2015 IEEE 14th International Conference on Machine Learning and Applications

Multi-Period Prediction of Solar Radiation Using ARMA and ARIMA Models

Ilhami Colak[1], Mehmet Yesilbudak[2], Naci Genc[3], Ramazan Bayindir[4]

[1]Istanbul Gelisim University, Faculty of Engineering and Architecture, Department of Mechatronic Engineering, 34315, Istanbul, Turkey.
[2]Nevsehir Haci Bektas Veli University, Faculty of Engineering and Architecture, Department of Electrical and Electronics Engineering, 50300, Nevsehir, Turkey.
[3]Yuzuncu Yil University, Faculty of Engineering and Architecture, Department of Electrical and Electronics Engineering, 65080, Van, Turkey.
[4]Gazi University, Faculty of Technology, Department of Electrical and Electronics Engineering, 06500, Ankara, Turkey.
icolak@gelisim.edu.tr, myesilbudak@nevsehir.edu.tr, nacigenc@yyu.edu.tr, bayindir@gazi.edu.tr

***Abstract*—Due to the variations in weather conditions, solar power integration to the electricity grid at a high penetration rate can cause a threat for the grid stability. Therefore, it is required to predict the solar radiation parameter in order to ensure the quality and the security of the grid. In this study, initially, a 1-h time series model belong to the solar radiation parameter is created for multi-period predictions. Afterwards, autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models are compared in terms of the goodness-of-fit value produced by the log-likelihood function. As a result of determining the best statistical models in multi-period predictions, one-period, two-period and three-period ahead predictions are carried out for the solar radiation parameter in a comprehensive way. Many feasible comparisons have been made for the solar radiation prediction.**

Keywords—Solar radiation; multi-period prediction; ARMA; ARIMA

I. INTRODUCTION

According to the *Renewables Global Status Report 2015* [1], the solar photovoltaic capacity in the world has reached to 177 GW in 2014. Besides, it is projected to be 1721 GW by 2030 [2]. So, solar energy is one of the most promising renewable energy sources and the solar power integration in electricity grids is constantly increasing all over the world [3, 4]. However, solar power shows high variations due to the intermittency nature of solar energy [5]. For this reason, the generation schedules are mostly planned for hourly, daily, weekly, etc. in order to ensure reliable operation and economic dispatch of solar power systems [6]. As a result, it is indispensible to predict the solar radiation parameter in solar power plants. Since, the solar radiation parameter is considered as the most significant indicator for the solar energy conversion and for the sizing of stand-alone solar systems [7, 8]. The world map of global horizontal irradiation is shown in Figure 1.

Several authors have proposed various models for solar radiation prediction in the literature. *Yadav et al.* and *Qazi et al.* reviewed artificial neural network techniques for solar radiation prediction and the prediction accuracy was found to be dependent on input parameter combinations, training algorithms and architecture configurations [9, 10]. *Chen et al.* investigated the feasibility of support vector machines in order to predict solar radiation using air temperatures and the impacts of inputs and kernel functions on the prediction accuracy were determined [11]. *Bhardwaj et al.* analyzed the inter-dependence of solar radiation and other meteorological parameters by the generalized fuzzy model and short-term prediction assessments were made under different climatic conditions [12]. *Salcedo-Sanz et al.* evaluated the effectiveness of temporal Gaussian process regression for the estimation of daily global solar radiation and a time-based composite covariance was presented in order to account for the relevant seasonal variations [13]. *Licciardi et al.* used the nonlinear principal component analysis to reduce the dimensionality of spatiotemporal input vector and improved the forecasting of ground horizontal irradiance from satellite-based images [4]. *Wu et al.* proposed a multi-model framework for short-term prediction of solar radiation time series and the nonlinear relationship of different patterns were modeled for capturing the general trend of whole series [14]. *Fatemi et al.* utilized the zenith angle along with exponentially weighted recursive least squares method and the seasonal/daily effects in solar radiation data were removed [15]. *Huang et. al.* detected the solar irradiance fluctuations from cloud movements and the solar power volatility was mitigated in electric grids [16]. In addition, numerous hybrid methods such as grey-based support vector regression [17], wavelet-based recurrent neural networks [7], wavelet-based support vector machines [18], Kalman-based radial basis functions [19], Kalman-based neuro-fuzzy inference systems [20] etc. were employed for solar radiation prediction in the literature. Apart from these hybrid methods, many numerical weather prediction models such as MM5 (Mesoscale Modeling) [21], GFS (Global Forecasting System) [22], WRF (Weather Research and Forecasting) [23], NAM (North American Mesoscale) [24], ECMWF (European Centre for Medium-Range Weather Forecasts) [25], etc. were also utilized for solar radiation prediction in the literature.

