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Research Article

A weather-based forecasting system for the solar power plants in the Konya region

Cankat YAVUZ[1], Ahmet Reha BOTSALI[2,*]

[1]Peren Education and Consulting Ltd. Sti. Konya, Turkey
[2]Department of Industrial Engineering, Necmettin Erbakan University Konya, Turkey

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ABSTRACT

Increasing energy demand along with decreasing environmental resources necessitates looking for alternative energy sources. With this respect, solar power has gained considerable importance over recent years. This study analyzes the forecasting problem for the amount of electric power generated by solar power plants. The amount of electric power generated by solar power plants is not constant and changes depending on several variables such as the weather conditions, seasonal effects, t ype of solar panel, etc. On the other hand, to meet the electric power demand and minimize electric transfer cost, forecasting the electric power generated by solar power plants is critical. We test several neural network models with various weather-related input parameters. Among these parameters, we choose the most promising ones (radiation, humidity, hour, month) for further analysis to forecast the electric power generated by solar power plants located in the Konya region. Our test results over the past data show that it is possible to forecast the electric power generated by solar panels in the Konya region with less than 5% error.

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INTRODUCTION

Due to environmental issues, the importance of renewable energy resources is increasing rapidly. The limitations on fossil-based fuels and their negative impact on the environment direct the world to make the most out of renewable energy resources. Many countries attempt to increase the share of renewable energy in their energy consumption and creative ideas emerge to make use of solar energy as much as possible [10],[16]. In parallel to this, Turkey also has a set of incentive regulations to encourage the use of solar power within the country. These regulations are given under the title "Renewable Energy Resources Support Mechanism (YEKDEM)" and according to YEKDEM the forecast of short-term renewable energy generation, especially for solar power, has gained considerable importance.

***Corresponding author.**
*E-mail address: rbotsali@erbakan.edu.tr

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In several regions of Turkey, the potential for solar power generation is seriously analyzed [4],[6].

The need for the accurate forecast of power generation mainly depends on the planning of power distribution and also the pricing issues for the extra power that is going to be procured from local power suppliers. In Turkey, there are several regions and in each region the control of power distribution is given to a private company based on a contract by the state [1]. In this study, we focus on the Konya region which is in mid Anatolia. In Konya, the power distribution firm MEPAŞ is responsible for the distribution of power to local consumers and industry zones at predetermined cost rates per kw/hour. Basically, power is supplied by the state and MEPAŞ informs the state authorities for the estimated power usage for the future period. For accurate planning purposes, if the forecast of power usage for the planning period differs greatly from the actual usage, the surplus/deficit that occurred between the actual and power usage forecast causes extra cost for MEPAŞ. A simple explanation for the extra cost occurred due to forecast errors is the following. As known, it is not possible to store electric power in large amounts for city consumption. For this reason, the main power supply capacity should be allocated to demand points carefully. For accurate planning purposes, the state requires electric power distribution firms to order their future usage of electric power in advance at a fixed unit cost rate shown by C. However, if there is a discrepancy between the pre-ordered electric power and the current demand, then the state provides extra electric power to the electric power distribution firm at a unit cost rate higher than C. In the reverse case, if the pre-ordered electric power is higher than current demand, then the electric power distribution firm can resell the excess electric power to the state at a unit cost less than C. Consequently, the accurate forecast of power usage for the planning period becomes crucial for all electric power distribution firms including MEPAŞ due to cost purposes.

The uncertainty in power demand has two dimensions. First dimension of uncertainty is due to the variable usage of power by the final consumers. The effect of this uncertainty type can be alleviated by using forecasting techniques based on past demand data. The second dimension of uncertainty is related to the supply side. There are various local power suppliers having different sized solar power plants. These solar power plants are divided into two groups as licensed and unlicensed solar power plants. For the licensed plants, the power generation capacity information is available. However, for the unlicensed plants there is no information other than the past power supply data. For this reason, in order to decrease the uncertainty in power supply caused by the local unlicensed power plants, an efficient forecasting technique is necessary.

