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Evaluation of artificial neural network methods to forecast short-term solar power generation: a case study in Eastern Mediterranean Region

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Abstract: Solar power forecasting is substantial for the utilization, planning, and designing of solar power plants. Global solar irradiation (GSI) and meteorological variables have a crucial role in solar power generation. The ever-changing meteorological variables and imprecise measurement of GSI raise difficulties for forecasting photovoltaic (PV) output power. In this context, a major motivation appears for the accurate forecast of GSI to perform effective forecasting of the short-term output power of a PV plant. The presented study comprises of four artificial neural network (ANN) methods; recurrent neural network (RNN) method, feedforward backpropagation neural network (FFBPNN) method, support vector regression (SVR) method, and long short-term memory (LSTM) for daily total GSI prediction of Tarsus by using meteorological data. Moreover, this study proposes a model that utilizes the predicted daily GSI for output power forecasting of a grid-connected PV plant. The obtained results are compared with the output power generation data of a 350 kW solar power plant. The results are evaluated with the performance indices as mean absolute percentage error (MAPE), normalized root mean squared error (NRMSE), weighted mean absolute error (WMAE), and normalized mean absolute error (NMAE). FFBPNN method is chosen with the best results of MAPE 7.066%, NMAE 3.629%, NRMSE 4.673%, and WMAE 5.256%.

Key words: Artificial neural networks, long short-term memory, multilayer perceptron, photovoltaic power forecasting, global solar irradiation forecasting

1. Introduction

The energy production amount of a country determines its external dependence, economic growth, and level of development. Renewable energy sources have become more popular due to the world increasing energy demand, being clean energy sources and limitless. The Renewables 2020 Global Energy Report shows that by the end of 2019 renewable energy share of global electricity production was estimated as 27.3%. Moreover, the report shows the annual additions of renewable and nonrenewable energy shares. According to the report in 2019, the renewable energy share reached 75% of the total annual additions of renewable and nonrenewable energy sources while it was estimated under 50% in 2013 [1]. The recent data of The Renewables 2021 Global Energy Reports show more than 256 GW renewable energy was added in 2020, 54% of the addition was calculated as PV power around 139 GW, followed by wind power 36% or 93 GW power and hydropower around 8% or 20 GW power and 2% other sources [1].

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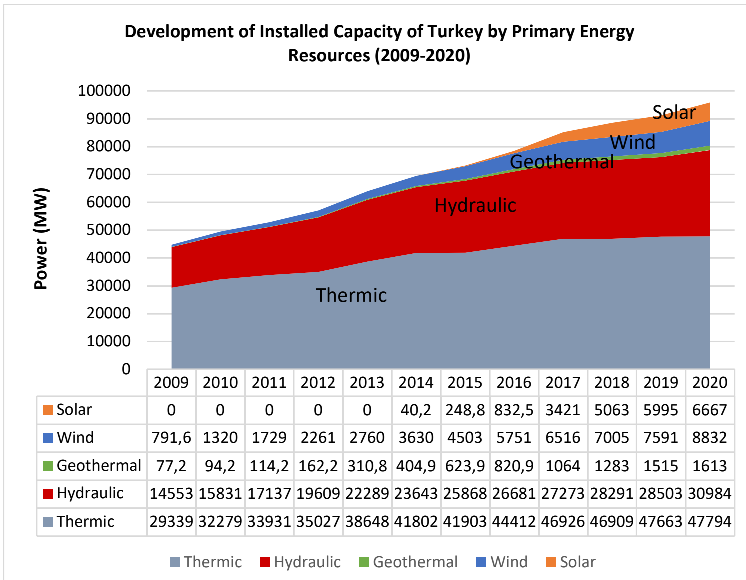
The PV power installed capacity of Turkey was announced as 7815.6 MW while the total installed power capacity was announced as 99,819.6 MW according to the Turkish Electricity Transmission Company (TEİAS) 2021 December Report [2]. Based on the information above, the installed PV Power capacity has been exponentially increasing not only in Turkey but also worldwide. The development of the installed capacity of Turkey by primary energy resources between the 2009 and 2020 years is shown in Figure 1 with an area graph. PV installation acceleration is far greater than the other renewable energy sources.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Solar	0	0	0	0	0	40,2	248,8	832,5	3421	5063	5995	6667
Wind	791,6	1320	1729	2261	2760	3630	4503	5751	6516	7005	7591	8832
Geothermal	77,2	94,2	114,2	162,2	310,8	404,9	623,9	820,9	1064	1283	1515	1613
Hydraulic	14553	15831	17137	19609	22289	23643	25868	26681	27273	28291	28503	30984
Thermic	29339	32279	33931	35027	38648	41802	41903	44412	46926	46909	47663	47794

Figure 1. Development of installed capacity of Turkey by primary energy sources (2009–2020).

PV power is not PV power is not intermittent due to being dependent on the fluctuated on the fluctuated atmospheric variables such as cloudiness, solar irradiance, humidity, wind force, and temperature. PV plant's output power fluctuations may cause frequency and voltage deviations that highly affect the reliable grid operation. These difficulties make PV power forecasting more essential for a stable, efficient, controllable, and cost-effective system operation. On the other hand, if the daily produced output power is more than power consumption for a load and the system does not have a storage system, the remaining power will be wasted. Forecasting of PV plant power provides us planning power distribution and transmission, working on various features of system sustainability and power quality, and declining the impact of ambiguity of PV power generation. This will contribute to the injection level of the PV systems in the energy mix [3].

In the previous researches, plenty of PV power forecasting techniques has been improved. According to the forecast interval, forecasting techniques can be classified into four types; very short-term forecasting with a time interval changing from a few seconds to one hour; short-term forecasting one hour to two weeks; medium-term forecasting from two weeks to three years; long-term forecasting more than three years [4]. Very short-term forecasts are used for PV power and storage control, short term forecasts are crucial for various decision-making problems that occur in the electricity market and power system operation, medium-term forecasts are convenient for maintenance planning of PV plants, conventional power plants, power transformers, and power transmission lines, long-term forecasts can be used for long-duration solar energy and PV plant planning [5]. Forecasting terms based on the time horizon are illustrated in Figure 2.

