV system modeling, artificial intelligence, and power systems. He can be contacted at email: imam@ep.its.ac.id.

Ali Musyafa received a bachelor of engineering (Ir.) degree in engineering physics from Institut Teknologi Sepuluh Nopember, Surabaya, in 1986 and a master of science (M.Sc.) in electrical engineering from Institut Teknologi Bandung, Bandung, in 1990 and the Ph.D. degree in electrical engineering from Institut Teknologi Sepuluh Nopember, in 2012. Presently, he is working as a senior lecturer and professor at the Department of Engineering Physics, Institut Teknologi Sepuluh Nopember. He has been involved in major projects in industry and national companies. He has many publications in international journals and conferences in the field of power systems and renewable energy. His research interests include power systems, renewable energy, smart cities, smart energy, instrumentation and automation, and intelligent control. He can be contacted at email: musyafa@ep.its.ac.id.