International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 7, July - 2014

LS-SVM Based Wind Speed Forecasting

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***Abstract*— Wind energy is one of the most promising electricity sources of the 21st century, because it is clean, inexhaustible and free resource. Wind turbines convert the kinetic energy in moving air into rotational energy, which in turn is converted to electricity. Since wind speeds vary from month to month and second to second, the amount of electricity wind can make varies constantly, accurate forecasting of wind speed is necessary. This paper presents Least Square Support Vector Machine (LSSVM) based approach for wind speed forecasting. Actual wind speed data of one of the stations in Mumbai is used in the present work to validate the results of the algorithm.**

Keywords— ***Wind Speed, Wind speed forecasting, SVM, LSSVM***

I. INTRODUCTION

The Indian economy has experienced unprecedented economic growth over the last decade. Today, India is the ninth largest economy in the world, driven by a real GDP growth of 8.7% in the last 5 years (7.5% over the last 10 years). In 2010 itself, the real GDP growth of India was the 5th highest in the world [1]. This high order of sustained economic growth is placing enormous demand on its energy resources. The demand and supply imbalance in energy is pervasive across all sources requiring serious efforts by Government of India to augment energy supplies as India faces possible severe energy supply constraints.

The original impetus to develop wind energy in India came in early 1980s from the Government, when the Commission for Additional Sources of Energy (CASE) had been set up in 1981 and upgraded to the Department of Non-Conventional Energy Sources, DNES in 1982. This was followed in 1992 by the establishment of a full-fledged Ministry of Non-Conventional Energy Sources, MNES, renamed as Ministry of New and Renewable Energy Sources, MNRE in 2006. The Indian Renewable Energy Development Agency, IREDA was established in 1987 as a financial arm of the ministry to promote renewable energy technology in the country. It provides finances to the manufacturers, consultancy services to the entrepreneurs, and also assists in the development and up gradation of technologies.

Traditionally, electricity utilities and system operators are accustomed to understanding the supply side of load balancing with regards to the source of the energy, dispatchability and reserves, as well as the relative cost of producing electricity from non-renewable resources. With the recent and continued increase in penetration of wind power, the energy industry will need to adjust its thinking on how to integrate this intermittent power source into the electricity grid. Various forecasting techniques, associated with wind power and speed, based on numeric weather prediction (NWP), statistical approaches, artificial neural network (ANN) and hybrid techniques over different time-scales are reported in literature [2-7].

This paper is organized as follows. Section 2 describes brief theory of LSSVM. The detailed algorithm is given in section 3. Section 4 deals with the implementation of the algorithm using LSSVM and results obtained.

II. LEAST SQUARE SUPPORT VECTOR MACHINE

Least Square Support Vector Machine classifier was proposed by Suykens and Vandewalle [8]. LS-SVM is a class of kernel based learning methods. By LS-SVM one can find the solution by solving a set of linear equations instead of a convex quadratic programming for classical SVM. LS-SVM tries to minimize primal cost function subject to equality constraints instead of inequality ones. Therefore LS-SVM solves a set of linear equations instead of computational cost quadratic programming problem.

The classification and regression problem is quite similar; therefore the two versions are described side by side as follows.

The goal is to approximate a $y = g(\mathbf{x})$ function, based on a training data set $\{\mathbf{x}_i, y_i\}_{i=1}^{N}$, where $\mathbf{x}_i \in \Re^N$ represents a N–dimensional input vector and $y_i \in \Re$ is the corresponding scalar target output for regression, while in case of classification $y_i \in \{-1,+1\}$ is a class label. Our goal is to construct an $y = f(\mathbf{x})$ approximating function, which represents the dependence of the d training outputs on the $\mathbf{x}$ inputs. Let's define the form of this function as:

Classification

$$y(\mathbf{x}) = sign\left[\sum_{j=1}^{h} w_j \varphi_j(\mathbf{x}) + b\right] = sign\left[\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b\right]$$

Regression

$$y(\mathbf{x}) = \sum_{j=1}^{h} w_j \varphi_j(\mathbf{x}) + b = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b \qquad \text{.....(1)}$$

where

$$\mathbf{w} = [w_1, w_2, ..., w_h]^T, \quad \boldsymbol{\varphi} = [\varphi_1, \varphi_2, ..., \varphi_h]^T.$$

The $\{\varphi_i(\mathbf{x})\}_{i=1}^{h}$ is a set of given linearly independent basis functions, which maps the input data into an h–dimensional feature space. The dimension of the feature space may be very large, even infinite.