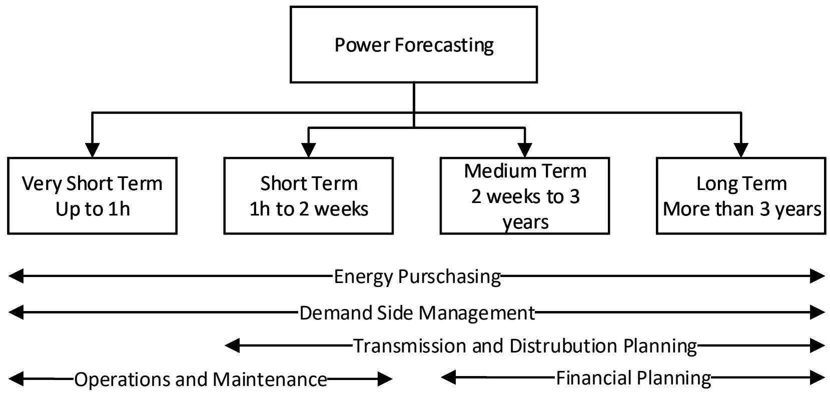


Figure 2. Forecasting terms based on the time horizon [5].

In this paper, meteorological data such as humidity, wind speed, temperature, and sunshine duration are used to forecast GSI of Tarsus for precisely forecast solar power of 350 kW PV plant located in Tarsus, Mersin by use of ANN methods. The main objective of this study can be expressed as the extraction of a strong relationship between the output power of a PV power plant located in Tarsus and the meteorological data measured by the Turkish State Meteorological Service. The main contributions of this study can be summarized as follows:

- A comprehensive literature review of PV power and GSI forecasting methods is performed. The investigated studies are categorized in detail and tabulated based on the approaching techniques, methods, and performance indices.

- Short-term PV power forecasting which enables the system power control, energy investment planning, system maintenance, and operation planning for sustainable renewable power generation is conducted.

- To the best of our knowledge, the presented paper is the first study to forecast output power generation of an installed PV power plant based on real measured data in Tarsus, Mersin.

- It becomes more difficult to obtain accurate results since meteorological data are variable in studies spread over a large area. Therefore, it is more appropriate for meteorological data that belong to a specific region to obtain an accurate forecasting model. This study was carried out in a specific area to obtain more accurate results.

- GSI measurements are mostly not available except in meteorological stations. An acceptable high-accuracy model is presented for all over Tarsus. The accuracy of the model has been tested in estimating the output power of PV plants located in different locations of the city. Since Tarsus is in the first region on the GSI map of Turkey, the performed study is important within the scope of energy investments that are planned to be made in Tarsus.

- Different ANN methods are compared to address the best method for PV power forecasting.

- An elaborate discussion of the results based on different statistical error analysis methods is carried out.

- The interpretable graphical results are provided to show the relationship between meteorological variables and the PV plant output power generation.

This paper is organized as follows: in Section 2 the related works in the literature are summarized, in Section 3 the structures of ANN-based methods are explained, followed by Section 4 with solar power forecasting based on ANN which details the data description, in Section 5 results and discussions are supported with graphics and in Section 6 conclusions are presented.

2. Related works

In the literature, there are various methods such as statistical models, physical methods, machine learning models, and hybrid models for PV power forecasting [6]. Recently, various studies have been carried out about PV power forecasting by use of ANN and Regression methods and hybrid methods that include ANN. Literature reviews of power and GSI forecasting are outlined in Table 1.

Table 1. Literature review of power and GSI forecasting.

Ref.	Year	Method	Power	Estimated value	Forecasting time	Location	Indices
[3]	2016	Multilayer Perceptron (MLP) with various learning rules and activation functions (ANN)	20 kWp	Power	24-h ahead	Tiruchi rappalli, India	MAPE
[7]	2019	LSTM- RNN compared with Multiple Linear Regression, Bagged Regression Trees, and neural networks (NN).	-	Power	Next time step (a window technique)	Aswan and Cairo, Egypt	RMSE
[8]	2018	A new Radial Basis Function Neural Network (RBFNN) compared with MLPNN and traditional RBF	-	Power	One-month prediction and one-year prediction	Jericho City	RMSE
[9]	2020	A local training strategy-based ANN compared with the benchmark Global Strategy Based ANN	264 kWp	Power	Daily for each hour intervals predictions	Amman, Jordan	RMSE, WMAE, MAE
[10]	2020	A hybrid convolutional neural network (CNN) and LSTM model compared with the Persistence, BPNN, RBFNN methods	451.82 MW	Power	15min. ahead and 45min.-ahead	Limberg, Belgium	MAE, RMSE
[11]	2018	SVR based on RBF with Cuckoo Search (CS-RBF), SVR based on RBF with Differential Evolution (DE-RBF), SVR based on linear function with CS (CS-Linear), SVR based on linear function with DE (DE-Linear), and BPNN methods	6.4 kW	Power	Hourly	Arlington, Virginia	MAPE, RMSE, R^2
[12]	2020	A modified model of SVR with Gauss-Newton method compared with SVR	434 kW	Power	Day-ahead	Australia	MAPE, MAE, MRE, MBE, RMSE
[13]	2018	A combination of genetic algorithm (GA), particle swarm optimization (PSO) algorithms are used to optimize adaptive neuro-fuzzy inference systems (ANFIS) methods compared with ANN, linear regression mode (LRM), and persistence methods	For each 100 kW	Power	A day ahead hourly	Beijing	NMAE, RMSE, MAE

Table 1. (Continued).