As seen in Figure 1, south region of Turkey has a considerable solar power potential. Especially, in the Konya region (see Figure 2), this potential is above the average of Turkey. Yet, in order to evaluate the performance, of solar power plants, just the geographical location information is not enough. There are several other factors that affect the efficiency and capacity of solar power plants. Some of these factors are terrain characteristics, built in material

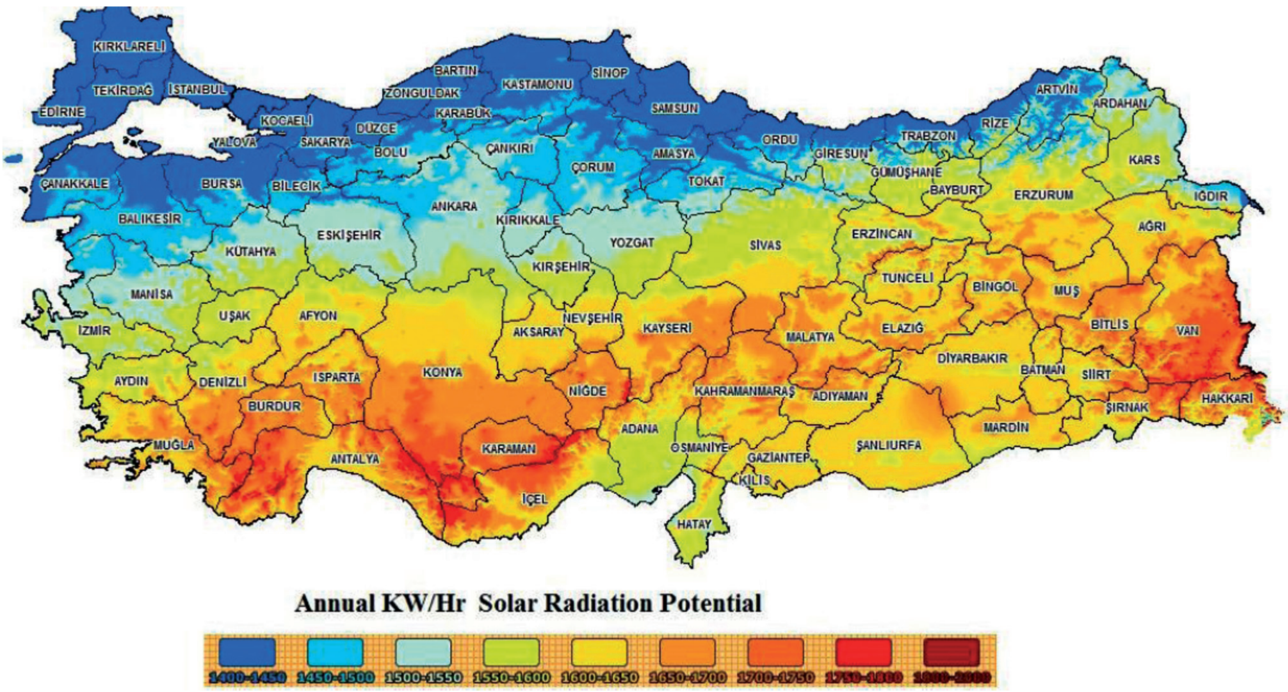

Figure 1. Solar Power Potential Map of Turkey [2].

quality, weather conditions, etc. Among these factors, some are fixed such as location or the built in material quality. On the other hand, weather conditions are variable and even they are required to be forecasted in advance. The variability of weather conditions has a great effect on the amount of power generated by a power plant. In this study, we analyze the dependence of local unlicensed solar power plants on weather conditions and provide a neural network model that effectively forecasts the amount of power supplied by these solar power plants based on several weather parameters.

