International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 5, October 2024, pp. 4838~4845
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i5.pp4838-4845

Development and assessment of solar radiation forecasting models based on operational data

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Article Info

Article history:

Received Dec 15, 2023
Revised Jun 12, 2024
Accepted Jun 17, 2024

Keywords:

Operational forecast
Solar energy
Sunlight
Weather prediction
Irradiation
Aerosols and clouds

ABSTRACT

Operational forecasting of solar radiation is critical for better decision-making by solar energy system operators, due to the variability of energy resources and demand. Although the numerical weather forecasting (NWP) model can predict solar radiation variables, there are often significant errors, especially in direct normal irradiation (DNI), which are influenced by the type and concentration of aerosols and clouds. This paper presents an artificial neural network (ANN) based method to generate operational DNI forecasts using weather and aerosol forecast data from the European Center for medium-range weather forecasts (ECMWF) and Copernicus atmospheric monitoring service (CAMS) respectively. The ANN model is designed to predict weather and aerosol variables at a certain time as input, while other models use the DNI forecast improvement period before the instant forecast. The model was developed using North Sumatra location observations and obtained DNI forecasting results every 10 minutes on the first day with DNI forecasting compared to the initial forecasting which was scaled down with the R^2, mean absolute error (MAE), and relative mean square error (RMSE) models were 0.6753, 151.2, and 210.2 W/m^2, so that and provides good agreement with experimental data.

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1. INTRODUCTION

Solar energy systems have variability as a renewable energy source and in general equatorial regions have enormous potential as an energy source in the future [1]. North Sumatra is a tropical region with vast potential for solar radiation and needs to be utilized as a renewable source to improve energy efficiency, electrification, and energy policy [2], [3]. Solar radiation is a clean and environmentally friendly source for transformation and other purposes. However, it is a renewable energy source with variability that can affect electricity generation, so it can disrupt the optimal balance between electricity generation and consumption because it is limited and unreliable availability of large-scale electrical energy storage systems [4].

Solar energy source only relies on direct solar radiation and diffuse radiation, resulting in accurate variable estimates and tend to influence certain forecasts [5]. A predictive model approach to solar radiation can be carried out using numerical weather forecasting (NWP) models and according to the weather and climate conditions at the research location [6]. NWP models provide weather information focusing on meteorological variables including weather and climate to predict solar radiation for the next 4 hours to several days [7]. This variability forecasting model was obtained from the weather where the research was conducted and used as a model to estimate it [8]. This model is an accurate approach to the components of global solar radiation and the energy balance on earth, but the integrated forecasting system (IFS) model developed at the European Center for Medium-Range Weather Forecasts (ECMWF) is a global NWP model that has long been developed and used in Europe with the best performance as found by researchers [9], [10], where 24-hour global solar terms from IFS and the American global forecasting system (GFS) are compared with observations made at several research stations. The researchers provided findings that the combined IFS and ECMWF models had the best performance when compared to the GFS model for all-sky conditions based on the average refractive error and correlation coefficient. In the research from [11], and [12], hourly global horizontal irradiance (GHI) estimates from the IFS and ECMWF global models as well as the weather research forecasting (WRF) model used by GFS are compared with observations in the US and European countries showing that the models from ECMWF have significantly better performance in all different locations and climatic conditions. Studies [13], [14] analyze the immediate normal radiation forecast for one year is compare it with observations made in the territory of Portugal, for different forecasts for the next 0 to 3 days, the result obtained is that the model reproduces hourly and daily experimental values with RMSE as big as 210.6 and 68.5 W/m^2, respectively, for the first day ahead and the model performance tends to decrease with higher forecast horizons.

Accuracy of solar radiation variables on research using the NWP model has been obtained for the needs of solar energy system development [15], [16]. Direct normal irradiation (DNI) very it is difficult to estimate because it is highly dependent on the presence of clouds and the type and concentration of aerosols in the atmosphere [17]. For the NWP models produced by IFS and ECMWF, the monthly climatological averages are compared with a more detailed approach to reduce computational time. Researchers who use NWP models provide excellent results under certain weather and climate conditions, as stated by [18] and [19]. The Copernicus atmospheric monitoring service (CAMS) and Goddard Earth Observing System Version 5 (GEOS-5) global models have been of particular interest, as noted by [20], [21], and achieved a relative mean square error (RMSE) reduction of 4.3% for hourly IFS and ECMWF GHI estimates based on aerosol estimates and experimental data, as suggested by [22], [23], while other researchers obtained between NWP and WRF models combined with chemistry for modeling aerosol and solar radiation data were compared with observations showing short wave radiation power 2 to 5 times higher during dust storms compared to values on dustless days proposed by [24].

