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Future Solar Irradiance Prediction using Least Square Support Vector Machine

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***Abstract*— Support vector machine (SVM) based on statistical learning theory has shown its advantage in regression and prediction. This paper presents the future prediction of the solar irradiance using least square support vector machine (LSSVM) which is a kind of SVM with quadric loss function. SVM has greater generalization ability and guarantee global minima for given training data set which will give good performance for solar irradiance with time series prediction. In order to improve the prediction performance of the LSSVM, the experimental data have to be normalized and appropriate parameters are selected by generic algorithm. In this research, solar irradiance data are collected daily at monitoring station located at Green Energy Research Centre (GERC) UiTM, Shah Alam. This related information will be used in prediction of the future data which useful for designing new PV systems and monitoring existing systems performance. The results show good agreement between the predicted against the actual values measured. The proposed solar irradiance time series prediction method is considerable practical value which can be used in other datasets.**

***Keywords*— Solar irradiance; support vector machine; least square support vector machine; time series prediction**

I. INTRODUCTION

Energy is important in all aspects of development to support population growth, urbanization, industrialization as well as tourism industry. Seventy five percent of total global energy demand is supplied by the burning of fossil fuels which contribute to air pollution, global warming concerns, diminishing fossil fuels and increasing costs. Energy consumption is also increasing and several alternative green energy sources are seriously taken into consideration to fulfill energy demand.

The possibility to obtain electrical energy from the sun and to supply electrical energy has been realized due to development of solar panel and power electronic converters. Photovoltaic (PV) technology provides an attractive method of power generation and meets the criteria of clean energy and sustainability [1-3].

Photovoltaic systems are the most promising way to produce clean electricity which directly converts sunlight into electricity easily. Changes in the intensity of the solar irradiance give a major impact to the performance of the PV systems. Fluctuations of the solar irradiance cause troubles between demand and supply and reduce the power quality. Accurate solar irradiance data is required for modelling and designing of solar energy systems such as photovoltaic, solar thermal and any other applications.

Many research have been carried out related to the estimation of solar energy potential in various locations based on conventional physical models or some statistical assumptions [4-13]. Advanced development in computer technology especially in artificial intelligent techniques have been used for prediction in many engineering areas. Several methods for estimating solar irradiance with artificial intelligent techniques have been done by previous researchers [14-28].

In recent years, Support Vector Machine (SVM) theory was developed by Vapnik [29-30]. There have been an intensive studies on SVM for regression and prediction in which SVM is quite satisfying in theoretical point of view, which leads to a great potential and superior performance in practical applications. The structural risk minimization (SRM) in SVM has been proved superior to the empirical risk minimization (ERM) principle as adopted in neural network. SVM shows powerful generalization ability and guarantee global minima. In addition, SVM is adaptive to complex systems and robust in dealing with corrupted data. Least Square Support Vector Machine (LSSVM) [31-32] uses equality constraints instead of inequality constraints and a least squares error term in order to obtain a linear set of equations in the dual space. This unique feature make LSSVM have the advantages of simple structure and high speed. Many great research have been successfully adopted SVM and LSSVM techniques such as fingerprint recognition [33], document categorization [34], traffic pattern recognition [35], forecasting of financial market [36], forecasting of electricity price [37], estimation of power consumption and time series prediction [38].

This research is carried out to investigate the capability of least square support vector machine in forecasting solar irradiance by using the actual measured data obtained from measurement stations. LSSVM model for predicting one day ahead of solar irradiance values by using the real climate data obtained from the monitoring station located at Green Energy Research Centre (GERC) UiTM, Shah Alam. MATLAB was employed for LSSVM applications.

II. Description Of The GCPV System

The Grid Connected Photovoltaic (GCPV) power system involved in this research situated in Green Energy Research Center (GERC), University of Technology MARA (UiTM) Shah Alam, Selangor. The system can be described as Table 1. The data of solar irradiance, module temperature, power, voltage and current has been analysed from May 2012 which are recorded every 5 minutes interval using dedicated in-built data logger in the individual grid inverter.

TABLE I
GCPV System Description

Description	System
Parameters P_{mp} (W) V_{mp} (V) I_{mp} (A) γ_{pmp} (% C^{-1}) γ_{imp} (% C^{-1}) f_{dirt} f_{cable_loss} f_{mm} f_{aging} (%)	Monocrystalline 250 30.5 8.2 -0.42 0.04 0.97 0.98 0.95 1
Array Configuration	2 parallel X 20 series
Total Capacity	10kWp
Type of Inverter/ Efficiency (%)	Sunny Tripower STP8000TL 98.3
Type of Mounting Structure	Retrofitted on metal deck

III. Least Square Support Vector Machines

LSSVM is an alteration of the standard SVM and was improved by Suykens et al. [39]. LSSVM uses equality constraints instead of inequality constraints and a least squares error term instead of the standard error term.

