# The Solar Energy Forecasting by Pearson Correlation using Deep Learning Techniques

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Abstract: Solar energy is one of the most important renewable energy sources (RES) with many advantages as compared to other types of sources. Climate change is gradually becoming a global challenge for the sustainable development of humanity. There will potentially be two key features, for future electricity systems, high penetration or even dominance of renewable energy sources for clean energy e.g., onshore/offshore wind and solar PV. Solar energy forecasting is essential for the energy market. Machine learning and deep learning techniques are commonly used for providing an accurate forecasting of the energy that will be produced. The weather factors are related to each other in terms of influence, a wide range of features that are necessary to consider in the prediction process. In this paper, the effect of some atmospheric factors like Evapotranspiration and soil temperature are investigated using deep learning techniques. Higher accuracy is achieved when new features related to solar irradiation were considered in the forecasting process.

Keywords: Pearson correlation, Deep Learning, Solar irradiation, Forecasting process, Solar energy.

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## 1. Introduction

A variety of renewable energy sources (RESs) play important roles in the global energy markets, they gradually replace conventional fossil fuel-based power plants which leads to reduce carbon emissions [1]. The problem with RESs is that the produced energy is not easily predictable in advance, it varies with weather conditions such as cloud, humidity, precipitation, wind speed and temperature [2]. This problem can be overcome by using accurate forecasting [3].

The RESs are sustainable and are low in environmental pollution. Growing load requirement need efficient energy management to enhance the real time wide area monitoring systems in order to increase the power system efficiency and performance [4]. Phasor measurement units (PMUs) also known Synchrophasors measure the magnitude and phase of transmission line voltage and current at a reporting rate up to 120 times per second. As shown in figure 1, a time reference provided by a global positioning system (GPS) is used to synchronize measurements from all the PMUs in a power system to provide an accurate, real-time picture of an entire transmission system [5]. PMU measurements are aggregated by a phasor data concentrator and relayed to the grid protection and control system. PMU systems are expected be installed at solar energy plants to enhance the wide-area situational awareness and to facilitate integration of RESs [6].

Energy forecasting methods play a vital role in power system developments. Introducing smart grid technologies is becoming very essential especially when the level of renewables penetration is high (Capacity penetration level exceeds 30% on any section of the power grid) to ensure reliable and stable operation of the power grid [7]. The transition from traditional grid into smart grid requires upgrades of traditional grid systems and new innovative solutions to accommodate the nature of renewable energy generation [8].

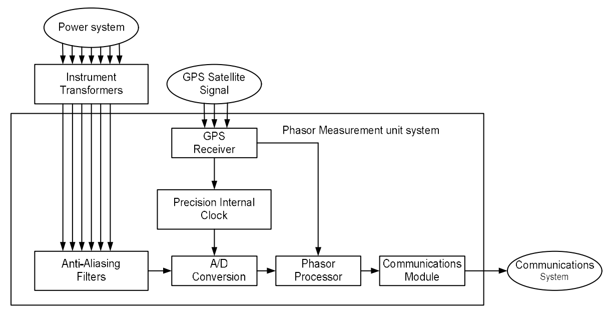


Fig.1 PMU unit structure [9]

Worldwide, Solar power plants is progressively being integrated into electric power grids. However, the integration of RESs into the power systems suffers of two problems, namely, the intermittent electricity delivery and unpredictability. Therefore, solar power forecasting is now very important for the stabile operation of electric grid and optimal dispatch. Machine learning techniques are employed to overcome these problems and successfully integrate these PV sources into the national electric grid [10].

In literature, the PV energy output forecasting can be classified into three main methods, mainly, physical, time-series statistical [11], and hybrid methods [12]– [15]. The physical method uses the meteorological data obtained by numerical weather predictions to build forecasting models. The more accurate the weather parameters related to the solar irradiance, the more accurate is the forecasting of the amount of the solar energy produced.