The main objective of this study is to analyze multi-period predictions of solar radiation using ARMA and ARIMA models in detail. As a distinct contribution to the literature, not only mean absolute errors and mean absolute percentage errors but also improvement percentages of prediction results are revealed in multi-period predictions. Since, most of studies in the literature ignore the persistence comparison that is

978-1-5090-0287-0/15 $31.00 © 2015 IEEE
DOI 10.1109/ICMLA.2015.33

employed as a reference analysis for conducting a proper benchmark test. In addition, many reasonable comparisons have been realized among ARMA and ARIMA models in terms of their prediction accuracy.

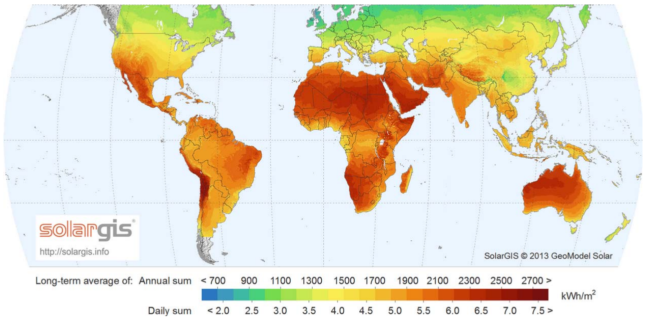

Fig. 1. The world map of global horizontal irradiation [26]

II. Multi-Period Prediction Approach

In this study, autoregressive moving average and autoregressive integrated moving average models have been used for multi-period predictions. ARMA and ARIMA models are applied to stationary and non-stationary stochastic time series data, respectively and ARIMA process is an ARMA process for the differenced time series [27]. The detailed theoretical instructions about ARMA and ARIMA models are included in [28]. The Log-Likelihood Function (LLF) has been employed for the goodness-of-fit determination among ARMA and ARIMA models in this paper. More statistical formulations about the LLF are found in [29]. In the log-likelihood criterion, the closer the log-likelihood value is to zero, the more likely it is that the parameters could produce the observed data [30]. The LLF values belong to ARMA and ARIMA models are given in Table I. It is obvious that ARMA(1,2) and ARIMA(2,2,2) models achieved the optimum log-likelihood values in here.

Table I. LLF Values of ARMA and ARIMA Models

Statistical Model	LLF Value	Statistical Model	LLF Value
ARMA(1,1)	-97.95	ARIMA(1,2,1)	-68.63
ARMA(1,2)	*-96.82*	ARIMA(2,1,1)	-82.00
ARMA(2,1)	-98.84	ARIMA(1,2,2)	-68.14
ARMA(2,2)	-97.77	ARIMA(2,1,2)	-81.40
ARIMA(1,1,1)	-81.94	ARIMA(2,2,1)	-68.12
ARIMA(1,1,2)	-81.31	*ARIMA(2,2,2)*	*-68.08*

