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A least squares support vector machine model for prediction of the next day solar insolation for effective use of PV systems

Betul Bektas Ekici *

Department of Construction Education, Firat University, Elazığ 23119, Turkey

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ABSTRACT

Accurate prediction of daily solar insolation has been one of the most important issues of solar engineering. The amount of solar insolation on a given location is a vital data for photovoltaic plants. Systems efficiency is easily affected by the changes in solar radiation so, this study is aimed to develop a Least Squares Support Vector Machine (LS-SVM) based intelligent model to predict the next day's solar insolation for taking measures. Daily temperature and insolation data measured by Turkish State Meteorological Service for three years (2000–2002) were used as training data and the values of 2003 used as testing data. Numbers of the days from 1st January, daily mean temperature, daily maximum temperature, sunshine duration and the solar insolation of the day before parameters have been used as inputs to predict the daily solar insolation. The simulations were carried out with SVM Toolbox of MATLAB software. As a conclusion the results show that LS-SVM is a good method in estimating the amount of solar insolation of a given location with 99.294% accuracy.

1. Introduction

The studies concerned with renewable energy in recent years gives clues of the solution of the problems of global warming and extinction of fossil fuels with solar energy. The sun is the widest source with its huge amount of expansive energy. It is a current working area of recent years because of it advantages like easily accessibility, local applicability, usability without complex technology and its cleanliness. Due to its geographical position between 36° and 42° latitudes, Turkey is abundant with solar energy and has an opportunity to benefit from this endless energy source in building design, developing renewable energy technologies, in agriculture and many other applications [1]. Turkey is divided into four regions according to its solar potential as shown in Fig. 1 [2]. By the way, the amount of total solar radiation and sunshine duration of the seven geographical regions of Turkey are given in Table 1 [2].

Especially photovoltaic systems are one of the most beneficial plants in clean electricity production. The system is directly converts sunlight into electricity so it is easily affected with the changes in the intensity of solar radiation. These fluctuations cause troubles between demand and supply and reduce the power quality. To overcome this important problem the daily solar radiation data of the next day is vital for continuing the systems efficient working and storage the solar power.

The efficient usage of solar energy in a region is directly proportional to the determination of the potential of the region. For solar applications it is hard to predict the same value with empirical methods. Because there are many factors that affect the amount of solar radiation (cloud cover, moisture, etc.) which are generally neglected in most of the solar radiation calculation methods. In some cases the measured values of solar radiation will differ from each other because of the sensibility of the measuring devices. Accurate solar radiation data is required for modeling and designing of solar energy systems like photovoltaic, solar thermal systems and passive solar design applications.

* Tel.: +90 424 2370000x4316
E-mail address: bbektas@firat.edu.tr

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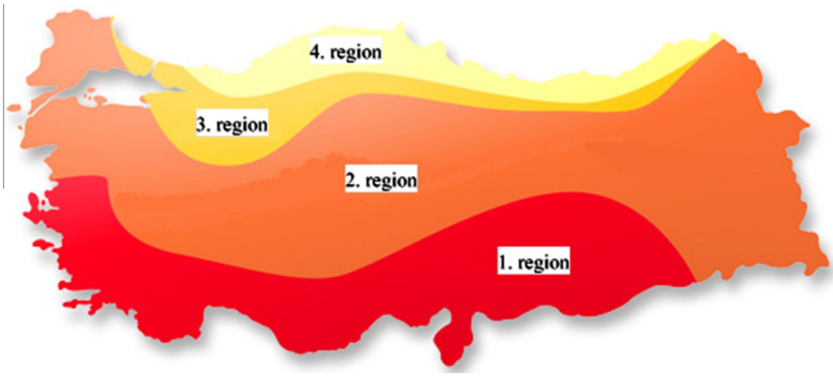

Fig. 1. The solar map of Turkey [2].

Table 1
The solar potential of Turkey's geographical regions [2].