Ref.	Year	Method	Power	Estimated value	Forecasting time	Location	Indices
[14]	2018	Grey Box model, Neural Network model Quantile Random Forest, k-Nearest Neighbors (k-NN), SVR, Ensemble Averaging methods	Between 10 MW to 114 MW (32 power plants)	Power	Day-ahead	Italy	NMAE, MAE, NMBE, NRMSE
[15]	2018	A robust MLP, compared with Generic-MLP Persistence Robust-MLP methods	68.48 kW	Power	Day-ahead hourly	USA	RMSE, MAE
[16]	2017	An SVR method compared with the ANN method	1.875 kWp-2 kWp-2,7kWp PV plants	Power	Daily and monthly (average)	Kuala Lumpur	MBE (W), MAE (W), NRMSE (%)
[17]	2018	An extreme machine learning method compared with the BP-ANN method	264 kWp	Power	24h-ahead	Amman, Jordan.	RMSE, MAE, WMAE
[18]	2020	A deep learning-based Convolutional Self-Attention based LSTM method compared with DNN, LSTM, LSTM with canonical self-attention methods	150 kW	Power	Day-ahead hourly	Korea	MAPE (%), MAE (kWh), RMSE, NMAE
[19]	2018	A comparative study between ANNs, SVR, and regression tree (RT) methods	1.175 kWp	Power	Day ahead	Cyprus	MAPE (%), RMSE (W), NRMSE (%), SS (%)
[20]	2020	ANN, ANFIS, LSTM, RNN, and dynamic neural network methods	-	Power	Day-ahead based hourly	Korea	RMSE, COR, BIAS, MAE
[21]	2021	A BP neural network model and a wavelet neural network method	-	Power	Hourly	-	SSE, MSE
[22]	2019	Two different methods are based on FFNN; the first method consists of an MLP based forecaster while the second method consists of a Physical Hybrid Artificial Neural Network (PHANN) method for prediction.	285 Wp	Power	Day ahead	Milan, Italy	MAE, NMAE%, MAPE%, WMAE%, NRMSE%, EMAE%, OMAE%
[23]	2020	A hybrid model (SDA-GA-ELM) based on extreme learning machine (ELM), GA, and customized similar day analysis methods	4.95 kW	Power	Hourly	Alice Spring, Australia	NRMSE (%), MAE (kW)
[24]	2017	An experimental study based on ANN method	90 W	Power	Daily	Batman, Turkey	RMSE, MAE, RAE, RRSE, R
[25]	2018	A multivariate NN forecast ensemble framework	433 kW-2077.65 kW	Power	One day ahead	Australia	MAPE
[26]	2021	A stacked LSTM method, which is a remarkable component of the deep RNN	-	Power	Hourly	Nicosia, Cyprus	RMSE

Table 1. (Continued).

Ref.	Year	Method	Power	Estimated value	Forecasting time	Location	Indices
[27]	2021	A deep Convolutional Neural Network (CNN) structure compared to BT, SVR, LR, DTR.	1000 kW	Power	1h-ahead,2h-ahead,3h-ahead	Kilis, Turkey	RMSE, MAE, SMAPE
[28]	2021	Mathematical methods, fuzzy logic methods as; ANFIS and the zero-order Takagi-Sugeno model with specially selected linear and non-linear membership functions	330 Wp	Power	Daily	Rzeszów	ME, MEA, MAPE, RMSE
[29]	2021	Linear Regression, SVR, MLP, Random Forest (RF) methods that based on machine learning and deep learning methods	30 MW-30 MW-35 MW-30 MW	Power	Hourly	Errachidia, Morocco	RMSE [MW], MAE(MW), RMSE, MAE
[30]	2021	Gaussian Process Regression and Matern 5/2 as a kernel function method	30 MW-30 MW-35 MW-30MW-0.433 MW	Power	Hourly	USA	RMSE [MW], MAE(MW), RMSE, MAE
[31]	2021	Feed forward Backpropagation method with 5 different combinations of input parameters ANN1-ANN5	-	Irradiation	Daily	India, Uttarakhand	MAPE, R, RMSE, MAE
[32]	2020	The forecasting method is a hybrid method that consists of ANNs and a novel similar hour-based selection algorithm method	-	Irradiation	Hourly	-	MAPE, NRMSE
[33]	2019	Four different machine learning algorithms support vector machine (SVM), ANN, k-NN, and deep learning methods are used for the prediction	-	Irradiation	Daily	Kırklareli, Tokat, Nevsehir and Karaman	R^2, RMSE, NRMSE, MBE, MABE, t-stat, MAPE
[34]	2019	A comparison of empirical ANN methods and two new coupled ANN methods with GA (MLP−GA(n) and MLP−GA(t))	-	Irradiation	Daily	Iran	R^2, RMSE, MBE
[35]	2021	Seasonal clustering and ANN	-	Irradiation	1 hour-ahead	Portugal	RMSE, NRMSE, MBE, NMBE
[36]	2019	A nonlinear autoregressive, a nonlinear autoregressive exogenous, and a proposed hybrid method	-	Irradiation	Daily	Nigeria	R^2, RMSE, MBE, MABE, MPE, t-test, R
[37]	2018	Daily global solar radiation for Eastern Mediterranean Region (EMR) is forecasted by use of ANN method, linear and nonlinear methods (ten different models) based on Angström-Prescott	-	Irradiation	Daily	Turkey	(SSE), RMSE, R^2

Table 1. (Continued).