In addition to the mentioned specifications above, mean absolute error (MAE) and mean absolute percentage error (MAPE) have been utilized for measuring the prediction accuracy of ARMA(1,2) and ARIMA(2,2,2) models in this study. These error metrics are given in Equation (1) and (2) by assuming n as the number of test data, y_i as the observed solar radiation and $\acute{y}_i$ as the predicted solar radiation [31]. Besides, ARMA(1,2) and ARIMA(2,2,2) models have been compared with the persistence model in terms of the improvement percentage of prediction results. Since, the persistence comparison is made as a reference analysis for proper benchmark tests in the literature [32]. As well, the last three observations have been used as the most important predictors in each multi-period prediction approach. It should be noted that other ARMA and ARIMA models that are not included in Table I are not employed owing to their high errors.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} |\acute{\mathrm{y}}_{\mathrm{i}} - \mathrm{y}_{\mathrm{i}}| \tag{1}$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\left|\frac{\acute{\mathrm{y}}_{\mathrm{i}} - \mathrm{y}_{\mathrm{i}}}{\mathrm{y}_{\mathrm{i}}}\right|\right) \times 100 \tag{2}$$

In multi-period predictions, a 1-h time series model is created for the solar radiation parameter. Figure 2 shows the concept of a multi-period prediction with the 1-h time series model [33, 34]. In Figure 2(a), the mean hourly solar radiation at the subsequent interval of [03:00, 04:00) is predicted using the mean observed hourly solar radiation at the intervals of [00:00, 01:00), [01:00, 02:00) and [02:00, 03:00). In Figure 2(b), the mean hourly solar radiation at the subsequent interval of [04:00, 05:00) is predicted using the mean observed hourly solar radiation at the intervals of [01:00, 02:00), [02:00, 03:00) and the previously predicted solar radiation at the interval of [03:00, 04:00). In Figure 2(c), the mean hourly solar radiation at the subsequent interval of [05:00, 06:00) is predicted using the mean observed hourly solar radiation at the interval of [02:00, 03:00) and the previously predicted solar radiation at the intervals of [03:00, 04:00), [04:00, 05:00).

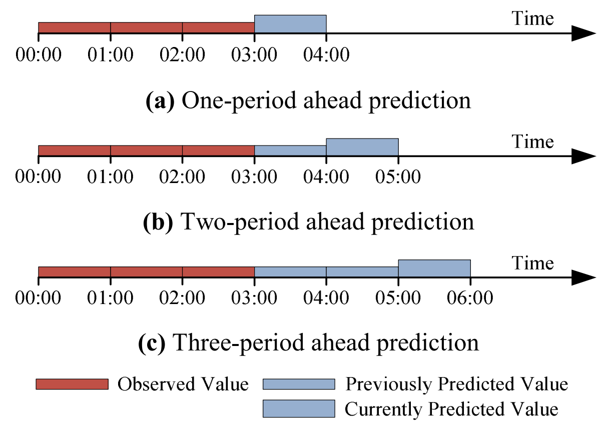

Fig. 2. The concept of a multi-period prediction with the 1-h time series model

III. Multi-Period Prediction Results

In this section, it should be noted that one-, two- and three-period ahead predictions represent the 1-h, 2-h and 3-h ahead solar radiation predictions, respectively. In addition, the starting time of the prediction process is different from each other in the conducted prediction analyses. Since, the solar radiation values averaged at the intervals of [00:00, 00:01), [01:00, 02:00) and [02:00, 03:00] are equal to zero. So, the prediction process starts at the time that has the first positive value measured for the solar radiation parameter and it continues up to the time that has the first zero value measured for the solar radiation parameter. As mentioned in the previous section, ARMA(1,2) and ARIMA(2,2,2) models are only considered in multi-period predictions for the reason of achieving optimum log-likelihood values.