Giving a training data set of N samples {x_k,y_k }_(k=1)^Nwith input data x_k∈R^n and output data y_k ∈ R one considers the following optimization problem in primal weight space:

$$min\left\{J(w,e)=\frac{1}{2}w^Tw+\frac{1}{2}\gamma\sum_{k=1}^{N}e_k^2\right\} \quad (1)$$

Subject to

$$y_k=w^T\varphi(x_k)+b+e_k, \quad k=1\ldots\ldots N$$

With $\varphi(\cdot):R^{n_k}$ a function which maps the input space into a higher dimensional feature space, weight vector $w\in R^{n_k}$in primal weight space, error variables $e_k\in R$ and bias term *b*. Note that the cost function *J* consists of a sum squared error fitting error and a regularization term, which is also a standard procedure for the training of multilayer perceptrons's and is related to ridge regression. The relative importance of these terms is determined by the positive real constant γ.

In primal weight space one has the model

$$y(x)=w^T\varphi(x)+b \quad (2)$$

The weight vector *w* can be infinite dimensional, which makes a calculation of *w* from (2) impossible in general. Therefore, one computes the model in the dual space instead of the primal space. One defines the Lagrangian

$$L(w,b,e,\alpha)=J(w,e)-\sum_{k=1}^{N}\alpha_k\{w^T\varphi(x_k)+b+e_k-y_k\} \quad (3)$$

With Lagrange multipliers $\alpha_k\epsilon R$ called support values.

The conditions for optimality are given by

$$\begin{aligned}&\frac{\partial L}{\partial w}=0\rightarrow w=\sum_{k=1}^{N}\alpha_k\varphi(x_k)\\&\frac{\partial L}{\partial e_k}=0\rightarrow\alpha_k=\gamma e_k, \quad k=1\ldots\ldots\ldots N\\&\frac{\partial L}{\partial b}=0\rightarrow\sum_{k=1}^{N}\alpha_k=0\\&\frac{\partial L}{\partial\alpha_k}=0\rightarrow w^T\varphi(x_k)+b+e_k-y_k=0, \quad k=1\ldots.N\end{aligned} \quad (4)$$

These conditions are similar to standard SVM optimally conditions, expect for the condition $\alpha_k=\gamma e_k$. At this point one loses the sparseness property in LSSVM.

After elimination of *w*, *e* one obtains the solution

$$\begin{bmatrix}0 & 1_v^T\\1_v & \Omega+\frac{1}{\gamma}I\end{bmatrix}\begin{bmatrix}b\\a\end{bmatrix}=\begin{bmatrix}0\\y\end{bmatrix} \quad (5)$$

with

$$y=[y_1\ldots\ldots y_N], 1_v=[1,\ldots..1], \alpha=[\alpha_{1\ldots\ldots}\alpha_N]$$

and

$$\Omega_{kl} = \varphi(x_k)^T \varphi(x_l) for\ k, l = 1 \dots \dots N$$

According to Mercer's condition, there exists a mapping φ and an expansion

$$K(x, y) = \sum_i \varphi_i(x)\varphi_i(y), \quad x, y \in R^n \tag{6}$$

If and only if, for any $g(x)$ such that $\int g(x)^2 dx$ is finite, one has

$$\int K(x, y) g(x)\, g(y)\, dx dy \geq 0 \tag{7}$$

As a result, one can choose a kernel $K(\cdot,\cdot)$ such that $K(x_k, x_l) = \varphi(x_k)^T \varphi(x_l), \quad k, l = 1 \dots \dots N$. The resulting LSSVM model for function estimation becomes

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{8}$$

Where *a*, *b* is the solution for (8). Chosen different kernel function can build up different LSSVM.

A. LSSVM Model

The design process of LSSVM predictor, error parameter γ called hypermeter and kernel function with its parameter are assigned by user. Parameter γ determines the trade-off between margin maximization and training error minimization. Large γ give higher penalties to errors and lower generalization. With different kernel function, the predictor will perform differently. This research focused on RBF kernel $K(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$ for solar irradiance prediction.