Time series models use a large amount of historical data statistical approach to forecast the average hourly solar irradiance; it does not require geographic information of PV power plants. These models provide accurate forecasts of the average monthly or annual production [16]. The time series models used in solar power forecasting include autoregressive model, moving-average model, autoregressive–moving-average model, autoregressive integrated moving average model. The statistical methods such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Markov chain are capable to extract and model unseen relationships and features [17]. They are easy to build with good prediction accuracy. Major Network Architectures of Deep learning are

- Deep Belief Networks (DBNs)
- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNN)s –(LSTM)
- Recursive Neural Networks.

The accuracy of these forecasting methods depends mainly on the variables used. Hybrid methods use both previous approaches at the same time. The hybrid approach significantly improves the efficiency and quality of forecasts. According to the Renewable Energy Policy Network for the Twenty-First Century (REN21), Solar energy is expected to reach 8000 GW in 2050 [18-21].

Solar radiation is the energy or radiation received from the sun, it is measured in kW or W. The Insolation (solar irradiation) is the total quantity of solar radiation energy received on a particular surface area over a particular period. solar irradiation is commonly measured and expressed it in watt-hour per square meter (Wh/m²) [22]. It is more convenient to quantify it in days (Wh/m² per day). The distance between the sun and the Earth ranges from 1.47x10^8 km to 1.52x10^8 km. The solar irradiance, E, ranges from 1325 to 1420 W/m$^2$. The solar constant $E$:

$$E = 1.367 kW / m^2 \quad (1)$$

The solar irradiation is normally absorbed, scattered, and reflected by the different components of atmosphere such as ozone, carbon dioxide, and water vapor, as well as other gases and particles. About 30% of the solar irradiation passes through the atmosphere, resulting in an insolation at the earth's surface of about 1 kW/m² at sea level [24].

In this paper, many features or weather conditions are incorporated, to the best of author’s knowledge, some of them have never been considered before, such as Sunshine Duration, Precipitation, Wind Speed and Direction on 10m height, Wind Speed [900 milli bar], Wind Direction [when the atmospheric pressure equal 900 milli bar], Cloud Cover Total, temperature, CAPE [180-0 milli bar above ground], Soil Moisture [0-10cm down], Mean Sea Level Pressure [MSL], Evapotranspiration, Relative Humidity. Long Short-Term Memory (LSTM) algorithm is used as a deep learning technique, it is a type of Recurrent Neural Network that has been specifically developed for the use of handling sequential prediction problems, like weather forecasting for wind and solar energy. Many researchers assured that LSTM is very convenient for regression of time series data.

# 2. The Data Set Description

The data set used in the study is between January 1, 2015, and January 1, 2021, for Basel city irradiation, in Switzerland. The weather observation data measured with a resolution of 1-hour intervals during all day. The free data was collected from “meteoblue” weather website which can be applied to research purpose.

The data set include many meteorological parameters such as humidity precipitation, temperature, wind speed on high 10 m, wind direction on high 10 m, wind speed [900 mb], wind direction [900 mb], relative humidity, cloud cover total, convective available potential energy (CAPE) [180-0 mb above gnd], sunshine duration, soil moisture [0-10 cm down], evapotranspiration and mean sea level pressure (MSL) [26-29]. The dataset contains 52632 values for 6 years, separated in 42105 samples for training process, and 10527 samples for testing process. The dataset is split up into train and test subsets with an 80:20 ratio according to the Pareto principle; the learning model uses 80% of the dataset for training and 20% (test subset) for the solar radiation prediction [30].

The weather classification algorithm, Support Vector Machine (SVM) and solar panel output prediction algorithm are nonlinear models [23]. the prediction accuracy is significantly reduced if these data are directly used as the input variables. The data normalization is required, it will extract the small range for same data, with range limited between 0 and 1 [24-26]. It can be calculated as follows:

$$x_n = \frac{x_{in} - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Where $x_{in}$ is the initial, $x_n$ is the normalized input data, and $x_{max}$ and $x_{min}$ are the input data's minimum and maximum values, respectively.

In figure 2 the y axis shows the normalized values of the humidity on 2 m elevation corrected during 6 years from Basel site, the measurements were taken for full duration of the day and measured at 1- hour intervals.