A. One-Period Ahead Prediction Results

One-period ahead prediction results and errors for solar radiation parameter are illustrated in Figures 3 and 4, respectively. The MAPEs of ARMA(1,2) and ARIMA(2,2,2) models are found as 18.11% and 7.87%, respectively. However, it is obtained as 38.44% for the persistence model. In case of making a benchmark test with respect to the persistence model, ARMA(1,2) and ARIMA(2,2,2) models have improved the prediction results at the rates of 52.89% and 79.53%, respectively. From another perspective, it is obvious that ARIMA(2,2,2) model has outperformed ARMA(1,2) model in terms of the one-period ahead prediction of solar radiation parameter. In addition, the mean absolute error of ARIMA(2,2,2) model is acquired as 37.95 W/m^2. The absolute percentage errors of ARMA(1,2) and ARIMA(2,2,2) models in one-period ahead prediction are listed in Table II.

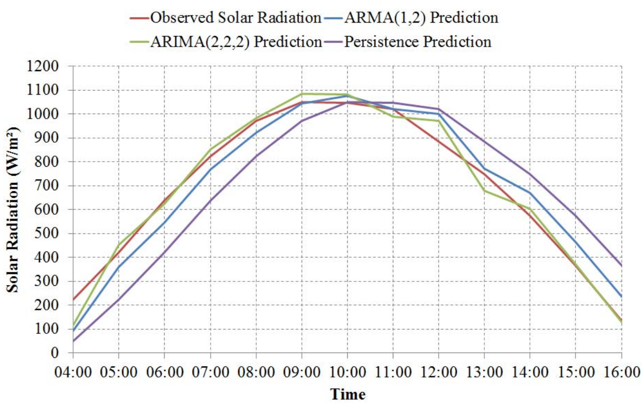

Fig. 3. One-period ahead prediction results for solar radiation

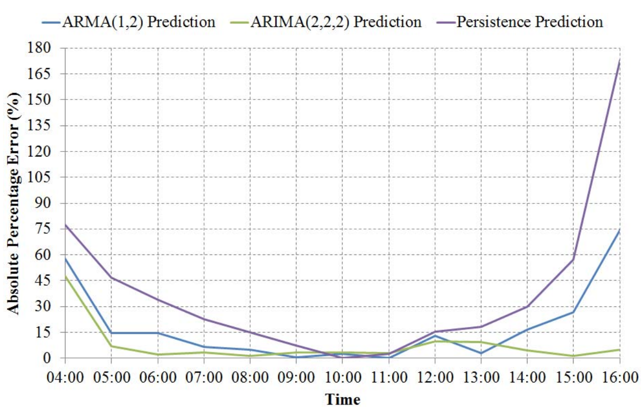

Fig. 4. One-period ahead prediction errors for solar radiation

TABLE II. ABSOLUTE PERCENTAGE ERRORS OF ARMA(1,2) AND ARIMA(2,2,2) MODELS IN ONE-PERIOD AHEAD PREDICTION

Time	ARMA(1,2)	ARIMA(2,2,2)	Time	ARMA(1,2)	ARIMA(2,2,2)
04:00	57.65	47.71	11:00	0.10	3.16
05:00	14.45	7.08	12:00	12.93	9.93
06:00	14.60	2.29	13:00	3.15	9.34
07:00	6.78	3.40	14:00	16.48	4.77
08:00	4.89	1.36	15:00	26.58	1.39
09:00	0.52	3.45	16:00	74.56	5.11
10:00	2.73	3.34	17:00	-	-

B. Two-Period Ahead Prediction Results

Two-period ahead prediction results and errors for solar radiation parameter are depicted in Figures 5 and 6, respectively. ARMA(1,2) and ARIMA(2,2,2) models produce the MAPEs of 43.24% and 16.06%, respectively. Nonetheless, the persistence model gives it as 67.37%. In the stage of conducting a benchmark test against the persistence model, the improvement percentages for the prediction results have been achieved as 35.82% and 76.16% for ARMA(1,2) and ARIMA(2,2,2) models, respectively. Apart from these inferences, it is clear that ARIMA(2,2,2) model has surpassed ARMA(1,2) model in the two-period ahead prediction of solar radiation parameter. As well, ARIMA(2,2,2) model brings out the mean absolute error of 88.51 W/m^2. The absolute percentage errors of ARMA(1,2) and ARIMA(2,2,2) models in two-period ahead prediction are listed in Table III.