Knowledge of all complex phenomena in the Earth's atmosphere, including interactions between solar radiation and the atmosphere, as well as between solar radiation and the Earth's surface is a constraint, and representation in the most complex and detailed NWP models is limited by data availability and computational limitations [25]. Several techniques have been developed and evaluated to further improve solar radiation estimates made by NWP models consisting of classical statistical methods [26] and machine learning (ML) methods [27], [28]. Support vector machine models (SVM), random forests (RF), artificial neural networks (ANN), and focus on global solar irradiation predictions have been researched by [29], [30].

Due to the problems above, it is necessary to develop and model solar radiation. The paper proposed a solar radiation forecast in North Sumatra with an iterative combination model between two parameters namely weather and climate obtained from the Medan City meteorology, climatology, and geophysics agency. Two models are designed with weather and climate predictions at a certain time as input, and one model suggests improving solar radiation forecasts based on operational data. Implementation of the proposed model with an approach time of 10 minutes and obtained results respectively with the R^2, MAE, and RMSE model statistics, then this model was evaluated at different periods and locations in North Sumatra which can provide equality with experimental data [31].

Development and modeling on GHI forecasting with four ML models produces an accuracy of 81%. This model can find systematic errors in the output of the NWP model and relevant variables in the estimation of historical data and observations by comparing the basis of the two data and providing the best assessment with a short time and a more detailed model [32], [33]. In several studies about forecast hourly GHI, DNI, and DHI with several machine learning models and solar radiation as input, as well as aerosol observations against wind and aerosol forecasts, were evaluated to obtain the best ANN model performance [34], while a comparison of models with feed-forward artificial neural networks and recurrent neural networks to estimate global solar radiation at the research location which shows that, artificial neural networks can improve prediction performance, but incur additional computational costs [35] and the results are getting closer solar radiation one day ahead via SVM with NWP data from the meteorology, climatology, and geophysics agency scale model produces an RMSE of 15.98%, while using artificial neural networks to approximate solar radiation with NWP from the WRF model, a reduction in model bias is obtained, MSE and RMSE [36]. Meanwhile, ML models have been developed to be applied to solar irradiation forecasting with a focus on GHI which is used to obtain an approach to the power output of solar energy systems with temporal resolution and forecast time horizons that are not synchronous with real-time forecasts. condition [37], [38].

Method development and modeling for the proposed operational DNI forecasting consists of i) specific locations and times used for IFS/ECMWF and aerosol forecasts; ii) ANN models are used for certain weather and aerosol forecasts; iii) the ANN model is used to improve the DNI before the prediction time step at certain seasons and times. The results of observing developments and evaluating research proposals show that this method can be applied and generalized and contribute to discoveries that can be applied to certain locations and times.

2. RESEARCH METHOD

2.1. Predictive data and weather forecasts

Developing models to estimate IFS/ECMWF and CAMS model data as well as solar radiation observation data from a network of stations in Medan, North Sumatra, Indonesia. Some models are operational and models are developed so that daily data can be used operationally. The data period and area used are January 2017 to December 2022 with positions 1.0°N and 4.0°N and 98°E and 100°E respectively.