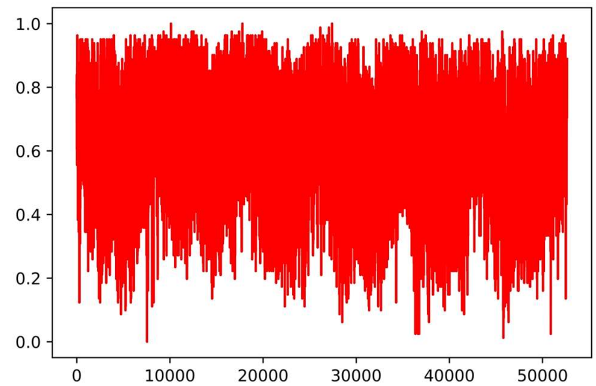


Fig. 2 Basel Relative Humidity [2 m] For 6 years

Figure 3 shows the normalized values of the Wind Speed at 900 mb corrected during 6 years from Basel site. The measurements taken for full duration of the day and measured at 1-hour intervals. The y axis shows the normalized values of the Wind Speed.

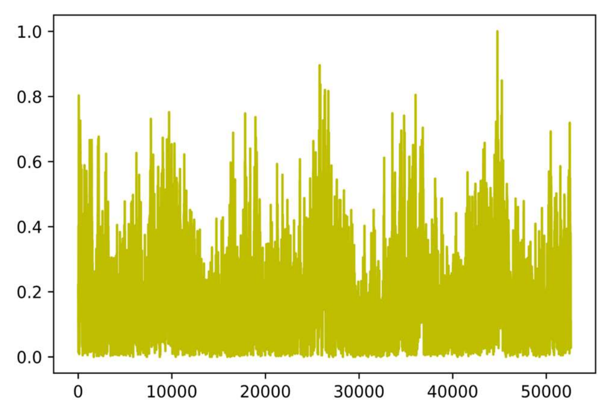


Fig. 3 Basel Wind Speed [900 mb] For 6 years

Figure 4 shows the convective available potential energy (CAPE) [180-0 mb above ground] corrected during 6 years from Basel site the measurements taken for full duration of the day and measured at 1-hour intervals. the y axis shows the normalized values of the (CAPE).

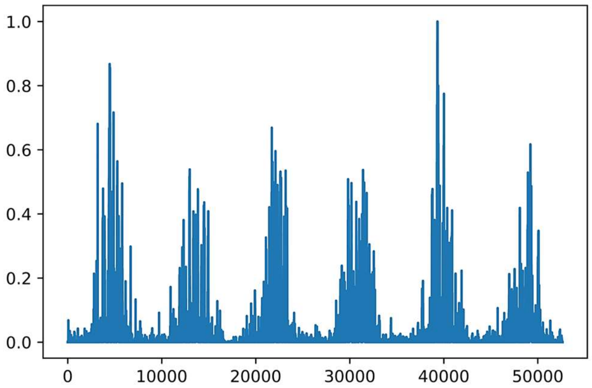


Fig. 4 Basel CAPE [180-0 mb above gnd] For 6 years

In figure 5, the x axis shows the samples of measurements for 6 years and y axis show the normalized values of the MSL pressure**.** The MSL pressure values are collected during 6 years from Basel site the measurements for full duration of the day and measured at 1-hour intervals.