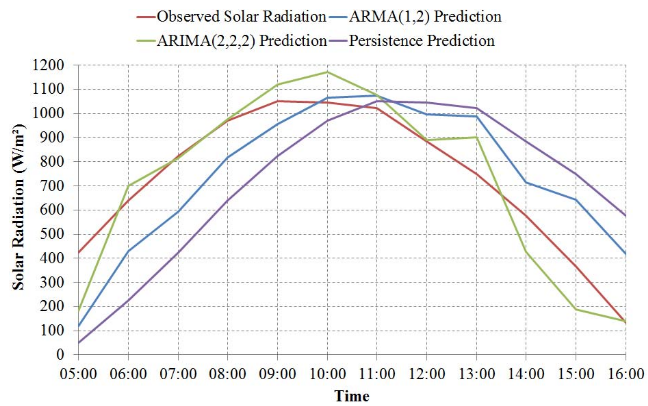

Fig. 5. Two-period ahead prediction results for solar radiation

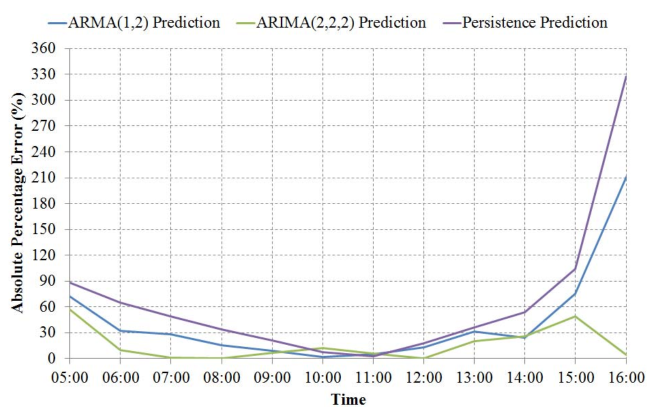

Fig. 6. Two-period ahead prediction errors for solar radiation

TABLE III. ABSOLUTE PERCENTAGE ERRORS OF ARMA(1,2) AND ARIMA(2,2,2) MODELS IN TWO-PERIOD AHEAD PREDICTION

Time	ARMA(1,2)	ARIMA(2,2,2)	Time	ARMA(1,2)	ARIMA(2,2,2)
04:00	-	-	11:00	5.16	5.52
05:00	71.88	56.99	12:00	12.71	0.69
06:00	32.57	9.58	13:00	31.84	20.36
07:00	28.02	1.09	14:00	24.17	26.00
08:00	15.71	0.54	15:00	75.23	48.80
09:00	9.02	6.63	16:00	210.86	4.48
10:00	1.75	12.11	17:00	-	-

C. Three-Period Ahead Prediction Results

Three-period ahead prediction results and errors for solar radiation parameter are picturized in Figures 7 and 8, respectively. Similar to the one-period and two-period ahead prediction results, ARIMA(2,2,2) model provides lower prediction errors than ARMA(1,2) and persistence models. MAPEs of them are determined as 32.07%, 71.67% and 92.81%, respectively. As a result of comparing ARMA(1,2) and ARIMA(2,2,2) models with the persistence model on the basis of the enhancement occurred in the prediction results, the improvement ratios have been accomplished as 22.78% and 65.45%, respectively. Besides, ARIMA(2,2,2) model have gave the mean absolute error of 172.07 W/m^2. The absolute percentage errors of ARMA(1,2) and ARIMA(2,2,2) models in three-period ahead prediction are listed in Table IV.