Weather data for forecasting is obtained from the IFS/ECMWF model, while the NWP model is a wave range radiation scheme in 1D radiation, by estimating temperature, humidity, effective cloud radius, and climatology of monthly averages of aerosols, CO_2, ozone, residual gas, albedo, land surface temperature, and emissions in different spectral bands and solar zenith angle with radiation transfer in different wavelength ranges in 14-16 spectral bands [39]. The *McRad* model has shortcomings so it is necessary to develop a new ECMWF radiation scheme, namely *ecRad*, and its development consists of, First, flexibility: the development of science requires the ability to exchange each component of the radiation scheme with components that are faster, more efficient and more accurate, but the *McRad's* non-modular design makes this very difficult. Second, efficiency: the (252) spectral intervals required for RRTM-G make *McRad* 3.5 times slower than previous findings. The results obtained with the radiation scheme are run on a much coarser grid compared to the other models, and in all operational model configurations except high-resolution forecasting (HRES), it only records the radiation scheme every 3 hours, whereas in HRES with hourly scheme calls. Schematic illustration of the five main components of *ecRad* (different colors) and the data flow between them (arrows) as shown in Figure 1.

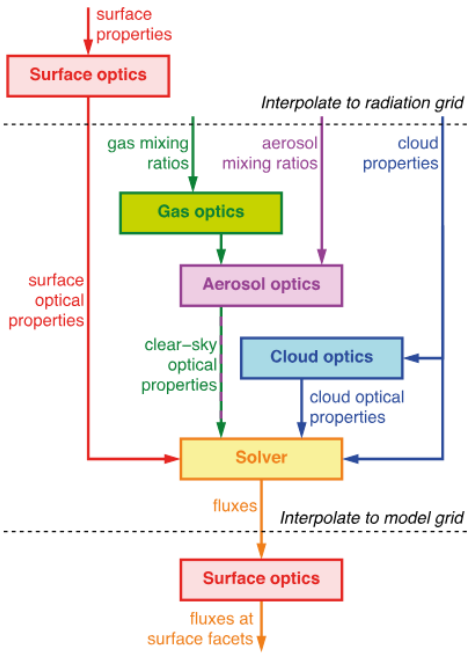

Figure 1. Schematic illustration of the five components of *ecRad*

Data are taken for maximum grid point density and temporal forecast horizons up to 72 hours. These data are used to obtain hourly average values of direct and normalized global horizontal radiation in W/m^2. The aim is to convert air temperature (T) to °C and calculate wind speed (WS) in m/s and wind direction (WD) in degrees North at the wind speed at the time the research was conducted.

2.2. Aerosol forecasts and scale models

The proposed development of CAMS provides an estimate of the global atmospheric composition based on the IFS model with additional modules enabled. To support the proposal, it is necessary to add aerosols, reactive gases, and greenhouse gases by considering phenomena such as emissions and trace gases and aerosols, absorption, and release by vegetation, soil, and ocean-atmosphere with dry deposition on the precipitation surface, chemical conversion, and aerosol microphysics. The combination of these components produces atmospheric variables, and aerosol optics at different wavelengths in 3D with a horizontal spatial resolution of 40 km and a time step of 1 hour [40].

Spatial and temporal degradation models are generally used for simulation, while bilinear interpolation for different grid points. The development of models to validate solar radiation measurements at research locations is very necessary. For models on a temporal scale, it is calculated using hourly mean radiation scaling interpolation. This method aims to obtain data during the research period that can represent solar radiation data as input for a more complex machine-learning model to improve DNI estimates. This proposal is a compromise between developing a more complex physical downscaling method to maintain hourly energy predictions that feed the original hourly radiation values into the machine learning model directly and developing the model for each time step of interest. This model has deviations caused by the downscaling method on the input energy predicted values and assimilated by the machine learning model.

2.3. Solar radiation prediction results and data quality

The development of the model that has been presented above provides an assessment of the complex DNI estimation. Based on DNI and GHI observation data every 1 minute at the research point in North Sumatra, is shown in Figure 2. Experimental data from this location have been widely validated and used by several other studies. To validate the model based on the results of DNI, DHI, and GHI observations for 1 minute for solar radiation from the station. The assessment is based on the mean, maximum, minimum, and standard deviation values for 1 minute. The results of the calculation of the average radiation value for various temporal resolutions used in the study are shown in Figure 2.