The parameters included σ in RBF function $K(x, y) = exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$ and error parameter γ in estimate function.

IV. Results and Discussion

This research focused on the one day ahead prediction of solar irradiance. With the time series model and parameters listed above, the solar irradiance predictors built up with LSSVM. According to the theory of LSSVM, model should be built under the training samples. Utilize the 864 groups minutes solar irradiance (00.00 a.m. to 11.55p.m, Jun 1st-3th, 2014) as training set and the other 864 groups minutes solar irradiance as testing set to predict solar irradiance values for the next day (Jun 4th,2014). Prediction on the next day followed the same steps with previous day solar irradiance data's. After grid search and cross validate, RBF kernel function was selected as shown in Table 2. Fig 1- Fig.3 shows the final prediction results.

By using the assigned γ, σ values, the testing of the model is performed. Fig. 1 shows the prediction of solar irradiance for the whole day. From the graph we can see changes in three different periods of time including in the morning, in the noon (maximum sun peak) and the evening. LSSVM predictor can analyze the characteristic of the solar irradiance and accurately forecast the solar irradiance for the next day with 95.43% of accuracy.

TABLE II
Parameters Values in Solar Irradiance Predictors.

Parameters	Jun 4th	Jun 5th	Jun 6th
σ	21.9453	14.5980	16.4697
γ	2.0029	1.1534	6.0540

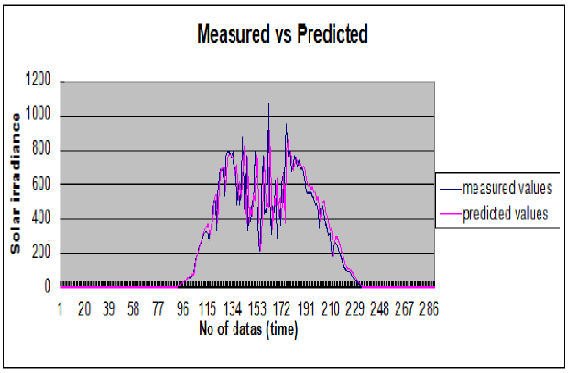

Fig.1. Measured and predicted values (Jun 4th)

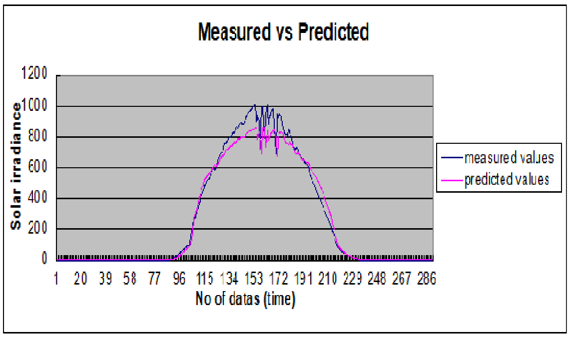

Fig. 2. Measured and predicted values (Jun 5th)

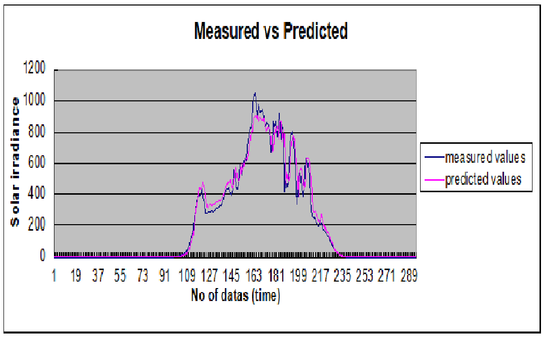

Fig. 3. Measured and predicted values (Jun 6th)

Fig. 2 describes the prediction for Jun 5th . We can see that the trend of solar irradiance almost the same from the previous day. LSSVM predictor accurately forecast the solar irradiance with 96.87% accuracy. In Fig.3 we can see the prediction for the next day based on the previous data. LSSVM predictor successfully forecast the values and gave 97.75% accuracy. From the results obtained, The LSSVM predictor gave the accuracies which can meet engineering practice needs.

V. Conclusions

The performance of the grid connected PV system is majorly influence by the solar irradiance and module temperature. The one day ahead of solar irradiance has been predicted by the LSSVM model. Based on the results, it shows LSSVM accurately estimating solar irradiance values by using the previous measured data as inputs. As solar irradiance change continuously during the day, this prediction will help preventing from the unbalanced electricity production caused by uncertain irradiance conditions.

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