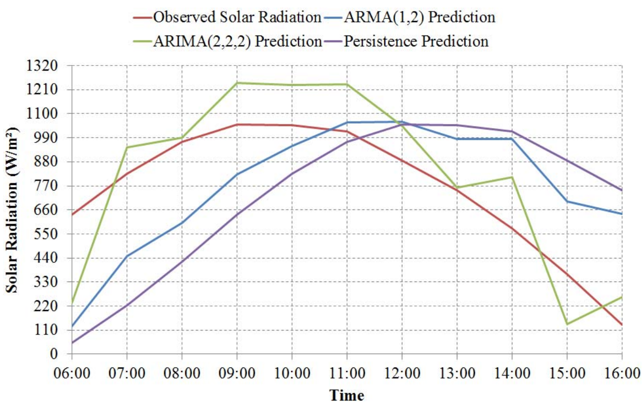

Fig. 7. Three-period ahead prediction results for solar radiation

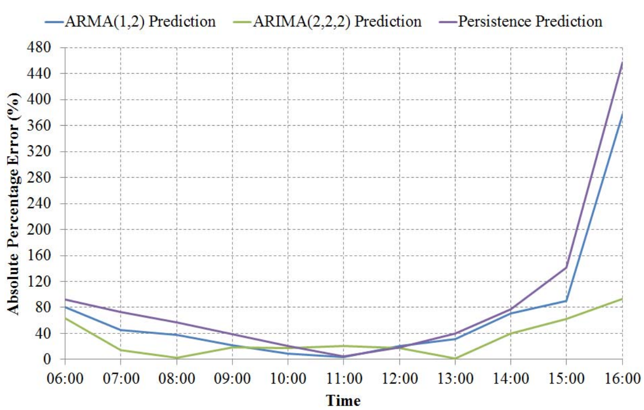

Fig. 8. Three-period ahead prediction errors for solar radiation

TABLE IV. ABSOLUTE PERCENTAGE ERRORS OF ARMA(1,2) AND ARIMA(2,2,2) MODELS IN THREE-PERIOD AHEAD PREDICTION

Time	ARMA(1,2)	ARIMA(2,2,2)	Time	ARMA(1,2)	ARIMA(2,2,2)
04:00	-	-	11:00	3.91	20.95
05:00	-	-	12:00	20.31	17.88
06:00	80.17	63.26	13:00	31.52	1.62
07:00	45.44	14.69	14:00	70.90	40.34
08:00	38.29	2.12	15:00	90.34	62.65
09:00	21.55	18.26	16:00	377.05	93.37
10:00	8.92	17.58	17:00	-	-

IV. CONCLUSIONS

In this study, ARMA and ARIMA models are employed for one-period, two-period and three-period ahead predictions of the solar radiation parameter. In case of comparing all of multi-period prediction results, ARIMA(2,2,2) model provides the lowest mean absolute percentage errors and leads to the largest improvement percentages. It is followed by ARMA(1,2) and persistence models in terms of the prediction performance, respectively. In other words, the persistence model shows the worst prediction accuracy in all of multi-period predictions. From a different perspective, it is revealed for persistence, ARMA(1,2) and ARIMA(2,2,2) models that the mean absolute percentage error increases and the improvement percentage decreases as the prediction period progresses. In addition, the first prediction errors are usually high in all of multi-period predictions for the reason that two of the first three important predictors equal to zero at the beginning of the prediction process.

In future studies, not only the solar radiation parameter but also air temperature and sunshine duration parameters should be considered for multi-time series and multi-time scale modeling.

REFERENCES

[1] Renewable Energy Policy Network for the 21st Century, Renewables 2015 Global Status Report. Available at: http://www.ren21.net/wp-content/uploads/2015/06/REN12-GSR2015_Onlinebook_low1.pdf, 06 August 2015.

[2] International Energy Agency, Technology Roadmap Solar Photovoltaic Energy 2014. Available at: https://www.iea.org/publications/freepublications/publication/TechnologyRoadmapSolarPhotovoltaicEnergy_2014edition.pdf, 06 August 2015.