Ref.	Year	Method	Power	Estimated value	Forecasting time	Location	Indices
[39]	2021	A new hybrid method based on ML algorithms and daily classification techniques is used for forecasting. And also, Random Forest (RF), gradient boosting (GB), SVM, and ANN methods	-	Irradiation	1h-ahead	Evora	NRMSE, NMAE
[40]	2021	An ANN method, an RNN method, and a CNN method	-	Irradiation	Hourly	Nigeria	R, RMSE, MAE, NMBE
[50]	2021	A novel hybrid solar irradiance forecasting based on three steps a hybrid model adaptive to three stages including PMI input selection strategy, the optimized deep CNNs and deep Q-learning RL algorithm called ODERLEN (optimized deep RL ensemble model) compared with AHM, HFS, ORHM, NHDNNM, OHS-LSTM, GA-RL-Ens, PSO-RL-Ens, ACO-RL-Ens, BBO-RL-Ens, WOA-RL-Ens models.	-	Irradiation	Hourly	Phoenix, Los Angeles	RMSE, MAE
[51]	2022	Comparison of 8 different model, DWT-CLSTM,MEA-ANN, Auto-LSTM,XGBF-DNN,LSTM,CLSTM,SCA-LSTM and proposed model MSCA-CLSTM	-	Irradiation	Hourly	Detroit, Columbus, San Antonio	RMSE, MAE, R

3. Methodology

3.1. Recurrent neural network

RNNs are neural networks with memories that can capture any information stored in a sequence of previous elements [41]. The learning mechanism used to calculate new states recursively by applying activation functions over the inputs and previous states of the network is called RNNs. It differs from the conventional feedforward network by its feedback connectivity given to hidden units [42]. Layer structure of RNN is illustrated in Figure 3. The multiplication of x_t and input vector u gives the first hidden neuron input. After calculating first hidden neuron, the next hidden neuron input h_{t+1} will have the input of both x_{t+1} and the previous hidden neuron h_t by the weights (w) of the hidden neuron and the input weight vector. The output neurons are obtained by multiplying the hidden neurons by the output weight (v).

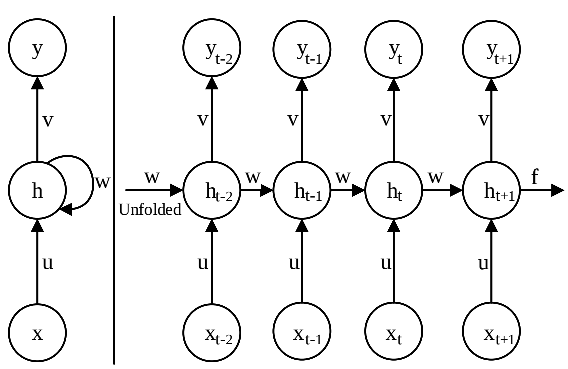


Figure 3. Layer recurrent neural network structure.

3.2. Long short-term memory

LSTM is a form of RNN with some alteration comprising cell, input gate, output gate, and forget gate [38]. LSTM is improved by adding a new gate for solving the gradient vanishing problem in RNN and also the structure of LSTM is advanced by increasing the number of interacting layers [43]. LSTM is generally used for time series prediction by evaluating short-term dependencies as well as long-term dependencies. It consists of three kinds of gates; input gate, forget gate, and output gate. The general configuration of LSTM is demonstrated in Figure 4.

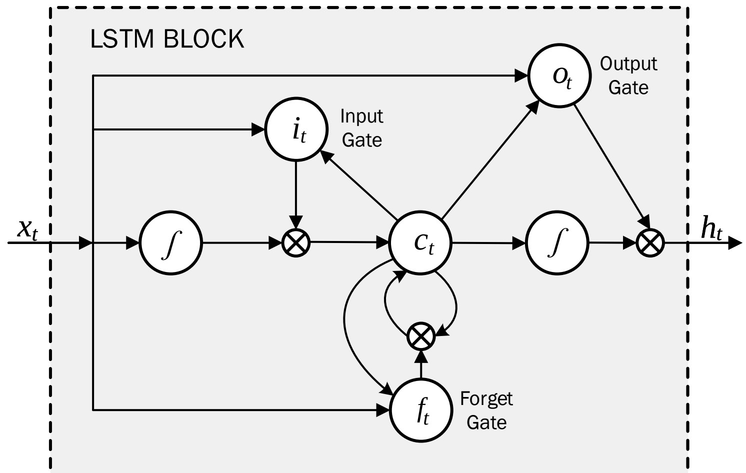


Figure 4. LSTM unit [44].

3.3. Support vector regression

SVM is a robust supervised learning tool used for handling classification and regression problems [45]. In general, SVMs are divided into two groups, support vector classifier (SVC) is used for classification problems and SVR is used for regression problems [46]. In this case, SVR is used for GSI forecasting. The linear SVR regression function f(x) is expressed as

$$f(x) = w^t \varphi(x) + b, \tag{1}$$

where x is the input data, w is the weight vector of the feature, φ is the transfer function and the bias value is b. To determine a proper SVR function approximation, equations can be expressed as follows [45]:

$$\text{Minimize} = \left[\frac{1}{2}w^2 + C\sum_{i=1}^{k}(\xi_i^- + \xi_i^+)\right] \tag{2}$$

$$\text{Subject to:} \begin{cases} y_i - (w^T.\varphi(x_i) + b) & \leq \epsilon + \xi_i^+ \\ (w^T.\varphi(x_i) + b) - y_i & \leq \epsilon + \xi_i^- \\ \xi_i^-, \xi_i^+ \geq 0, & i = 1, 2, .., n \end{cases} \tag{3}$$

where ϵ is the insensitive loss function, C is the regularization parameter, ξ_i^+ and ξ_i^- are the two slack variables. The solution of nonlinear regression problems on the basis of the optimization by using Lagrangian functions can be represented as

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x, x_i) + b, \tag{4}$$

where $K(x, x_i)$, α_i, α_i^* are kernel function and dual variables. C, α_i and $\alpha_i^* > 0$. There are different kernels' functions $K(x_i, x)$; the most common and effective ones are the polynomial, Gaussian, and radial basis (RB) functions [46]. The common kernel functions are as follows:

$$K(x, x_i) = \begin{cases} x_i, x_j & \text{Linear} \\ (\gamma x_i . x_j + c)^d & \text{Polynomial} \\ \exp(\gamma |x_i - x_j|^2) & \text{Exponential RB} \\ \tanh(\gamma x_i . x_j + c) & \text{Sigmoid} \\ \exp(-\frac{||x_i - x_j||^2}{2\sigma^2}) & \text{Gaussian} \end{cases} \tag{5}$$

3.4. Feedforward neural network

FFBPNN is a type of supervised learning method used for finding the relationship between independent variables [47]. In FFBPNN, firstly the input data has transferred to the network, then data start to propagate from the input layer, hidden layer, and finally output layer in order. Then the error between output results and desired outputs is calculated [48]. This error is propagated backward through layers starting from the output layer to the input layer and weights are updated continuously until the error reaches a predetermined range or the number of iterations reaches the upper limit. After the training process model gets ready to test data.