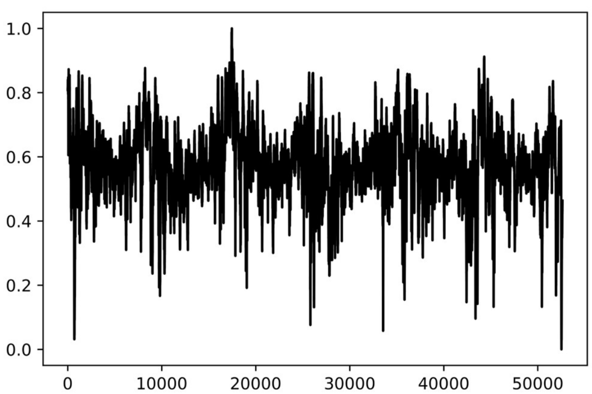


Fig.5 Basel Mean Sea Level Pressure for 6 years

# 3. The Pearson Correlation Coefficient (PCC)

When an Artificial Neural Network (ANN) model with a strong nonlinear fitting function is used to predict solar energy output, then selecting ANN's input variables will be the key issue [27]. In case of the coexistence of multiple meteorological factors, it is important to identify the meteorological factors with a greater impact on solar power output. The PCC method is a very common method for main feature extraction [28]. PCC is a measure of linear correlation between two sets of data. It is the ratio between the covariance of two variables and the product of their standard deviations; thus, it is essentially a normalized measurement of the covariance, such that the result always has a value between −1 and 1.

$$corr = \frac{\sum_{k=1}^{m}(s_k-\bar{s})}{\sqrt{\sum_{k=1}^{m}(s_k-\bar{s})^2}\sqrt{\sum_{k=1}^{m}(t_k-\bar{t})^2}} \quad (3)$$

where m is the sample size, $s_k$ , $t_k$ are the individual sample points indexed with *k* the sample point and *s, t* is the average value of S and T [29] .

The correlation coefficient technique shows the most features effected with irradiation forecasting and that will help for our aim to provide the highest accuracy of forecasting with our model [30-33].

Figure 6 shows all possible correlations between the 16 features and irradiation, the most correlation with irradiation is evapotranspiration with 0.89 correlation, then temperature and sunshine duration with 0.68, soil temperature with 0.52, temperature at 2 meters with 0.5, them the correlation start decrees like CAPA with 0.18, wind speed with 0.041, wind direction with 0.014, pressure with -0.018, soil moisture with -0.16, cloud cover with -0.25, humidity with -0.62, precipitation with -0.093.

# 4. Accuracy Evaluation

The most common forecasting indices are root mean squared error (RMSE) and mean square error (MSE) as given in equations (4) and (5), respectively [34-35]. They are used to evaluate the prediction performance of the solar radiation; they are an excellent general-purpose error metric for numerical predictions. However, RMSE is more robust since it is less sensitive to extreme values than MSE. The error between predicted and actual values in the test set is calculated using these formulae. Actual and predicted values are denoted by Y and X, respectively

$$MSE = \sqrt{\left(\frac{1}{N}\cdot\sum_{n=1}^{N}(Y-X)^2\right)} \quad (4)$$

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\cdot\sum_{\mathrm{n}=1}^{\mathrm{N}}(\mathrm{Y}-\mathrm{X})^2 \quad (5)$$

The random number seed is usually fixed to ensure the reproducibility of the results. Using suitable number for modeling with a neural network to load the data set as pandas' data frame by extracting the Numpy array from data frame, then getting the floating-point values by converting the integer values from Numpy array [36-37].

The sequence of the numbers is very important for time series data. Using a simple technique, the ordered data set are divided into train and test datasets with 80% of the observations suitable for training and the remaining 20% suitable for testing [38-39]. The LSTM model is built for this forecasting, with 3 hidden layers selected. By 'earlystopping', LSTM can avoid over fitting with 50 epochs using 200 neurons with 'relu' activation in first hidden layer, 100 neurons with 'relu' activation in the second hidden layer, and 50 neurons with' relu 'activation in the last hidden layer. then single output layer with 'sigmoid' activation [40].

# 5. Results

In this paper, LSTM learning models are used to predict the amount of solar radiation available. The data sets for 6 years contained about 16 weathers measurements. The PCC is used to determine the most measurements affecting irradiation forecasting. In the first step, 6 features that normally applied in previous research are used to predict the irradiation. In the second step, more features with different irradiation correlation are added until we use all features to predict the irradiation. The RMSE and MSE are calculated each time. The process is repeated twice to confirm the results.

