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PREDICTION OF GLOBAL SOLAR RADIATION BY USING LS-SVM ALGORITHM

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***Abstract*- Solar radiation is an essential and important variable to many models. It is the radiant energy emitted from the sun. Various solar radiation predictive models has developed on the basis of data. The drawbacks in the predictive models include, local minima errors, optimization problem, over fitting problems, random error. To overcome all these problems, Least Squares Support Vector Machine (LS-SVM) algorithms are applied to predict the monthly average daily global solar radiation. The data sets are divided into training and validation data sets. The input variables include air temperature, diurnal range of air temperature, relative humidity, precipitation, atmospheric pressure and Sunshine hours. From this method, the RBF kernel function σ^2 and regularization parameter γ are calculated by 5-fold cross validation.**

***Index Terms*- Least Square-Support Vector Machine, Radial Basis Function, Kernel function, Regularization parameter**

I. INTRODUCTION

Prediction is the calculation or estimation of future events. Accurate information about the future in many cases is impossible, therefore prediction can be useful to assist in making plans about possible developments. Solar radiation is the radiant energy emitted by the sun. It is also known as short wave radiation. Due to the cost and difficulty in measurement, the observation data of global solar radiation are often missing and unavailable in many places. As a result various solar radiation models[4] has been developed.

The earliest model is the *Angstrom formula* [1], which employ the sunshine duration and clear sky radiation data to simulate the monthly global solar radiation. the clear sky radiation was not accurately. So *Prescott* [9][10], shifted the clear sky radiation to the extra terrestrial radiation and this method has been received almost world-wide acceptance. Other models consider parameters, such as air temperature, relative humidity, and precipitation. *Artificial Neural Networks (ANN)* [7], has been applied. ANNs are found to be unstable predictors due to the local minima errors, and over fitting problems. Local minima errors is defined as the point such that all the points in neighbor hood have an error value greater than or equal to error value of that point. Over fitting problems occurs when statistical model describes random error or noise. Generally occurs when a model is excessively complex such that having too much of parameters. Over fit have poor predictive performance. Recently, extensive applications have been performed by *Support Vector Machine (SVM)*[5], which is a novel machine-learning tool and especially useful for solving problems in nonlinear classification, function and density estimation. Compared to ANN, SVM has more advantages on forecast. Because SVM is based on the statistical learning theory and structural risk minimization, which can get the best solution of entire data set and better ability of generalization. The *Least Squares Support Vector Machine (LS-SVM)* [2], is the variant of SVM was applied to develop the global solar radiation model using the conventional meteorological data, and then map the global solar radiation resources.

II. GLOBAL SOLAR RADIATIONS

Solar radiation is absorbed, scattered and reflected by components of the atmosphere. The amount of radiation reaching the earth is less than what entered the top of the atmosphere.The solar radiation reaching the Earth's surface can be divided into two types of solar radiation.

Direct beam solar radiation and diffuse solar radiation. As sunlight passes through the atmosphere, some of it enters the surface of the Earth direct and undisturbed - the so called beam solar radiation.We classify it in two categories,

Radiation from the sun that reaches the earth without scattering. It is also sometimes called "beam radiation" or "direct beam radiation". It is used to describe solar radiation traveling on a straight line from the sun down to the surface of the earth. Radiation that is scattered by the atmosphere and clouds. Direct radiation has a definite direction but diffuse radiation is just going any which way. Because when the radiation is direct, the rays are all travelling in the same direction, an object can block them all at once. This is why shadows are only produced when direct radiation is blocked.

III. LS-SVM ALGORITHM

LS-SVM algorithm[3], especially useful for solving problems in nonlinear classification, Here, consider x_i and y_i as the input variables, the original data is mapped into high dimensional space, the non-linear separable problems turns into linear separable in space.

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

Where,

w is the weight vector

b is the bias term.