The definitions of FFBPNN model parameters in Figure 5 are as follows: $x_1, x_2, .., x_n$ are inputs, $y_1, y_2, .., y_m$ are outputs, n is the total number of neurons in the input layer, h is the total number of neurons in the hidden layer, m is the total number of neurons in the output layer, a_j is the bias of j' th hidden neuron, bk is the bias of k' th output neuron, w_{ij} represents the weight of the i' th input neuron over the j' th hidden layer neuron, w_{jk} represents the weight of the j' th hidden layer neuron over the k' th output layer neuron.

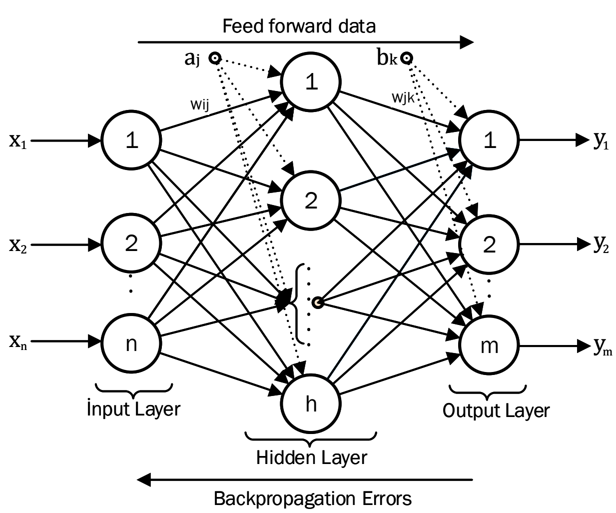


Figure 5. Feedforward backpropagation model.

The output of the hidden layer h_j is calculated as follows [49]:

$$h_j = f\left(\sum_{i=1}^{n} w_{ij} - \alpha_i\right) \quad \text{j=1,2,..h.} \tag{6}$$

The value of the output layer can be found as

$$O_k = \sum_{i=1}^{n} w_{ij} - b_k, \tag{7}$$

where b_k is bias of k' th neuron at the output layer, m is the neuron number of the output layer.

4. Solar power forecasting with ANN: a case study

The overview of the system structure is summarized below in Figure 6. Meteorological parameters are subjected to the preprocessing procedure for GSI estimation that is performed with ANN methods. The accuracy of these methods is evaluated by the use of statistical error analysis indices to select the best-performing method. The PV model is designed based on the best performing ANN model for power estimation in MATLAB/ Simulink.

4.1. Data description

Tarsus is in the Eastern Mediterranean Region of Turkey and under the Mediterranean climate. The winters over Mediterranean coasts are cool and rainy, summers are hot and dry moderately [37]. The temperature and GSI monthly characteristics of Tarsus between 2018 and 2020 are shown graphically in Figure 7. By looking at these graphs, in which months the temperature and GSI are high and in which months they are low for solar power generation potential are observed.

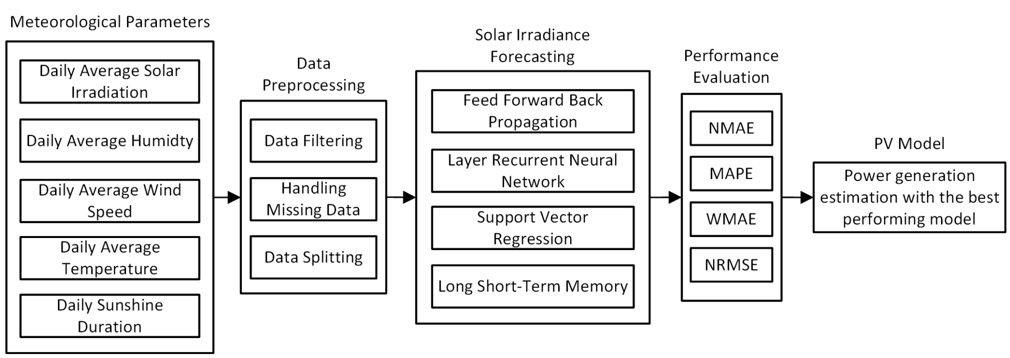


Figure 6. System structure of solar power prediction.

The meteorological data of Tarsus which is used in the present study was taken from the Turkish State Meteorological Service. Meteorological data consists of daily average temperature, daily average humidity, daily average wind speed, daily total sunshine duration, and daily average GSI for ten years from 2010 to 2020. The meteorological data is analyzed and some abnormal data such as missing data or data that are beyond the theoretical limits are observed. These abnormalities come from incorrect readings from logging devices, missing sensor readings, or data that are beyond the theoretical data limits [42]. To make data suitable for ANN models preprocessing procedure is required. In this dataset, the linear interpolation method is used to handle abnormal data, then filtering data and splitting data processes are done. After preprocessing procedure data is divided into two parts 3714 days is used for the training process and 183 days for testing purpose.