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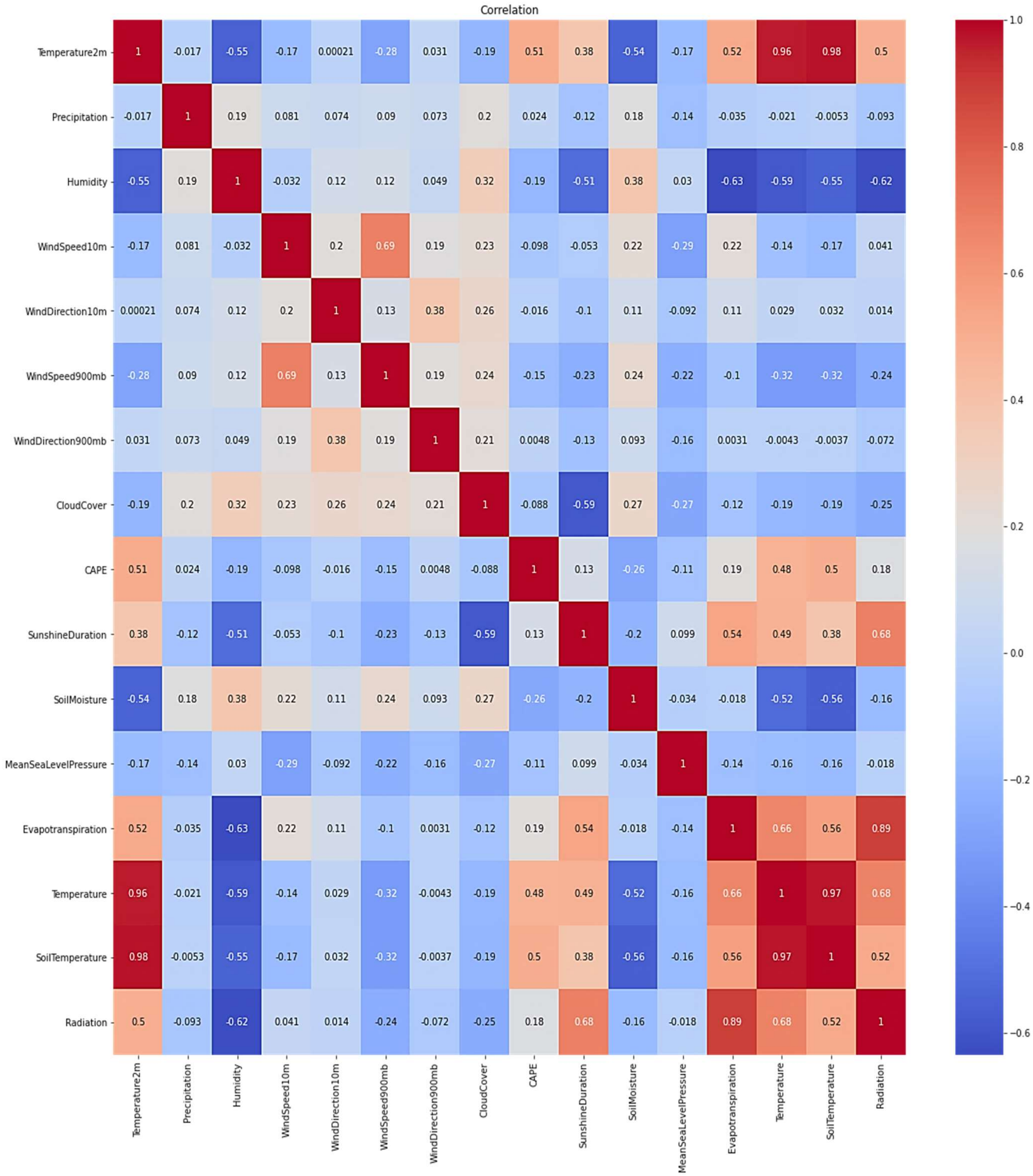


Fig.6 correlation coefficient heatmap

It is clear from the figure 6 that the correlations between the 16 features and irradiation may vary from small values up to values near to one, the most correlation with irradiation is evapotranspiration with 0.89 correlation. There are very interesting results like the correlation of evapotranspiration with soil temperature, it is 0.59 and with temperature 0.66.