Region	Total solar radiation (kW h/m^2 year)	Sunshine duration (hour/year)
South-Eastern Anatolia	1460	2993
Mediterranean	1390	2956
Eastern Anatolia	1365	2664
Central Anatolia	1314	2628
Aegean	1304	2738
Marmara	1168	2409
Black Sea	1120	1971

For years a great number of studies have been carried out for the estimation of solar energy potential in various locations which are based on conventional physical models or some statistical assumptions [3–16]. However with the development in computer technology, artificial intelligence techniques started to be used for prediction problems of many engineering areas. Several methods have been presented, for estimating the amount of solar radiation with artificial intelligence techniques on a given location [17–31].

In recent years, Support Vector Machines (SVM) has been a popular technique developed by Vapnik [32] and employed in many engineering studies [33–36]. Then, Suykens and Vandevalle [37] proposed a SVM based Least Squares Support Vector Machines (LS-SVM) model. In literature; Zhao et al. [38] proposed a new LS-SVM based prediction algorithm to forecast the actual gas emissions in a coal mine in Shanxi Province. After comparing with other related algorithm they found out that LS-SVM is very effective in gas prediction. Gencoglu and Uyar [39] developed a LS-SVM model regression method in order to form a flashover model of the polluted insulators. They claimed that their proposed method is a strong tool in determining the critical flashover voltage (FOV) and in selecting the insulator type of any region by using the detailed information of the region and electrical transmission system. Esen et al. [40] predicted the efficiency of solar air heater system with double flow aluminum cans absorber plate for a three type collector in Elazig, Turkey by using least squares support vector machines. They achieve 0.0024 RMSE and 0.9997 R^2 value. Baylar et al. [41] employed an intelligent LS-SVM tool for predicting the air entrainment rate and aeration efficiency of weirs. They have obtained a correlation of 0.99 between the predicted and measured values.

This study delineates a LS-SVM based model for predicting the amount of solar insolation values of Elazig city located in the east of Turkey by using the real climatic data obtained from the Turkish State Meteorological Service. The number of the day from 1st January, daily mean temperature $\left(T_{mean} = (\sum_{i=1}^{24}(T_{oi}))/24\right)$, daily maximum temperature, sunshine duration and the insolation of the previous day parameters were used as inputs and the daily insolation as output of the proposed model. MATLAB was employed for LS-SVM applications.

2. Least squares support vector machines

LS-SVM proposed by Suykens et al. [42], is a modificated version of SVM and a more simple technique than SVM [43]. The LS-SVM enables to deal with linear and non-linear multivariable calibration and solves multivariable calibration problems comparatively fast way.

The process of LS-SVM for regression is expressed below. In LS-SVM a linear estimation is done in kernel induced feature space. By considering a data set $\{x_i, y_i\}, \quad i = 1, 2, \ldots N$ with input data $x_i \in R$ and output data $y_i \in R$. While $\phi(.)$ denotes the feature map the regression model can be constituted as follows [37,46,47]:

$$y = \omega^T \cdot \phi(x) + b \tag{1}$$

where ω, is the weight vector of the target function and b is the bias term. As in SVM, it is necessary to minimize a cost function (C) containing a penalized regression error as shown below [48,49]:

$$C = \frac{1}{2}\omega^T \cdot \omega + \frac{1}{2}\gamma\sum_{i=1}^{N} e_i^2 \tag{2}$$

Such that:

$$y_i = \omega^T \cdot \phi(x_i) + b + e_i \quad i = 1, 2, \ldots N \tag{3}$$

The first part of this cost function is a weight decay which is used to regularize weight sizes and penaltize large weights. Due to this regularization, the weights converge to similar value. Large weigths deteriorate the generalization ability of the LS-SVM because they can cause excessive variance. The second part of Eq. (2) is the regression error for all training data. The parameter γ, which has to be optimized by the user, gives the relative weight of this part as compared to the first part. The restriction supplied by Eq. (3) gives the definition of the regression error. This convex optimization problem can be solved by using the Lagrange multipliers method, as follows [40,49,50]:

$$L(\omega,b,e:\alpha)=\frac{1}{2}\|\omega\|^2+\gamma\sum e_i^2-\sum_{i=1}^{N}\alpha_i\left\{\omega^T\phi(x_i)+b+e_i-y_i\right\} \tag{4}$$

where α_i, are Lagrange multipliers. To obtain the optimum solution for Eq. (4) all corresponding partial first derivatives are set to zero; the weights obtained are linear combinations of the training data [40,51].