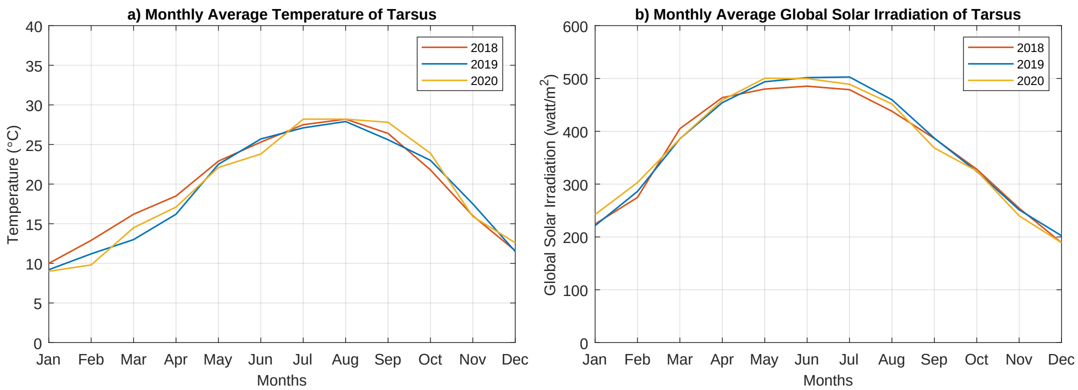


Figure 7. a) Monthly average temperature of Tarsus, b) Monthly average GSI of Tarsus.

4.2. PV power plant

The total installed power capacity of the plant located at Tarsus; Mersin is 350 kW. To convert produced energy to usable energy 7 × 50 kW DC-AC inverters are used.

The PV module features such as type, power, voltage, and current characteristics of the system under the standard test conditions are shown in Table 2. These features are used for modeling the PV array in MATLAB/Simulink tool. Then this model is used for power estimation based on the ANN methods. Historical real power production data of PV plant for 183 days are handled and used for comparison with predicted power.

Table 2. The parameters of the installed PV system.

Properties of system	
PV power capacity	350kW
Location	Tarsus- Mersin
Coordinates	36°55’38.84”N-34°55’11.64”E
Technical properties of utilized inverter	
Inverter rated apparent power	50 kVA
Inverter rated DC voltage	610 Vdc
Inverter MPPT voltage range	260-850 Vdc
Inverter rated grid voltage	3/N/PE ~ 380/400V
Inverter rated current	80A (AC)
Inverter AC grid frequency	50/60Hz

4.3. Statistical error analysis methods

To evaluate the accuracy of forecasting methods NMAE, MAPE, WMAE, and NRMSE performance indices have been considered in this work. The daily error is defined as

$$e_t = G_t - {G'}_t, \tag{8}$$

where G_t is daily total GSI and ${G'}_t$ is prediction provided by one of the forecasting methods. NMAE is the percentage of the total error of samples divided by the number of samples (N) and the maximum irradiation value (C). MAPE is the mean absolute percentage error. WMAE is the weighted mean absolute error. NMRSE is the normalized root mean square error.

$$NMAE(\%) = \frac{1}{NC}\sum_{t=1}^{N}|G_t - G'_t|x100 \tag{9}$$

$$MAPE(\%) = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{G_t - G'_t}{G_t}\right|x100 \tag{10}$$

$$WMAE(\%) = \frac{\sum_{t=1}^{N}|G_t - G'_t|}{\sum_{t=1}^{N}G_t}x100 \tag{11}$$

$$NMRSE(\%) = \frac{\sqrt{\frac{\sum_{t=1}^{N}|G_t - G'_t|}{N}}}{max(G_t)}x100 \tag{12}$$

5. Results and discussion

Four different ANN models are used for GSI prediction. These FFBPNN, SVR, RNN, and LSTM models' results are compared according to four performance indices as shown in Table 3. In addition to meteorological data, day of the month, the month of the year, and year data are used as inputs of four models that are formed in MATLAB individually. Then Simulink is used for power estimation as shown graphically in this section.

The GSI regression graphs of ANN models are given in Figure 8. In order to better see the differences between the GSI prediction results obtained from the models; the actual GSI values, the prediction result of each model are compared and the error graph for each model is also given in Figure 9. As can be seen from Figure 9, all methods perform well. Since it is difficult to understand which method is better by observing from these graphs, the performance of ANN methods is evaluated according to the four statistical performance indices in Table 3 to select the method that gives the best results.

Table 3. Performance comparison of ANN methods.

Model	MAPE	NMAE	NRMSE	WMAE
SVR	10.912	3.868	5.038	5.602
FFBPNN	7.066	3.629	4.673	5.256
RNN	8.027	4.339	5.617	6.285
LSTM	9.807	4.708	8.381	6.827

In the SVR model, the MATLAB regression toolbox is used for forecasting GSI. Crossvalidation and holdout validation ratios with combination various Regression methods are tried for best results. The best results are obtained from polynomial kernel function with a 7% crossvalidation value. In the LSTM model a deep learning algorithm with different parameters is created for forecasting. ADAM optimizer is used for the algorithm. The number of the hidden units, the gradient threshold, the initial learn rate, and the mini-batch size is essential for the optimizer and they are specified for the best result of the LSTM algorithm depending on the data properties. In RNN and FFBPNN models, MATLAB is employed for network creation. In FFBPNN and RNN models different numbers of hidden neurons with various training functions such as