The results of RMSE and MSE show that there is a significant impact of some of the features that have been introduced with the participation of irradiation for the forecasting process, this affects the accuracy of the forecasting process. The RMSE decreases when the 16 features are used for forecasting.

Table 1 presents the experiments that are conducted to calculate the RMSE and MSE.

TABLE 1 THE ACCURACY RESULT OF FORECASTING

| % Training | Layers | Datasets (type) | MSE | RMSE |
|---|---|---|---|---|
| 80% | 200<br>100<br>50 | Full day<br>6 years<br>Real time<br>6 Features | 0.03160809 | 0.1777866 |
| 80% | 200<br>100<br>50 | Full day<br>6 years<br>Real time<br>11 Features | 0.00397981 | 0.0630857 |
| 80% | 200<br>100<br>50 | Full day<br>6 years<br>Real time<br>14 Features | 0.00188 | 0.0433988 |
| 80% | 200<br>100<br>50 | Full day<br>6 years<br>Real time<br>16 Features | 0.00125388 | 0.0354102 |

# 6. Conclusions

This work presents forecast solar energy radiation using LSTM model. The model processed meteorological data for the last 6 years from the Meteobleu site. Many new factors are considered in our study. The PCC is applied to identify the most effective factors correlated with solar radiation to facilitate the training process.

In this study, the results clearly show that there are some atmospheric factors have greater effect on the forecasting process than other factors. Considering these differences will greatly improve the accuracy of the forecasting process. some of these important weather factors are the evapotranspiration and soil temperature. The study affirms that the LSTM model is superior for solar radiation forecasting when the PCC is not high.

## *References*

[1] J. D. de Guia, R. S. Concepcion, H. A. Calinao, J. Alejandrino, E. P. Dadios and E. Sybingco, "Using Stacked Long Short Term Memory with Principal Component Analysis for Short Term Prediction of Solar Irradiance based on Weather Patterns," 2020 IEEE Region 10 Conference (TENCON), 2020, pp. 946-951, doi: 10.1109/TENCON50793.2020.9293719.

[2] X. Wang, B. Gao & X. S. "Wang, Investigating the ability of deep learning on actual evapotranspiration estimation in the scarcely observed region", Journal of Hydrology, 607, 2022.

[3] A. Muhammad, J. M. Lee, S. W. Hong, S. J. Lee and E. H. Lee, "Deep Learning Application in Power System with a Case Study on Solar Irradiation Forecasting," 2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), 2019, pp. 275-279, doi: 10.1109/ICAIIC.2019.8668969.

[4] A. Al-Odienat & K. Al-Maitah, "A New Wide Area Protection Scheme Based on the Phase Angles of the Sequence Components", Electric Power Components and Systems, Volume 49, Issue 4-5, 2021, pp. 504-516.

[5] A. Al-Odienat & K. Al-Maitah, "A New Wide Area Protection Scheme Based on the Phase Angles of the Sequence Components, Electric Power Components and Systems, 49:4-5, 504- 16, DOI: 10.1080/15325008.2021.1971335.

[6] A. Al-Odienat and K. Al-Maitah, "Local Decision Module for a more Reliable Wide Area Protection Scheme, "International Journal of Innovative Computing, Information and Control, (ICIC) International, Volume 17, Number 2, 2021.

[7] A. Azadeh, S. Ghaderi, & S. Sohrab khani, "Forecasting electrical consumption by integration of Neural Network, time series and ANOVA", Applied Mathematics and Computation, 186(2), 2007, pp. 1753–1761. https://doi.org/10.1016/j.amc.2006.08.094.

[8] A. Al-Odienat, et al. "Low-Frequency Oscillation Analysis for Dynamic Performance of Power Systems" , 12th International Renewable Engineering Conference (IREC), IEEE, 2021.

[9] B. Pinte, M. Quinlan, A. Yoon, K. Reinhard and P. W. Sauer, "A one-phase, distribution-level phasor measurement unit for post-event analysis," *2014 Power and Energy Conference at Illinois (PECI)*, 2014, pp. 1-7, doi: 10.1109/PECI.2014.6804575.