According to the structural risk minimization principle, the risk bound is minimized by the following minimization problem. Minimizing process is carried after the function classification.

$$\min J(w,e)=\frac{1}{2}w^t w+\gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2 \tag{2}$$

Subject to equality constrains

$$y_i=w^T\varphi(x_i)+b+e \qquad i=1,\ldots,N \tag{3}$$

Where,

e_i is the random error

γ is a regularization parameter.

To overcome the optimization problem, Lagrange function is constructed. Now the LS-SVM model is expressed as

$$y=\sum_{i=1}^{N} a_i K(x_i,x)+b \tag{4}$$

Where,

α_i is the Lagrange multiplier which is called a support value.

$K(x_i , x)$ is the kernel function. Where k is chosen by the user.

The kernel function which is carried out here is Radial Basis Function (RBF), RBF kernel function for implicit higher dimension mapping.

$$K(x_i,x_j)=\exp\left(-\frac{\|x-y\|2}{\sigma 2}\right) \tag{5}$$

Where,

σ^2 is the bandwidth of the RBF kernel.

A. LS-SVM Classifications

It performs classification by constructing an N-dimensional hyperplane that optimally separates data into two categories [14]. Data has a categorical target variable with two categories and the two predictor variables with continuous values. Here, the monthly average daily global solar radiation is estimated by classifying. The classification is done between the two input variables.

B. LS-SVM

LS-SVM deals with (a) more than two predictor variables, (b) separating the points with non-linear curves, (c) handling the cases where clusters cannot be completely separated, and (d) handling classifications with more than two categories.

IV. INPUT DATA SETS

The input variable includes:1) Global solar radiation, 2) Air temperature, 3)Diurnal range of air temperature, 4) Precipitation, 5) Sunshine hours,6) Relative humidity.

A. Training and validation data set.

The data sets are divided into training data and validation data. The monthly average of the month January to June is taken for training and daily average of the month July to December is taken as validation sets. The RBF kernel and regularization parameter set was tuned simultaneously.

V. LS-SVM EVALUATION

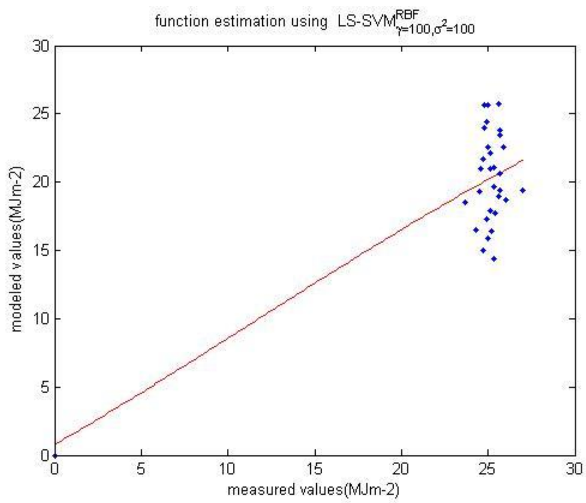
In this work, the statistical indices, the coefficient of determination (R^2), Mean square error (MSE), and the Root Mean Square Error are applied to evaluate the performance of the model. The result of the performance are listed in Table

DATA	R^2	MSE	RMSE
Training	0.12285	0.3606	0.6004
Validation	0.01747	0.5144	0.7173

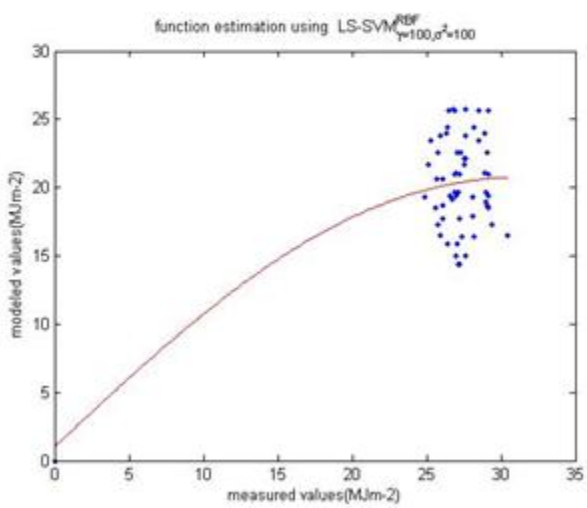
The predictability of LS-SVM model in different months and the generalization ability was evaluated with the validation data. The LS-SVM fits the excellent to the testing data with the value of R^2 being 0.12285, RMSE being 0.3606 $MJ.m^{-2}.d^{-1}$, respectively.