[3] X. Xu, C. Hao, M. Bishop, M.J.S. Edmonds, J. Sember and J. Zhang "Development and planning of solar power in China", IEEE Power and Energy Society General Meeting, 1-5, 21-25 July 2013, Vancouver, BC.

[4] G.A. Licciardi, R. Dambreville, J. Chanussot and S. Dubost, "Spatiotemporal pattern recognition and nonlinear pca for global horizontal irradiance forecasting", IEEE geoscience and Remote Sensing Letters, vol. 12, no. 2, pp. 284-285, February 2015.

[5] M.D. Felice, M. Petitta and P.M. Ruti, "Short-term predictability of photovoltaic production over Italy", Renewable Energy, vol. 80, pp. 197-204, August 2015.

[6] J. Liu, W. Fang, X. Zhang and C. Yang, "An improved photovoltaic power forecasting model with the assistance of aerosol index data", IEEE Transactions on Sustainable Energy, vol. 6, no. 2, pp. 434-442, April 2015.

[7] G. Capizzi, C. Napoli and F. Bonanno, "Innovative second-generation wavelets construction with recurrent neural networks for solar radiation forecasting", IEEE Transactions on Neural Networks and Learning Systems, vol. 23, no. 11, pp. 1805-1815, November 2012.

[8] M. Fidan, F.O. Hocaoglu and O.N. Gerek, "Harmonic analysis based hourly solar radiation forecasting model", IET Renewable Power Generation, vol. 9, no. 3, pp. 218-227, 2015.

[9] A.K. Yadav and S.S. Chandel, "Solar radiation prediction using artificial neural network techniques: A review", Renewable and Sustainable Energy Reviews, vol. 33, pp. 772-781, May 2014.

[10] A. Qazi, H. Fayaz, A. Wadi, R.G. Raj, N.A. Rahim and W.A. Khan, "The artificial neural network for solar radiation prediction and designing solar systems: A systematic literature review", Journal of Cleaner Production, vol. 104, pp. 1-12, October 2015.

[11] J.L. Chen, H.B. Liu, W.Wu and D.T. Xie, "Estimation of monthly solar radiation from measured temperatures using support vector machines - A

case study", Renewable Energy, vol. 36, no. 1, pp. 413-420, January 2011.

[12] S. Bhardwaj, V. Sharma, S. Srivastava, O.S. Sastry, B. Bandyopadhyay, S.S. Chandel and J.R.P. Gupta, "Estimation of solar radiation using a combination of Hidden Markov model and generalized fuzzy model", Solar Energy, vol. 93, pp. 43-54, July 2013.

[13] S. Salcedo-Sanz, C. Casanova-Mateo, J. Muñoz-Marí and G. Camps-Valls, "Prediction of daily global solar irradiation using temporal gaussian processes", IEEE Geoscience and Remote Sensing Letters, vol. 11, no. 11, pp. 1936-1940, November 2014.

[14] J. Wu and C.K. Chan, "Prediction of hourly solar radiation with multi-model framework", Energy Conversion and Management, vol. 76, pp. 347-355, December 2013.

[15] S.A. Fatemi and A. Kuh, "Solar radiation forecasting using zenith angle", IEEE Global Conference on Signal and Information Processing, pp. 523-526, 3-5 December 2013, Austin, TX.

[16] H. Huang, J. Xu, Z. Peng, S. Yoo, D. Yu, D. Huang and H. Qin, "Cloud motion estimation for short term solar irradiation prediction", IEEE International Conference on Smart Grid Communications, pp. 696-701, 21-24 October 2013, Vancouver, BC.

[17] S.T. Sarena, K.L. Lian, T.H. Chen, T.D. Huang, K.S. Tung, Y. R. Chang, Y.D. Lee, Y.H. Ho, "Very short term solar irradiance prediction for a microgrid system in Taiwan based on hybrid of support vector regression and grey theory", IEEE 3rd International Conference on Electric Power and Energy Conversion Systems, pp. 1-6, 2-4 October 2013, Istanbul, Turkey.