[10] M. Almomani, et al. "The Impact of Wind Generation on Low-Frequency Oscillation in Power Systems." 2021 IEEE PES/IAS PowerAfrica. IEEE, 2021.

[11] Hua, Chi, et al. "Short-Term Power Prediction of Photovoltaic Power Station Based on Long Short-Term Memory-Back-Propagation", International Journal of Distributed Sensor Networks, 2019, doi:10.1177/1550147719883134.

[12] Gensler, J. Henze, B. Sick, and N. Raabe, "Deep Learning for solar power forecasting - An approach using Auto Encoder and LSTM Neural Networks, " IEEE Int. Conf. Syst. Man, Cybern. SMC 2016 - Conf. Proc., 2017, pp. 2858–2865.

[13] C. N. Obiora, A. Ali and A. N. Hasan, "Estimation of Hourly Global Solar Radiation Using Deep Learning Algorithms," 2020 11th International Renewable Energy Congress (IREC), 2020, pp. 1-6, doi: 10.1109/IREC48820.2020.9310381.

[14] K. Al-Maitah, A. Al-Odienat, "Wide Area Protection Scheme for Active Distribution Network Aided μPMU," 7th Annual IEEE PES/IAS PowerAfrica Conference (PAC 2020), 2020, pp. 1-5.

[15] H. Fraihat, A. Almbaideen,. A. Al-Odienat, B. Al-Naami, R. De Fazio, P. Visconti, "Solar Radiation Forecasting by Pearson Correlation Using LSTM Neural Network and ANFIS Method: Application in the West-Central Jordan", Future Internet 2022, *14*, 79. https://doi.org/10.3390/fi14030079

[16] C. M. Huang, Y. C. Huang, et al. "A hybrid method for one day ahead hourly forecasting of PV power output", Proceedings of the 2014 9th IEEE Conference on Industrial Electronics and Applications, ICIEA 2014, 5(3), 526–531. https://doi.org/10.1109/ICIEA.2014.6931220.

[17] I. Sansa, S. Missaoui, Z. Boussada, N. M. Bellaaj, E. M. Ahmed, and Ismail AM, Ramirez-Iniguez R, Asif M, et al, "Progress of solar photovoltaic in ASEAN countries: a review", Renew Sustain Energy Rev., 2015; 48:399-412.

[18] A. Al-Odienat and K. Al-Maitah, "A modified Active Frequency Drift Method for Islanding Detection," 2021 12th International Renewable Engineering Conference (IREC), 2021, pp. 1-6, doi: 10.1109/IREC51415.2021.9427796.

[19] J. Zeng and W. Qiao, "Short-term solar power forecasting using a support vector machine,"Renew. Energy, vol.52, 2013, pp.118–127.

[20] K. M. Alawasa and A. I. Al-Odienat, "Power quality characteristics of residential grid-connected inverter of photovoltaic solar system," 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), 2017, pp. 1097-1101.

[21] A. A. Ahmed, R. C. Deo, Q. Feng, A. Ghahramani, & L. Yang, "Hybrid deep learning method for a week-ahead evapotranspiration forecasting", Stochastic Environmental Research and Risk Assessment, 36(3), 2022, pp. 831-849.

[22] J. Han and W. -K. Park, "A Solar Radiation Prediction Model Using Weather Forecast Data and Regional Atmospheric Data," 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) 2018, pp. 2313-2316, doi: 10.1109/PVSC.2018.8547750.

[23] Jason Brownlee, Long Short-Term Memory Networks With Python (book), 2017.

[24] L. F. J. Alvarez, S. R. González, A. D. López, D. A. H. Delgado, R. Espinosa and S. Gutiérrez, "Renewable Energy Prediction through Machine Learning Algorithms," 2020 IEEE ANDESCON, 2020, pp. 1-6, doi: 10.1109/ANDESCON50619.2020.9272029.

[25] M. Orabi, ‘‘PV power forecasting using different artificial neural networks strategies, ’’in Proc. Int. Conf. Green Energy, Mar. 2014, pp.54–59.