$$\frac{\partial L}{\partial \omega}=0\rightarrow\omega=\sum_{i=1}^{N}\alpha_i\phi(x_i), \tag{5}$$

$$\frac{\partial L}{\partial b}=0\rightarrow\sum_{i=1}^{N}\alpha_i=0, \tag{6}$$

$$\frac{\partial L}{\partial e_i}=0\rightarrow\alpha_i=\gamma e_i,\quad i=1,2,\ldots,N, \tag{7}$$

$$\frac{\partial L}{\partial \alpha_i}=0\rightarrow\omega^T\phi(x_i)+b+e_i-y_i=\gamma e_i,\quad i=1,2,\ldots,N, \tag{8}$$

then:

$$\omega=\sum_{i=1}^{N}\alpha_i\phi(x_i)=\sum_{i=1}^{N}\gamma e_i\phi(x_i) \tag{9}$$

where a positive definite kernel is used as follows:

$$K(x_i,x_j)=\phi(x_i)^T\phi(x_j) \tag{10}$$

An important result of this approach is that the weights (ω) can be written as linear combinations of the Lagrange multipliers with the corresponding data training (x_i).

Putting the result of Eq. (9) into the original regression line ($y=\omega^T\phi(x)+b$), the following result is obtained [40,49].

$$y=\sum_{i=1}^{N}\alpha_i\phi(x_i)^T\phi(x)+b=\sum_{i=1}^{N}\alpha_i\left\langle\phi(x_i)^T,\phi(x)\right\rangle+b \tag{11}$$

for a point of y_i to be evaluated it is:

$$y_i=\sum_{i=1}^{N}\alpha_i\phi(x_i)^T\phi(x_j)+b=\sum_{i=1}^{N}\alpha_i\langle\phi(x_i),\phi(x_j)\rangle+b \tag{12}$$

The α vector follows from solving a set of linear equations [39,40]:

$$A\begin{bmatrix}\alpha\\ b\end{bmatrix}=\begin{bmatrix}y\\ 0\end{bmatrix}, \tag{13}$$

where A is a square matrix given by:

$$A=\begin{bmatrix}K+\frac{1}{\gamma} & 1_N\\ 1_N^T & 0\end{bmatrix} \tag{14}$$

where K denotes the kernel matrix with ijth element in Eq. (10) and I denotes the identity matrix $N\times N$, $1_N=[1\quad 1\quad 1\ldots1]^T$. Hence, the solution is given by:

$$\begin{bmatrix}\alpha\\ b\end{bmatrix}=A^{-1}\begin{bmatrix}y\\ 0\end{bmatrix}. \tag{15}$$

As can be seen from Eqs. (14) and (15), usually all Lagrange multipliers (the support vectors) are nonzero, which means that all training objects contribute to the solution. In contrast with standard SVM and LS-SVM solution is usually not sparse. However, as described by Suykens and Vandewalle [37] a sparse solution can be easily achieved via pruning or reduction techniques. Depending on the number of training data set either direct solvers can be used or an iterative solver such as conjugate gradients methods (for large data sets), in both cases with numerically reliable methods.