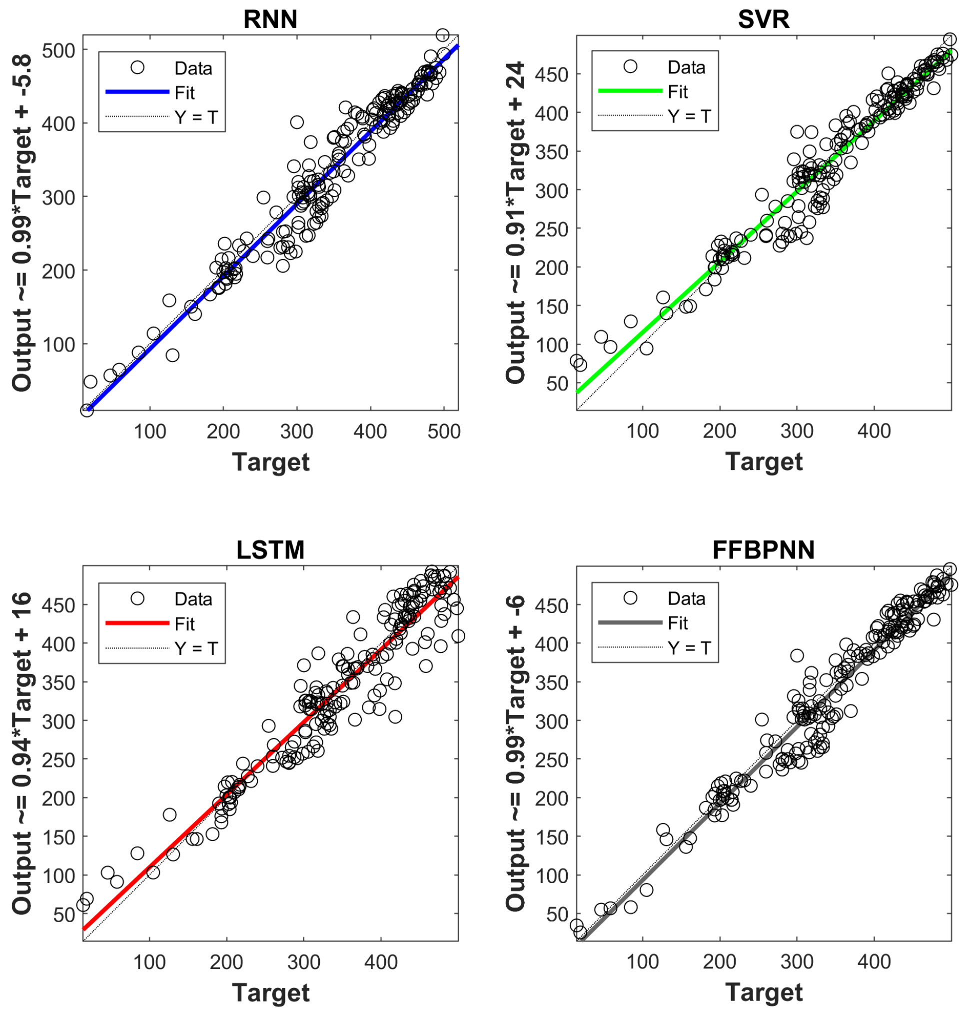


Figure 8. GSI Regression graphs of ANN methods.

trainlm, trainscg, traincgf, trainbfg, trainbr, traincgp, traincgb, trainrp, traingd, traingdm, traingda, trainoss, traingdx, combinations are tried and in RNN the model with 16 hidden neurons with trainlm training function and tansig transfer function give the best result. Also, trainlm function with 16 hidden neurons and tansig transfer function combination gives the best results for FFBPNN model. FFBPNN model gives the best results according to all performance indices individually as shown in Table 3.

The installed PV plant parameters in Table 2 are used for modeling the PV array by the use of MATLAB/Simulink. The GSI results of the FFBPNN model are utilized as input of the PV array Simulink model. Figure 10a shows the predicted and real output power of PV array results and Figure 10b is the error magnitude between predicted and real power for 183 days by the use of the FFBPNN model.

As given in Figure 10a the real and predicted power graphics show similar characteristics. Although there are some power fluctuations on certain days, forecasting error distribution is generally close to zero. The difference between predicted and real power is increasing in the autumn months as seen in the graphs above. These are caused by seasonal effects such as sunshine duration, temperature changes, humidity, wind speed, missing data, or inaccurate measurements. The graphics in Figure 11 show the comparison of two months July and November in terms of meteorological parameters that were used in this research as input; one month from

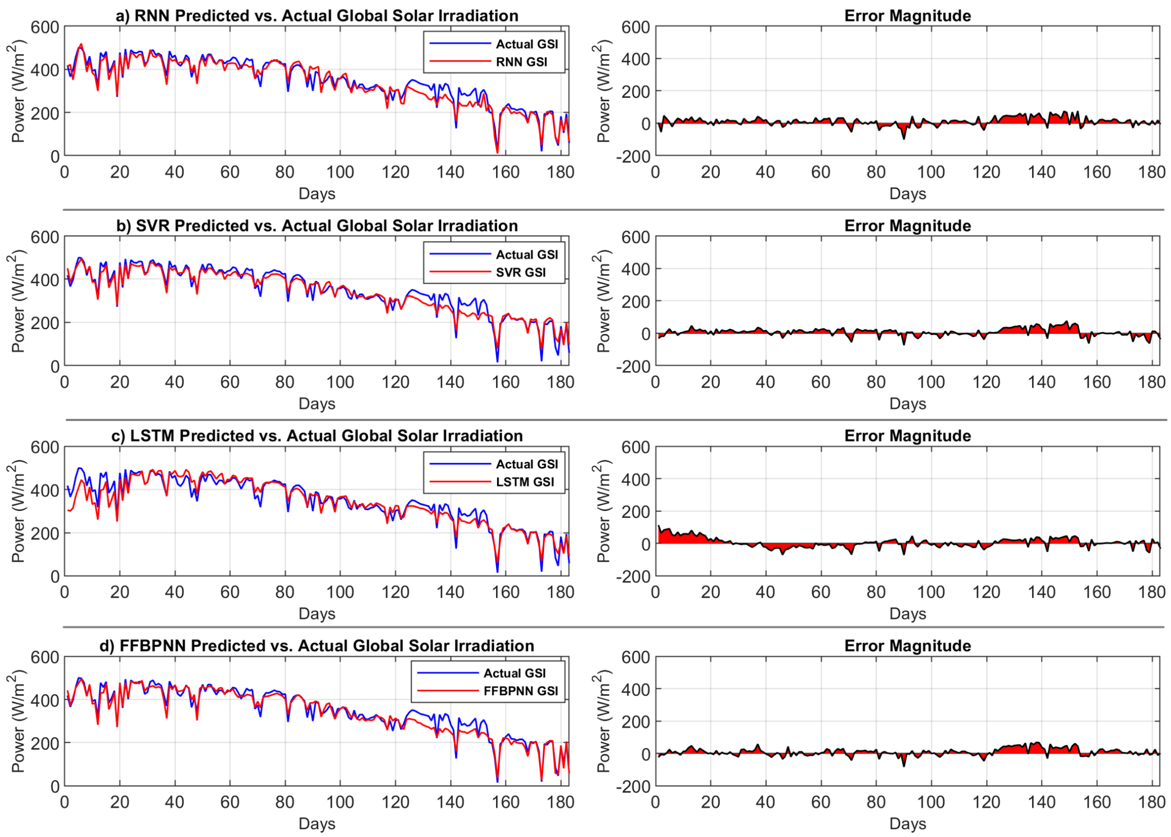


Figure 9. Actual GSI data vs. ANN method's prediction results and error magnitude.