Forecasting the radiation of sun is a common problem all over the world. For example Perveen et al. [14] analyze the relationship between solar energy and weather conditions for India and they show that Radial-Basis-Function-Neural Network (RBFNN) model provide significant reduction in error compared to other forecasting techniques. Abdel-Nasser and Mahmoud [3] show that the use of long short-term memory recurrent neural network (LSTM-RNN) to forecast the output power of photovoltaic systems is a good alternative compared to some other forecasting methods. Yoem et al. [15] propose a convolutional neural network and a long short-term memory network predictive model (ConvLSTM) which takes solar radiation images as an input. Their model is successful at predicting one-hour ahead solar radiation and spatially map solar energy potential. Bernecker et al. [5] also use sky images as an input to a Kalman filter system for short term (up to 10 minutes) forecast of solar irradiation. Cao and Cao [7] use recurrent neural networks integrated with wavelet analysis and they satisfactorily forecast the daily solar irradience using data for Shanhai. Chakraborty [8] suggests a mathematical model for predicting solar energy generated by power plants. His model used two parameters as an input to generate the final forecast. Chen et al. [9] develop a system based on neural networks and fuzzy logic to forecast solar radiation. Their forecast results are satisfactory as shown by small mean absolute percentage error values.

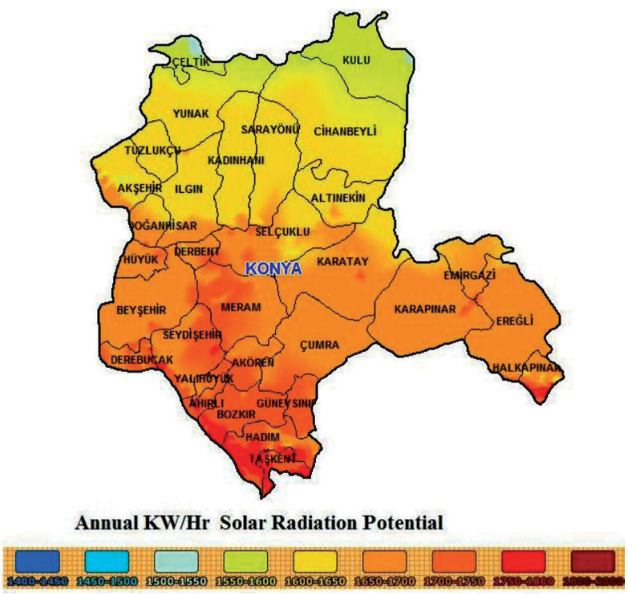

Figure 2. Solar Power Potential Map of the Konya Region [2].

As the related literature shows, use of neural networks is an efficient technique to predict solar radiation. Based on this knowledge, we also decided to use neural networks for forecasting the amount of energy generated by solar power plants in the Konya region that probably includes the highest solar power generation potential areas of Turkey. The interested reader in different forecasting methods for solar irradiation can refer to the study of Kumar et al. [11] that gives a review of the related literature. Also Obando et al. [12] give a review of the literature on solar radiation prediction using machine learning techniques.

The main contribution of this study is - to the best of our knowledge - providing an efficient solar power forecast technique for the unlicensed plants in the Konya region, Turkey. We also show that although the related studies in the literature state the radiation parameter as the main indicator for solar power-generation, other parameters such as humidity and time affect solar power related forecast errors according to our results.

ARTIFICIAL NEURAL NETWORK MODELS

There are 24 unlicensed solar power plants in the region focused in this study. One year length hourly power generation data of these plants are available. In addition, local weather data is available for the study term. Related to the weather data, the parameters considered at the beginning are temperature, humidity, wind speed, wind direction, cloudiness, radiation, and precipitation.

Before building the artificial neural network model, we observed some extreme/unrealistic data values that may be caused by measurement errors. For example, during

Table 1. Correlation Test Results

Parameter	Value	Degree
Year	–0.001	Weak
Month	–0.002	Weak
Day	0.007	Weak
Hour	0.063	Weak
Temperature	0.307	Weak
Humidity	–0.341	Medium
Wind Speed	0.114	Weak
Wind Direction	–0.285	Weak
Cloudiness	–0.097	Weak
Radiation	0.890	Strong
Rain	–0.052	Weak

Table 2. Neural Network Models

Model Name	Used Input Parameters
N-R	Radiation
N-R-H	Radiation and Humidity
N-R-Hr	Radiation and Hour
N-R-H-Hr	Radiation, Humidity and Hour
N-R-H-Hr-M	Radiation, Humidity, Hour and Month
N-R-Hr-M	Radiation, Hour and Month