In applications involving nonlinear regression it is enough to change the inner product $\langle\phi(x_i),\phi(x_j)\rangle$ of Eq. (12) by a kernel function and the ijth element of matrix K equals $K_{ij}=\phi(x_i)^T\phi(x_j)$. If this kernel function meets Mercer's condition the kernel implicitly determines both a nonlinear mapping, $x\rightarrow\phi(x)$ and the corresponding inner product $\phi(x_i)^T\phi(x_j)$. This leads to the following nonlinear regression function [52]:

$$y=\sum_{i=1}^{N}\alpha_iK(x_i,x)+b \tag{16}$$

For a point x_j to be evaluated it is:

$$y_j=\sum_{i}^{N}\alpha_iK(x_i,x_j)+b \tag{17}$$

3. Methods for model evaluation

The performance of the proposed method is evaluated with several statistical methods. These are root mean square error (RMSE), mean relative error (MRE), mean error function (MEF), absolute fraction of variance (R^2) and the coefficient of variance based on root mean square error (CVRMSE). All performance measures are defined as follows respectively:

$$\mathrm{RMSE}=[\mathrm{MSE}]^{1/2}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{q_i-\bar{q}_i}{\bar{q}_i}\right)}\times100\% \tag{18}$$

$$\mathrm{MRE}=\frac{1}{N}\sum\left|\frac{q_i-\bar{q}_i}{\bar{q}_i}\right|\times100\% \tag{19}$$

$$\mathrm{MEF}=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{|q_i-\bar{q}_i|}{\max(q_i)-\min(q_i)}\times100\right) \tag{20}$$

$$R^2=1-\sum_{i=1}^{N}\left[\frac{(q_i-\bar{q}_i)}{q_i}\right]^2 \tag{21}$$

$$\mathrm{CVRMSE} = \frac{\mathrm{RMSE}}{\bar{q}_i} \times 100 \qquad (22)$$

where q_i the measured value and $\bar{q}_i$ is the predicted value of the data point. N is the number of patterns. MSE is defined as the mean square error.

4. Application study

A LS-SVM model is developed for estimating the daily solar insolation of Elazig in Turkey. In the present study, prediction model has five inputs and one output. The number of the day from 1st January, daily mean temperature, daily maximum temperature, sunshine duration, and the insolation of the day before parameters forms up the input variables of the LS-SVM and the daily solar insolation (cal/cm^2) is the output variable of the SVM model. The solar insolation data cover a period of 4 years between 2000 and 2003 for 1461 days have been obtained from Turkish State of Meteorological Service. This data is separated into two dataset as 1096 days (the first three years solar insolation data) for training and the 365 days (the fourth year solar insolation data) for testing samples. The solar insolation values employed in the training process are given in Fig. 2.

Table 2
The training parameters for the proposed method.

The training parameters of the proposed LS-SVM model	
Number of training samples	1096
Number of testing samples	365
Number of inputs	5
Number of outputs	1
Coarse search boundaries for σ^2	$[2^1, 2^5]$
Coarse search boundaries for γ	$[2^{10}, 2^{15}]$
Optimum value of σ^2	$2^{4.1}$
Optimum value of γ	$2^{6.6}$

The training parameters are shown in Table 2. Daily maximum, minimum and mean temperature variation of the sample days used in the training process are shown in Fig. 3. For the best results, data were normalized between −1 and 1. SVM application is carried out with SVM Toolbox of MATLAB.

The selection of model parameters for improving the success of LS-SVM estimation is reasonably important. In this work, LS-SVM was performed with radial basis function (RBF) as a kernel function. The vital task in achieving a highly successful LS-SVM estimation is choosing a proper

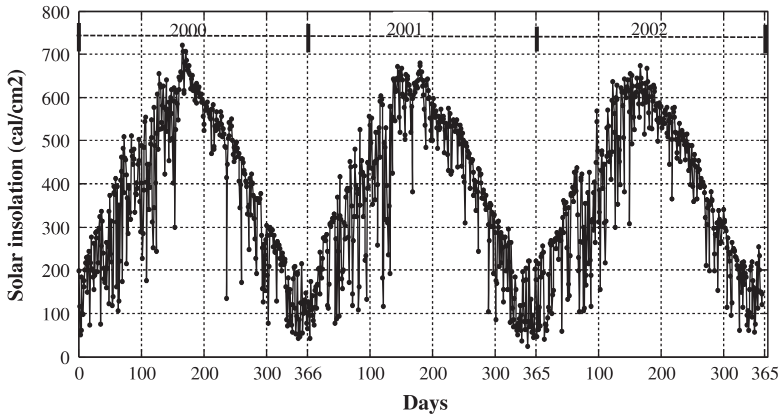

Fig. 2. The solar insolation values used in the training of LS-SVM.