A. Parameter calculations

In this paper, the RBF kernel σ^2 and the regularization parameter γ are tuned simultaneously with different orders of magnitude which performed on the basis of 5-fold validation. The optimum value of γ and σ^2 is 3.4486 and 0.10235 respectively for the LS-SVM model.



(a) Testing data



(b) Validation data

Fig 1. The predicted monthly average daily solar radiation vs measured data.

VI. CONCLUSION

In this paper, a LS-SVM method is applied to predict the global solar radiation. The predictability of LS-SVM model in different months and the generalization ability is evaluated with the training and validation data. The LS-SVM fits the excellent to the testing data with the value of R^2 being 0.12285, RMSE being 0.3606 $MJ.m^{-2}.d^{-1}$, respectively.

Results shows that the LS-SVM can successfully predict the global solar radiation. The RBF kernel σ^2 and the regularization parameter γ are tuned simultaneously with different orders of magnitude which performed on the basis of 5-fold validation. The optimum value of γ and σ^2 is 3.4486 and 0.10235 respectively for the LS-SVM model.

REFERENCES

[1] A.Ångström,"Solar and Terrestrial Radiation,"Q. J. Roy. Meteor.Soc., vol. 50, pp.121-126, 1924.

[2] Chunli Xie, Cheng shoa and dandan zhoa, "Parameters optimization of least square support vector machine and its application," Dalian Nationalities University/school of computer science and Engineering, Dialian, 116024, China.Journal of computers, vol 6,no.9, September 2011.

[3] Fangping Deng, Gaoli Su, Chuang Liu Zhengxing Wang, "Prediction Of Solar Radiation resources in China Using LS-SVM Algorithm," College of Resource Science and Technology,Beijing Normal University,China. 978-4244-5586-7/10/S26.00/2010 IEEE

[4] M.Jamil Ahmad, G.N.Tiwari, "Solar Radiation Models – Review," Center of Energy Studies,Indian Institute of Technology, Hauz Khas, New Delhi-16,India.IJEE Volume 1, issue 3,2010,pp.513-532 . www.IJEE.IJEFoundation.org

[5] Ji-Long Chen, Guo-Sheng Li, "Evalution of Support Vector Machine for Estimation of Solar Radiation from Measured Meteorological Variables," theorappl Climatol (2014) 115.627-638. Spring-verlag wein 2013.

[6] Jianwu Zeng,Wei Qiao, "short term solar powerprediction using a Support Vector Machine," dept of EEE, University of Nebraska-lincoln,USA. Renewable energy 52(2013)118-127.

[7] G.López, F. J. Batlles, J. Tovar-Pescador, "Selection of inputparameters to model Direct solar irradiance by using Artificial Neural Networks," Energy, vol.30,pp.1675– 1684, 2005.

[8] Pijush Samui, "Application of Least Square Support Vector Machine for determination of Evaporation losses in Reservoirs,"ofDisaster Mitigation Management, VITuniversity, vellore. Engineering,2011,3,43143. (http://www.sciRP.org/journal/eng).

[9] J. A. Prescott, "Evaporation from a water surface in relation to solar radiation," Trans.Soc.Sci. Aust., vol.64, pp. 114 – 125, 1940.

[10] R.C. Srivastava and Harsha pandey, "Estimating Angstrom-Prescott Coefficients for India developing a correlation between sunshine hours and global solar radiation for