Table 3. Performance of Neural Network Model Forecasts for the Next 96 Hours

Model Name	Total of Hourly Power Errors	Average Error
N-R	140.90 KWh	23.83%
N-R-H	97.45 KWh	16.48%
N-R-Hr	34.82 KWh	5.89%
N-R-H-Hr	29.19 KWh	4.94%
N-R-H-Hr-M	30.46 KWh	5.15%
N-R-Hr-M	46.28 KWh	7.82%

winter, if a solar power plant has very little power generation whereas the other solar plants in the near locations have considerably higher power generation, this may be an indication of a measurement error. Uncleaned snow above solar panels or break downs may cause such situations. In order to have stable data during neural network training, we filtered the raw data to eliminate measurement errors. After this step, we focus on the input output relationships between the weather parameter values and the power generation. Although we have defined seven weather related parameters, it is possible that some of these parameter values have no or little effect on power generation. In order to understand this, a correlation test is done between the weather parameter values and the power generation levels. The results of this correlation test is shown in Table 1.

The correlation values are supposed to be on the interval [−1,1] where a −1 shows an absolute negative correlation and +1 shows an absolute positive correlation. A correlation value close to zero means that the related parameters have no significant relationship between the analyzed subject. Considering this we classified the correlation values as weak, medium, and strong depending on the magnitudes that are in the intervals [0,0.333),[0.333, 0.667), and [0.667,1], respectively.

Our correlation test reveals that the amount of solar power generated has only a strong positive correlation with radiation parameter. Humidity parameter turns out to have a medium negative correlation with solar power generation. On the other hand it turns out that other weather related parameters have weak correlations with solar power generation amounts. Based on these correlation results, we decided to include radiation and humidity parameter values as inputs to our artificial neural network model. Although for month and hour parameters, there seems no significant correlation with solar power generation, we also wanted to use these parameters in some of our test models due to possible inherent seasonal effects.

Neural network models are built by the software IBM SPSS Modeler 17.1. 80% of the data is used for training purposes and the remaining 20% is used for verification of the models. The software allows at most two neural network layers and we try several parameter settings during our trials. It turns out that the optimal number of layers and neurons determined by the software itself outperforms other models, so we did not change the software parameter settings. Since we select four input parameters (radiation, humidity, month, hour), it is possible to generate $2^4 - 1$ different input combinations for the neural network models. Among different neural network models with different input combinations, we display the results of the six neural network models that give better results compared to the others. All the neural network models generated by the software has only one layer and all the neurons use hyperbolic tangent functions as activation function. These neural network models and the used input parameters are given in Table 2.

According to YEKDEM regulations, the power distribution company has to provide power generation forecasts for the next 48–96 hours that correspond to the next two to four days. For this reason, in testing the performance of the neural network models, the average error for the last four days are used. The performance of the generated neural network models are displayed in Table 3. In this table, average error is calculated by Equation 1:

$$\frac{\sum_{i=1}^{4}\left|Day\ i\ power\ supply - Day\ i\ power\ forecast\right|}{\sum_{i=1}^{4} Day\ i\ power\ supply} \quad (1)$$

All the generated neural network models have one layer and the number of neurons changes between three and ten. As an example, the N-R-H-HR neural network model's representation is given in Figure 3.

DISCUSSION

As seen in Table 3, the models' forecast error change between 24% and 5%. Although our initial correlation test shows that the radiation parameter has a very high correlation with generated power amount, the neural network models show that using only radiation as an input parameter