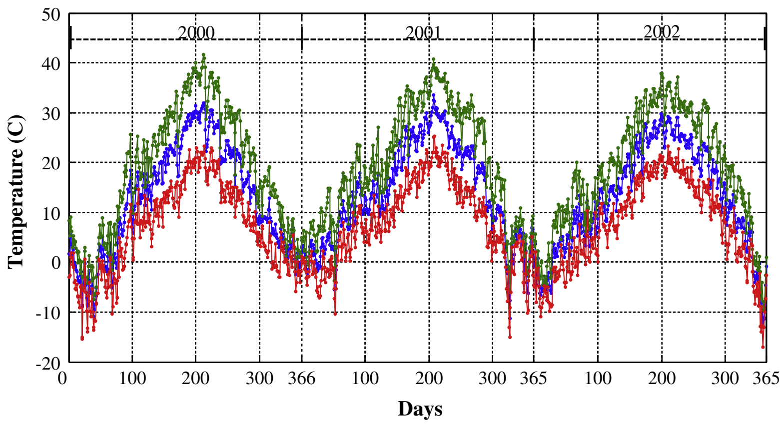

Fig. 3. The daily maximum, mean and minimum temperature values used in the training of LS-SVM.

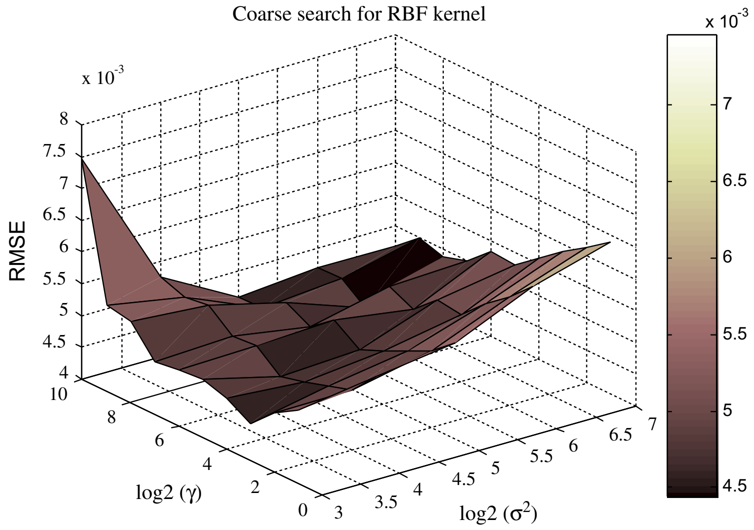

Fig. 4. RMSE vs. $\log 2(\gamma)$ and $\log 2(\sigma^2)$ for RBF kernel after applying the coarse search.

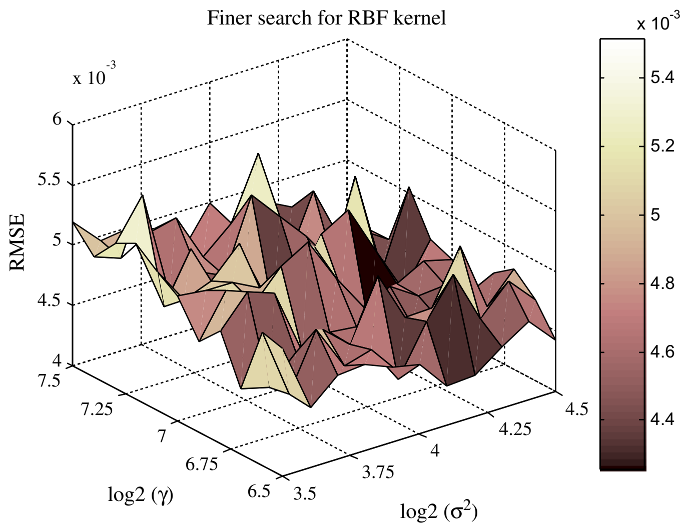

Fig. 5. RMSE vs. $\log 2(\gamma)$ and $\log 2(\sigma^2)$ for RBF kernel after applying the finer search.