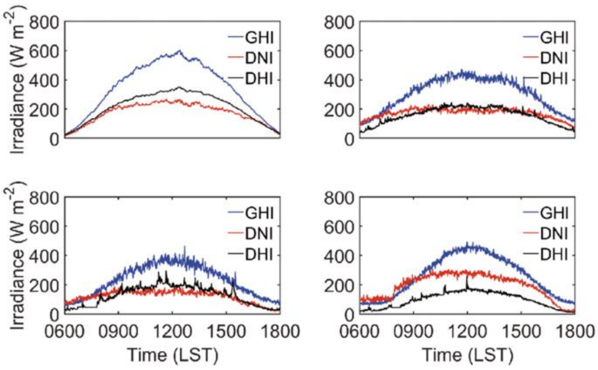

Figure 2. Solar radiation on GHI, DNI, DHI

3. RESULTS AND DISCUSSION

Based on the results of the discussion above, the following research results can be concluded. In sub-chapters 3.1, 3.2, and 3.3, with several considerations to produce the best research. The best results consist of GHI, DNI, and DHI and are validated with R^2, MAE, and RMSE which are comparisons as in Figure 3.

3.1. Direct normal radiation forecast analysis

Analysis of original solar radiation predictions from the IFS/ECMWF model against DNI forecasts and other atmospheric variables compared with observations of each first day at the specified forecast time with a value every 10 minutes which has been determined. The DNI forecast 10 minutes after downscaling the spatial and temporal scale of observations at the station location under study is shown in Figure 3. The research results show that the comparison of error correction with R^2, MAE, and RMSE shows better results, namely from the initial day (zero) to the next 2 days with R^2 of 0.6753; 0.6414; 0.6020 decreases further on days 0 to 3 days before the forecast, while for solar radiation with the MAE model it is 151.2; 157.1; 164.5 W/m^2 and model RMSE 210.2; 219.1; 233.3 W/m^2 increases from day 0 to the next 3 days like shown in Figure 3 which is also verified by other researchers in the literature [41], [42].

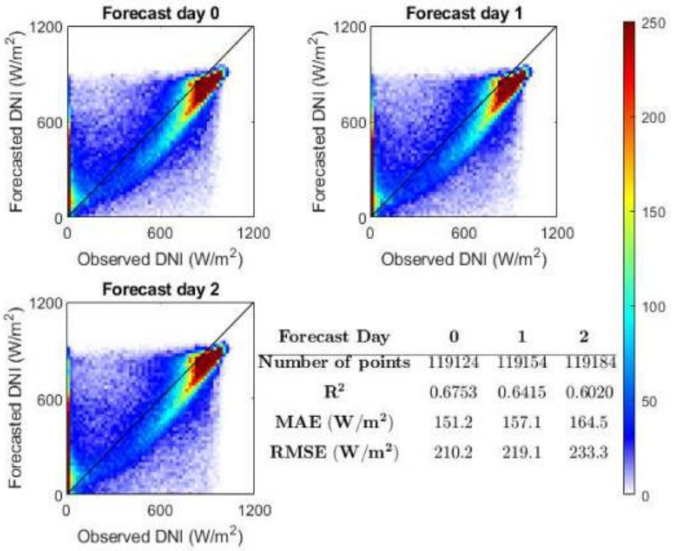

Figure 3. Model comparison with R^2, MAE, and RMSE

3.2. Correlation between forecast variables and DNI observations

Identify the correlation of several meteorological variables to a certain extent by calculating their linear correlation coefficient, to compare the estimated value of each variable after spatial and temporal downscaling (10 minutes) with the observed DNI for three forecast days. Pearson linear correlation coefficients for each forecast variable are similar, but there tends to be a decrease in correlation over the three-day forecast period. The highest absolute value of linear correlation occurred in the DNI forecast, followed by GHI with several variables such as clouds and solar zenith angle [43]. However, the aerosol variable shows a lower linear correlation value, this does not mean that the variable is more independent because it could have a nonlinear relationship as seen in Figure 4.