The main difference from the standard SVM is in the constraints. LS-SVM applies equality constraints, so the constrained optimization tasks will be ($k = 1,..., N$):

$$\min_{\mathbf{w},b,\mathbf{e}} J_p(\mathbf{w},\mathbf{e}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\frac{1}{2}\sum_{k=1}^{N} e_k^2$$

with constraints:

$$y_k\left[\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_k) + b\right] = 1 - e_k$$

$$\min_{\mathbf{w},b,\mathbf{e}} J_p(\mathbf{w},\mathbf{e}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\frac{1}{2}\sum_{k=1}^{N} e_k^2 \qquad \text{.....(2)}$$

with constraints:

$$y_k = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_k) + b + e_k$$

The first term is responsible for finding a smooth solution, while the second one minimizes the training errors (C is the trade–off parameter between the terms).

From this, the following Lagrangian can be formed:

$$L(\mathbf{w}, b, \mathbf{e}; \boldsymbol{\alpha}) = J_p(\mathbf{w},\mathbf{e}) - \sum_{k=1}^{N} \alpha_k \left\{d_k\left[\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_k) + b\right] - 1 + e_k\right\}$$

$$L(\mathbf{w}, b, \mathbf{e}; \boldsymbol{\alpha}) = J_p(\mathbf{w},\mathbf{e}) - \sum_{k=1}^{N} \alpha_k \left\{\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_k) + b + e_k - y_k\right\} \qquad \text{.....(3)}$$

where the α_k parameters are the Lagrange multipliers. The conditions for optimality are the followings ($k = 1,..., N$):

$$\begin{aligned}
\frac{\partial L}{\partial \mathbf{w}} = \mathbf{0} &\rightarrow \mathbf{w} = \sum_{k=1}^{N} \alpha_k y_k \boldsymbol{\varphi}(\mathbf{x}_k) \\
\frac{\partial L}{\partial b} = 0 &\rightarrow \sum_{k=1}^{N} \alpha_k y_k = 0 \\
\frac{\partial L}{\partial e_k} = 0 &\rightarrow \alpha_k = C e_k \\
\frac{\partial L}{\partial \alpha_k} = 0 &\rightarrow y_k\left[\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_k) + b\right] - 1 + e_k = 0
\end{aligned}$$

$$\begin{aligned}
\frac{\partial L}{\partial \mathbf{w}} = \mathbf{0} &\rightarrow \mathbf{w} = \sum_{k=1}^{N} \alpha_k \boldsymbol{\varphi}(\mathbf{x}_k) \\
\frac{\partial L}{\partial b} = 0 &\rightarrow \sum_{k=1}^{N} \alpha_k = 0 \\
\frac{\partial L}{\partial e_k} = 0 &\rightarrow \alpha_k = C e_k \\
\frac{\partial L}{\partial \alpha_k} = 0 &\rightarrow \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_k) + b + e_k - y_k = 0
\end{aligned} \qquad \text{....(4)}$$

The corresponding linear equation sets (a Karush–Kuhn–Tucker (KKT) system) are:

$$\begin{bmatrix} 0 & y^T \\ y & \boldsymbol{\Omega} + C^{-1}\mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{\mathbf{1}} \end{bmatrix}, \quad \Omega_{i,j} = y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)$$

$$\begin{bmatrix} 0 & \vec{\mathbf{1}}^T \\ \vec{\mathbf{1}} & \boldsymbol{\Omega} + C^{-1}\mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}, \quad \Omega_{i,j} = K(\mathbf{x}_i, \mathbf{x}_j) \qquad \text{.....(5)}$$