set of regularization parameter, γ and kernel parameters such as σ for radial basis function (RBF).

In many studies [39,40,44,45], a grid search for determining the optimal parameters by using cross validation is recommended. For finding optimum parameters of LS-SVM search process is formed on 5-fold cross validation error of the training set. In this study the σ and γ parameters are defined by applying a two stage grid search on the parameter space. Employing exponentially growing sequences of σ and γ is a practical method to identify good parameters. Instead of doing a complete search, a coarse search has been applied to constrict the search region as shown in Fig. 4. As it is seen from the figure the acceptable region by coarse search was selected with low prediction error. This region is $[2^1, 2^5]$ and $[2^{10}, 2^{15}]$ for σ, in the style of σ^2 and γ respectively. After defining the boundaries of the better region on the grid, a finer search on that region can be carried out and the results are seen in Fig. 5. The optimum γ and σ^2 values were 97.0059 and 17.1484 which are corresponded to $2^{6.6}$ and $2^{4.1}$, respectively. Hence, the lowest RMSE in the subarea was obtained by selecting those optimal parameters.

Table 3
Performance comparison in terms of statistical model validation parameters.

Statistical model validation parameters				
RMSE	MRE	MEF	R^2	CVRMSE
0.0043841	9.9617	3.3188	99.294	0.094611

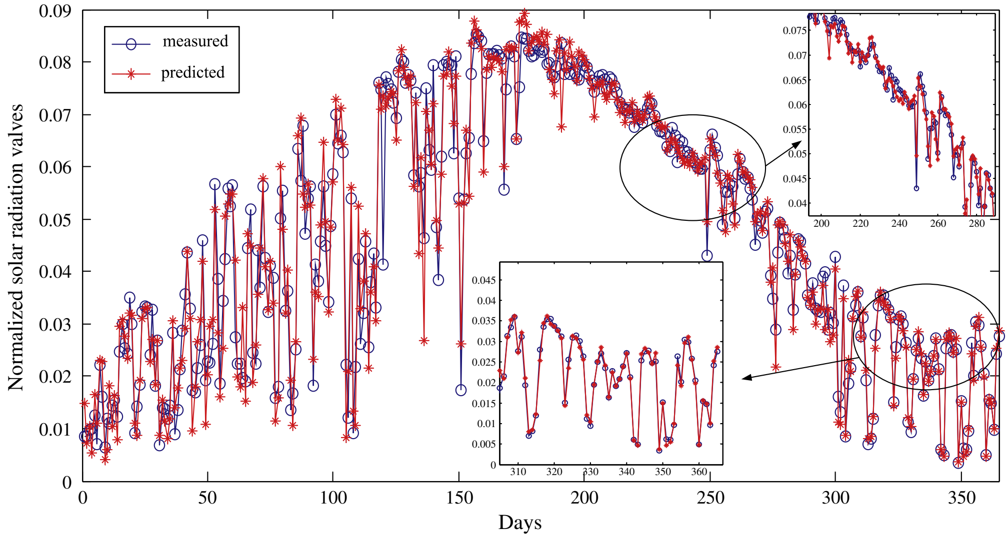

Fig. 6. Comparison of the normalized values of measured and predicted solar insolation.

Table 4
The comparison with some existing methods in literature.