[26] D. Lima, M. Ferreira, & A. Silva, "Machine Learning and Data Visualization to Evaluate a Robotics and Programming Project Targeted for Women", J Intell Robot Syst 103, 4 (2021). https://doi.org/10.1007/s10846-021-01443-w

[27] M. Zou, D. Fang, G. Harrison and S. Djokic, "Weather Based Day-Ahead and Week-Ahead Load Forecasting using Deep Recurrent Neural Network," 2019 IEEE 5th International forum on Research and Technology for Society and Industry (RTSI), 2019, pp. 341-346, doi: 10.1109/RTSI.2019.8895580.

[28] M. A. Munir, A. Khattak, K. Imran, A. Ulasyar and A. Khan, "Solar PV Generation Forecast Model Based on the Most Effective Weather Parameters," 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), 2019, pp. 1-5, doi: 10.1109/ICECCE47252.2019.8940664.

[29] Z. Zhou, L. Liu and N. Y. Dai, "Day-ahead Power Forecasting Model for a Photovoltaic Plant in Macao Based on Weather Classification Using SVM/PCC/LM-ANN," 2021 IEEE Sustainable Power and Energy Conference (iSPEC), 2021, pp. 775-780, doi: 10.1109/iSPEC53008.2021.9735777.

[30] N. Sharma, P. Sharma, D. Irwin and P. Shenoy, "Predicting solar generation from weather forecasts using machine learning," 2011 IEEE International Conference on Smart Grid Communications (SmartGridComm), 2011, pp. 528-533, doi: 10.1109/SmartGridComm.2011.6102379.

[31] P. Nejedly, F. Plesinger, I. Viscor, J. Halamek and P. Jurak, "Prediction of Sepsis Using LSTM Neural Network With Hyperparameter Optimization With a Genetic Algorithm," 2019 Computing in Cardiology (CinC), 2019, pp.1-4, doi: 10.23919/CinC49843.2019.9005911.

[32] R. Srivastava, A. N. Tiwari , V. K. Giri , "Prediction of Electricity Generation using Solar Radiation Forecasting Data", International Conference on Electrical and Electronic Engineering (ICE3-2020), 2020.

[33] K. Al-Maitah, A. Al-Odienat, "The Improvement of Weighted Least Square State Estimation Accuracy Using Optimal PMU Placement", Wseas Transactions on Power Systems, Vol. 15, 2020, pp. 1-7.

[34] Tauseef Gulrez, Abdullah Al-Odienat, "A New Perspective on Principal Component Analysis using Inverse Covariance", International Arab Journal of Information Technology (IAJIT), Vol. 12, Issue 1, 2015.

[35] L. Tarawneh, A. Kasasbeh, A. Al-Odienat and O. Radaideh, "The Accuracy Evaluation of State Estimation in Smart Power Grids," 2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), 2020, pp. 1-4.

[36] R. N. Senapati, N. C. Sahoo and S. Mishra, "Convolution integral based multivariable grey prediction model for solar energy generation forecasting," *2016 IEEE International Conference on Power and Energy (PECon)*, 2016, pp. 663-667, doi: 10.1109/PECON.2016.7951643.

[37] M. Raza, M. Nadarajah, C. Ekanayake, On recent advances in PV output power forecast, Solar Energy, Volume 136, 2016, pp.125-144.

[38] S. Tiwari, R. Sabzehgar and M. Rasouli, "Short Term Solar Irradiance Forecast based on Image Processing and Cloud Motion Detection," *2019 IEEE Texas Power and Energy Conference (TPEC)*, 2019, pp. 1-6, doi: 10.1109/TPEC.2019.8662134.

[39] W. Bendali, I. Saber, B. Bourachdi, M. Boussetta and Y. Mourad, "Deep Learning Using Genetic Algorithm Optimization for Short Term Solar Irradiance Forecasting," 2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS), 2020, pp. 1-8, doi: 10.1109/ICDS50568.2020.9268682.

[40] A. Al-Odienat, A. Al-Mbaideen, "Optimal length determination of the moving average filter for power system applications", International journal of innovative computing, information & control: IJICIC, January 2015, 11(2): pp. 691-705.