[18] L. Lyu, M. Kantardzic and E. Arabmakki, "Solar irradiance forecasting by using wavelet based denoising", IEEE Symposium on Computational Intelligence for Engineering Solutions, pp. 110-116, 9-12 December 2014, Orlando, FL.

[19] L. Ciabattoni, M. Grisostomi, G. Ippoliti, S. Longhi and E. Mainardi, "On line solar irradiation forecasting by minimal resource allocating networks", 20th Mediterranean Conference on Control & Automation, pp. 1506-1511, 3-6 July 2012, Barcelona, Spain.

[20] M. Chaabene and M.B. Ammar, "Neuro-fuzzy dynamic model with Kalman filter to forecast irradiance and temperature for solar energy systems", Renewable Energy, vol. 33, no. 7, pp. 1435-1443, July 2008.

[21] M.A. Shamim, R. Remesan, M. Bray and D. Han, "An improved technique for global solar radiation estimation using numerical weather prediction", Journal of Atmospheric and Solar-Terrestrial Physics, vol. 129, pp. 13-22, July 2015.

[22] R.A. Verzijlbergh, P.W. Heijnen, S.R. Roode, A. Los and H.J.J. Jonker, "Improved model output statistics of numerical weather prediction based irradiance forecasts for solar power applications", Solar Energy, vol. 118, pp. 634-645, August 2015.

[23] J.A. Ruiz-Arias, S. Quesada-Ruiz, E.F. Fernández and C.A. Gueymard, "Optimal combination of gridded and ground-observed solar radiation data for regional solar resource assessment", Solar Energy, vol. 112, pp. 411-424, February 2015.

[24] P. Mathiesen, J.M. Brown and J. Kleissl, "Geostrophic wind dependent probabilistic irradiance forecasts for coastal California", IEEE Transactions on Sustainable Energy, vol. 4, no. 2, pp. 510-518, April 2013.

[25] E. Lorenz, J. Hurka, D. Heinemann and H.G. Beyer, "Irradiance forecasting for the power prediction of grid-connected photovoltaic systems", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 2, no. 1, pp. 2-10, March 2009.

[26] SolarGIS © 2015 GeoModel Solar. Available at: http://solargis.info/doc/free-solar-radiation-maps-GHI, 06 August 2015.

[27] I. Colak, G. Fulli, S. Sagiroglu, M. Yesilbudak, C.F. Covrig, "Smart grid projects in Europe: Current status, maturity and future scenarios", Applied Energy, vol. 152, pp. 58-70, August 2015.

[28] P.J. Brockwell and R.A. Davis, Time Series: Theory and Methods, Springer, New York, USA, pp. 77-110, 273-326.

[29] Log-Likelihood Function. Available at: http://www.spiderfinancial.com/support/documentation/numxl/reference-manual/appendix/appendix -a, 06 August 2015.

[30] F.C. Pampel, Logistic Regression: A Primer, Sage Publications, California, USA, pp. 43-45.

[31] M. Yesilbudak, S. Sagiroglu and I. Colak, "A new approach to very short term wind speed prediction using k-nearest neighbor classification", Energy Conversion and Management, vol. 69, pp. 77-86, May 2013.

[32] M. Yesilbudak, S. Sagiroglu and I. Colak, "A novel intelligent approach for yaw position forecasting in wind energy systems", International Journal of Electrical Power & Energy Systems, vol. 69, pp. 406-413, July 2015.

[33] A. Kusiak, H. Zheng and Z. Song, "Short-term prediction of wind farm power: a data mining approach", IEEE Transactions on Energy Conversion, vol. 24, no. 1, pp. 125-136, March 2009.

[34] A. Kusiak and Z. Zhang, "Short-Horizon prediction of wind power: A data-driven approach", IEEE Transactions on Energy Conversion, vol. 25, no. 4, pp. 1112-1122, December 2010.