Proposed by	Reference number	Proposed method	Correlation
Muribu and Banda	[23]	ANN	0.97
Fadare	[17]	ANN	0.97
Moghaddamnia et al.	[41]	ELMAN NN	0.80
Moghaddamnia et al.	[41]	NNARX	0.69
Moghaddamnia et al.	[41]	ANFIS	0.66
Benghanem and Mellit	[42]	RBFNN	0.98
Existing intelligent method		LS-SVM	0.99

Table 5
The comparison with some existing empirical methods in literature [43].

Proposed by	R^2	Proposed by	R^2
Hargreaves and Samani model	0.87	Hunt model	0.89
Annandale model	0.87	Liu and Scott	0.90
Bristow and Campbell method	0.89	Richardson and Reddy model	0.72
Donatelli and Campbell model	0.89	Chen model	0.89
Goodin model	0.86	Skeiker model	0.79
Winslow model	0.88	Wu model	0.89
Mahmood and Hubbard model	0.87	Almorox model	0.92
McCaskill	0.82	Existing Intelligent Method	0.99

By using the assigned σ^2 and γ parameters the testing of the model is performed. The performance of the proposed model in terms of statistical model validation parameters RMSE, MRE, R^2 and CVRMSE are given in Table 3. A

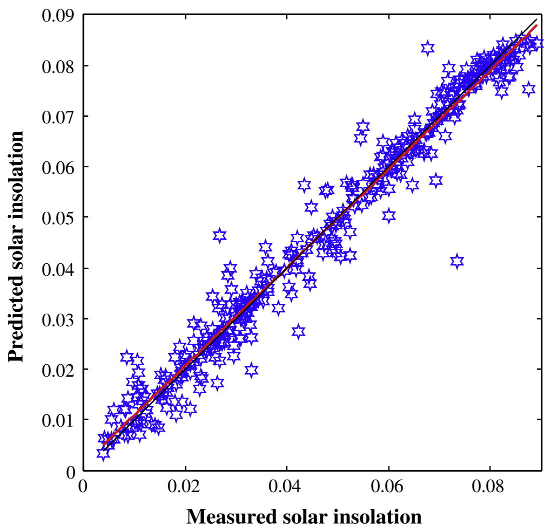

Fig. 7. The% error distribution between the predicted and measured values of solar insolation.

comparison between the normalized values of the measured data and the predicted data made to evaluate the proposed model's prediction performance. This situation is shown in Fig. 6. The performance of the proposed method is compared both with previous artificial intelligence techniques and empirical works in Tables 4 and 5 respectively. As the results were evaluated it is clearly seen that the success of the present work is higher than the expert systems and empirical models. It is evident that this amount of accuracy will be an important source data for PV systems efficient working and the storage of the solar power. And the% error distributions between the predicted and measured values are shown in Fig. 7. As it is clearly seen in figures and tables, the results were quiet satisfactory.

5. Conclusion

PV modules are generally tested under standard test conditions in laboratories. However they are all used in outdoors and sometimes do not meet the expected outputs in real life operating conditions. Solar irradiance is one of the most important factors that directly affect the power quality of the system. As the solar irradiance change continuously during the day precautionary measures must be taken for preventing from the unbalanced electricity production caused by uncertain irradiation conditions. Hence solar irradiation prediction of the next day is critically important for supplying the electricity needs flawlessly.

This study is carried out to investigate the applicability of an expert system, least squares support vector machines method, in solar insolation forecasting area by using the real measured data obtained from measurement stations. The daily solar insolation data collected during 2000–2003 years from the measurement stations of Turkish State Meteorological Service located in Elazig are employed.

From the total of 1461 data 1096 were used for training and 365 were used for testing of the LS-SVM. The number of the day from 1st January, daily mean temperature, daily maximum temperature, sunshine duration, and the insolation of the day before parameters used as inputs to predict the daily insolation as output. The results demonstrated that the proposed method based LS-SVM is very effective and feasible for estimating solar insolation values by using the previous meteorological data. A value of 0.004384 for RMS and 0.99294 for R^2 value were obtained with the proposed method.

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