where $y = [y_1, y_2, ..., y_N]^T$, $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, .., \alpha_N]^T$, $\vec{\mathbf{1}} = [1,...,1]^T$, $K(\mathbf{x}_i, \mathbf{x}_j) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x}_j)$ is a kernel function, $C \in \Re_+$ is a positive constant, b is the bias and the response of the LS-SVM can be obtained in the form:

$$y(\mathbf{x}) = sign\left[\sum_{k=1}^{N} \alpha_k y_k K(\mathbf{x}, \mathbf{x}_k) + b\right]$$

$$y(\mathbf{x}) = \sum_{k=1}^{N} \alpha_k K(\mathbf{x}, \mathbf{x}_k) + b \qquad \text{.....(6)}$$

III. WIND SPEED FORECASTING ALGORITHM

Step 1: Data Collection

IMD data consists of synoptic observations from over 400 stations. It consists of balloon observations at a height of 10 m. The data of 1998 to 2007 (10 years) at one of the stations in Mumbai is used in the present problem of wind speed forecasting.

Step 2: Data Preprocessing

IMD data consists of mean hourly wind speed in km/hr round the clock for all the days of the year 1998 to 2007. It is first converted into daily mean hourly wind speed in km/hr. For the best results all the data is normalized between 0 and 1.

Step 3: Design of LS-SVM model for Wind Speed Forecasting

The available wind speed data of 10 years is divided into two parts: training data and testing data. By conducting the series of experiments, different LS-SVM model is developed. Step 4: Calculate Mean Squared Error.

Step 4: Calculate Mean Squared Error

To evaluate the performance of the model mean squared error (MSE) is calculated. Let $x_1, \ldots\ldots, x_l$ be the testing data and $f(x_1), \ldots\ldots, f(x_l)$ be decision values (target values) predicted by SVM model. If the true labels (true target values) of testing data are known and denoted as $y_{1,\ldots\ldots}, y_l$, then,

$$MSE = \frac{1}{l}\sum_{i=1}^{l}(f(x_i) - y_i)^2 \qquad \ldots\ldots(7)$$

IV. IMPLEMENTATION AND RESULTS

The proposed algorithm for wind speed forecasting using LS-SVM is implemented using LS-SVM Lab MATLAB toolbox [9]. The main objective of the present work is to develop model for wind speed forecasting. In the present work, data is divided into five subsets of equal size. Sequentially one subset is used for testing using the LSSVM model trained on the remaining subsets. Fig.1 displays the results of the algorithm. It is observed that the forecasted values of wind speed are nearly equal to the observed values. Mean squared error of 7.54 x 10-4 is obtained.

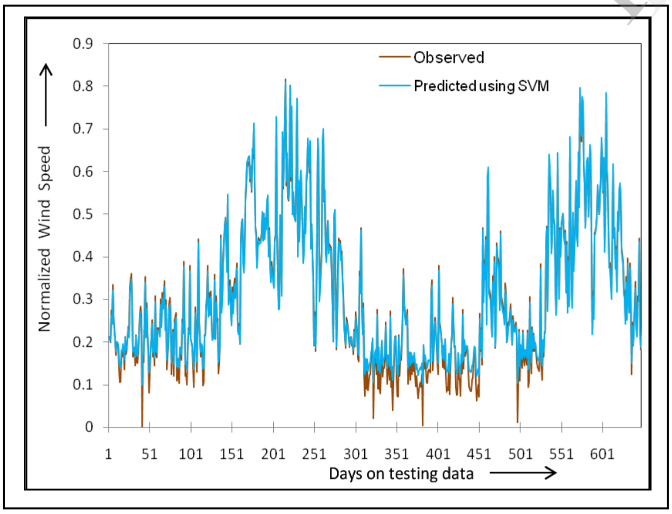

Fig. 1 : Wind Speed Forecasting Results

V. CONCLUSION

Forecasting wind speed is considered as one of the most important tasks for the large-scale integration of intermittent wind-powered generators into power systems. The LS-SVM regression models developed in this dissertation work serve as an introduction to wind speed forecasting mainly for wind power companies operating in electricity wholesale markets.

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