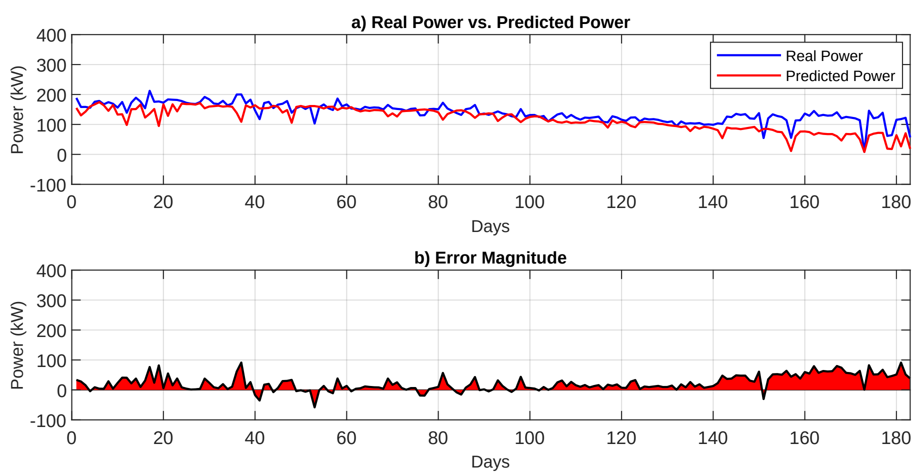


Figure 10. Real vs. predicted power of PV plant with FFBPNN model.

the summer season and the other month from the autumn season for understanding the increasing error in Figure 10b.

It is clear from these comparative graphs in Figure 11, summer months' GSI, temperature, and sunshine duration are distinctly higher than the autumn months. The developed model uses daily average temperature, daily average humidity, and daily total sunshine duration as inputs data and these meteorological parameters directly affect the model accuracy. The chaotic nature of meteorological parameters especially in the winter months causes a decrease in ANN model forecast accuracy. Although the overall performance of the model gives promising results.

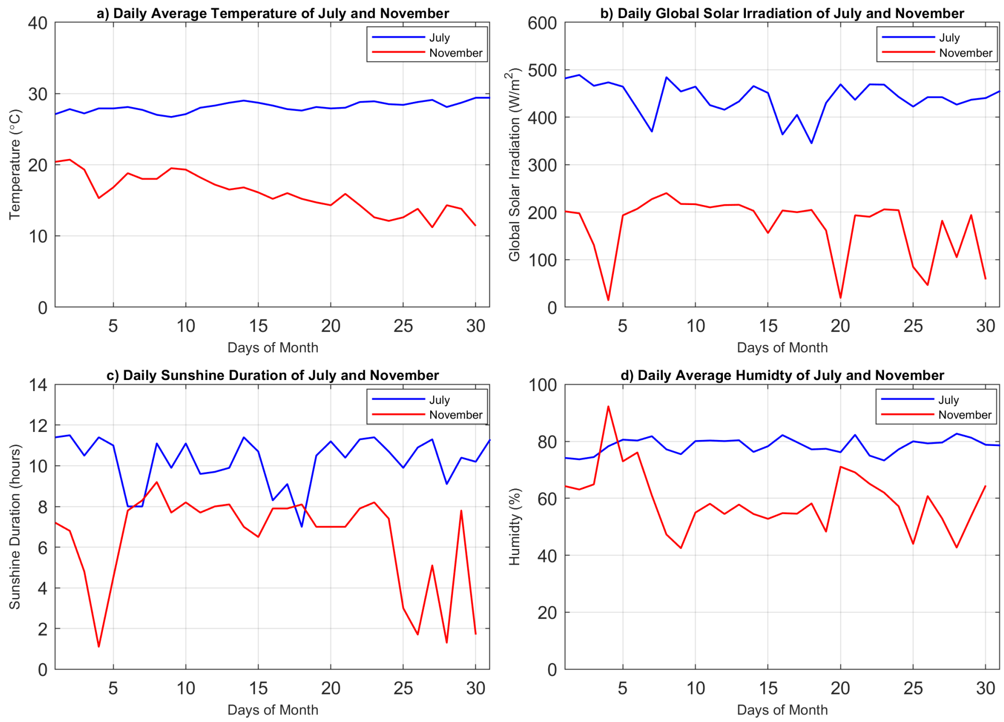


Figure 11. Comparisons of July and November months for a) daily average temperature, b) daily GSI, c) daily sunshine duration, d) daily average humidity.

6. Conclusion

In this study, short-term output power forecasting is realized by using the most prevalent four ANN methods for a 350 kW PV plant installed in Tarsus, Mersin. The performance of selected methods with different combinations is evaluated for the estimation of PV power. The developed model considers seven parameters as input data; daily temperature, daily average wind speed, the daily sunshine duration, the daily average humidity, day of the month, the month of the year, and year that are taken from the Meteorological Institute of Turkey for Tarsus to forecast GSI. Four statistical indexes are utilized to evaluate these ANN methods. The obtained results reveal that the FFBPNN method with Levenberg–Marquardt training algorithm gives the best results with MAPE 7.066%, NMAE 3.629%, NRMSE 4.673%, and WMAE 5.256%. Thus, it can be said that the developed model can be a promising alternative for accurate power forecasting of the actual PV power plants. The future works will be on the assessments of various deep learning neural network methods to increase accuracy in estimation of PV power in terms of planning economic and reliable integration of PV plants.

7. Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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