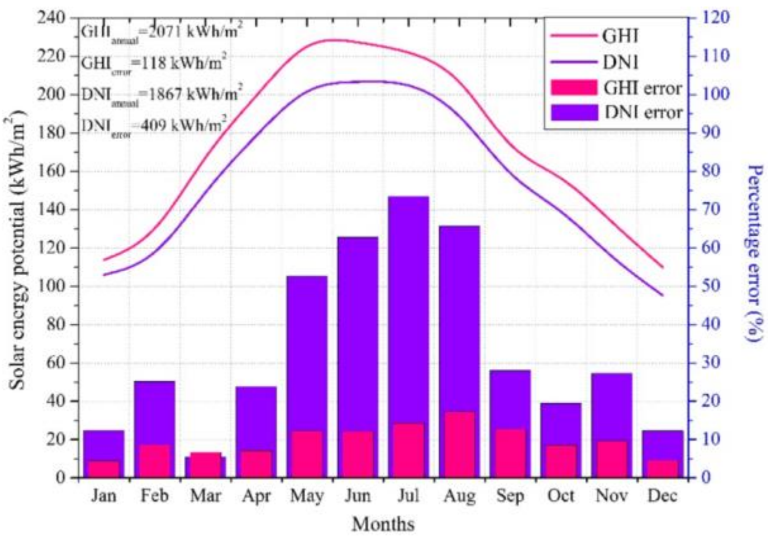

Figure 4. Solar energy potential in GHI, DNI

Development of the proposed model for prediction of DNI data over time before instant forecasting and in the evaluation, as well as comparison of three models, R^2, MAE, and RMSE, are used as metrics along with FS representing predictions with MAE to ANN with several parameters and specifications compared to ECMWF predictions, and GPI against three statistical indicators as comparison of model configurations. The coefficient of determination provides a measure of how well the outcome is observed by the model based on the proportion of total variation in the outcome explained by the model. According to the literature, MAE and RMSE metrics and indicators are the most commonly used to assess the performance of machine learning regression algorithms [44]. Each error contributes to the MAE in proportion to the absolute error, while RMSE involves squaring the difference so that several large differences will increase the RMSE more than the MAE. To calculate GPI, N metrics need to be normalized to a value that ranges from 0 to 1 and used the GPI value of the i^{th} model configuration is determined using the normalized median value of all indicators except the coefficient of determination, which is -1. In this study, R^2, MAE, and RMSE are used to calculate GPI with higher GPI values indicating better performance of the respective model configuration.

3.3. ANN model development model for weather and aerosol approaches

Development of the ANN model with weather and aerosol variables from the IFS/ECMWF global NWP model and CAMS for day 1 forecast, after reducing the temporal and spatial scales. DNI observations for 10 minutes are used as targets. In this research, the metric used to calculate GPI is R^2 using a training function with all input variables estimated at MAE and RMSE [45]. This metric and the high number of neurons indicate a more accurate estimate of DNI when used in field measurements considering observations as a reference. For configurations with reference performance, higher GPI values indicate better performance and there is an improvement over the original ECMWF estimates shown by each model configuration. Modeling development ANN consists of artificial neurons that form a network. This is relevant, each input given to these neurons is not the same, and a different weight is given to each input, so a linear network function is used to combine bias and weighted input, after that, a transfer function is applied to get the output from a neuron which then passed on to the next neuron [46].

4. CONCLUSION

This research contributes to the development of models for better estimation of DNI based on data from NWP models in operational environments. This model is applied to forecast data from IFS/ECMWF and CAMS with atmospheric variables and aerosol data that influence solar radiation through the atmosphere. To calculate spatial and temporal forecasts for the desired location and time resolution using bilinear interpolation of the values of four surrounding grid points and cubic interpolation with hourly average variables. Two different models based on artificial neural networks were designed and optimized to produce better DNI forecasts with the desired temporal resolution and for a forecast time horizon of 72 hours. To determine the accuracy of the results, it is necessary to configure the model being tested and the configuration selected using ANN. The model is run daily when ECMWF and CAMS operational forecasts are available for retrieval and the results for the next two days can be used by solar energy producers and grid operators to forecast energy production and make better decisions. This model is also applied to other locations spread across the area around the location study developed shows improved DNI forecasts on day 1 of the forecast based on the model R^2, MAE, and RMSE, when compared with ECMWF estimates and field measurements at each reference location (ref. Figure 3). With better forecasts, more accurate estimates of energy generation in solar energy systems can be achieved and this is very important for solar power plants.

ACKNOWLEDGEMENT

The researcher would like to thank all University leaders who have supported and funded this research, as well as all parties who cannot be mentioned one by one. Hopefully, the results of this research can provide benefits to all readers.

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