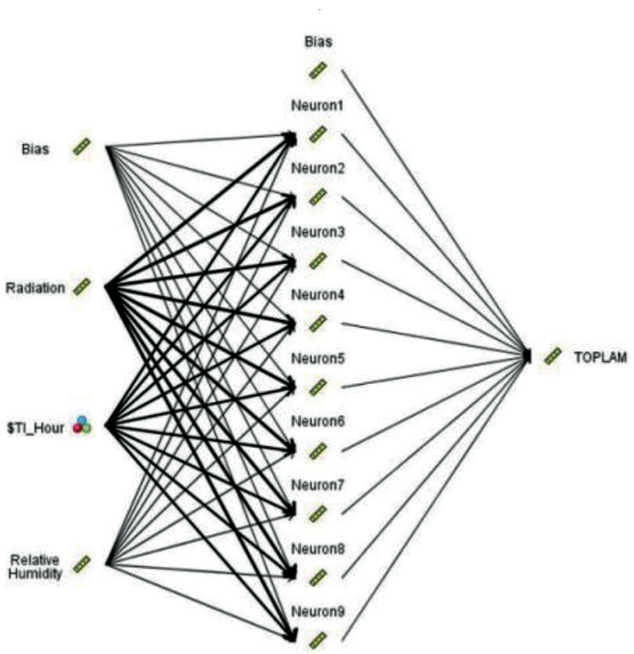

Figure 3. Neural Network Model for N-R-H-Hr.

for the neural network model gives poor results (23.83% error). On the other hand, if the radiation input parameter is supplemented by the hour or humidity parameter, the forecast error of the model decreases significantly. The results show that the hour input parameter is more effective than the humidity input parameter, since the model N-R-H has 16.48% error rate where as the model N-R-Hr has 5.89% error rate.

We think that if there are more input parameters for a neural network, then the neural network should give better forecasts, yet interestingly our results show that this may not be case. The model that uses all the parameter types as an input (Model N-R-H-Hr-M) has a slightly higher error value (5.15%) than the model (N-R-H-Hr) which excludes the month parameter value from the input set. The models N-R-H-Hr-M and N-R-Hr-M that both include the month parameter in the input set have error values 5.15% and 7.82%, respectively, but when we exclude from these models the month input parameter, the error values decrease to 4.94% and 5.89%, respectively. This makes us conclude that the input parameter month is not a significant variable in forecasting solar energy generated by solar power plants. In fact, including month values in neural network models creates noise effect in the models.

The results show that the forecast performance of the neural network models depends on the radiation, the hour, and the humidity parameters in decreasing order of importance, respectively. As mentioned previously, there are many studies in the literature analyzing the effect of radiation on solar power plants. Also the correlation test done at the beginning shows that there is a high positive correlation between the radiation and the generated solar power amount. For this reason, we can conclude that the radiation amount is a main indicator for the generated solar power level. The second important parameter, the hour parameter, also affects generated solar power amount. The relationship between the hour parameter and the generated solar power amount highly depends on the angle between the sun ray and on the solar panel surface. Finally, although it is not easy to see the direct relationship between the humidity parameter and the generated solar power, the humidity affects the performance of solar power plants in negative way. Panjwani et al. [13] state that the humidity can create a minimal layer of water on solar cells and decrease the efficiency of solar panels up to 20%.

There can also be other input parameters that may affect the output power level of solar panels. For example, the built-in material of solar plants affects the quality and the efficiency of solar panels. Also, the mobility of solar panels to receive maximum sun radiation can increase the performance of power generation plants. Unfortunately, we do not have such detailed data for the solar power plants in this study. Yet, our results are superior to the manually estimated forecast values and also third party software results used at the electric distribution company during the time of this study.

CONCLUSIONS

In this study, we analyze the forecast problem for the unlicensed solar power plants in the Konya region/Turkey. The government regulations require electric distribution firms to provide electric demand forecasts to the state so an efficient power distribution plan can be done. The more accurate forecasts a power distribution firm provides, the less/no extra cost occurs for the firm. In order to accurately forecast the power transferred from state sources, it is crucial to identify what portion of the total power demand is met by the solar power plants. Our study shows that it is possible to forecast the power generated by the unlicensed solar power plants with 5% error using neural network models. This study can be extended for the solar panels located at other regions in Turkey. Although we use weather based input parameters in the neural network models, the input parameters can also be enriched by considering several other factors like built-in material of solar panels, terrain characteristics of the solar power plants, etc. In addition the quality of weather forecasts directly affects the quality of solar power generation forecast. In this study, we use actual weather data, but as an extension to this study we want to analyze the relationship between weather data forecast and solar power generation. Using other forecasting techniques is also subject of a future study.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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