SHORT TERM LOAD FORECASTING SYSTEM BASED ON SUPPORT VECTOR KERNEL METHODS

Lal Hussain[1], M. Sajjad Nadeem[2], Syed Ahsen Ali Shah[3]

[1,2,3]University of Azad Jammu and Kashmir, City Campus – 13100, Muzaffarabad, Pakistan

ABSTRACT

Load Forecasting is powerful tool to make important decisions such as to purchase and generate the electric power, load switching, development plans and energy supply according to the demand. The important factors for forecasting involve short, medium and long term forecasting. Factors in short term forecasting comprises of whether data, customer classes, working, non-working days and special event data, while long term forecasting involves historical data, population growth, economic development and different categories of customers.In this paper we have analyzed the load forecasting data collected from one grid that contain the load demands for day and night, special events, working and non-working days and different hours in day. We have analyzed the results using Machine Learning techniques, 10 fold cross validation and stratified CV. The Machines Learning techniques used are LDA, QDA, SVM Polynomial, Gaussian, HRBF, MQ kernels as well as LDA and QDA. The errors methods employed against the techniques are RSE, MSE, RE and MAPE as presented in the table 2 below. The result calculated using the SVM kernel shows that SVM MQ gives the highest performance of 99.53 %.

KEYWORDS

Forecasting, Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), QuadraticDiscriminant Analysis (QDA), Mean Square Error (MSE), Relative Error (RE) and Mean Absolute Percentage Error (MAPE), Cross Validation (CV)

1. INTRODUCTION

Accurate models predict electricity load power necessary for the operation and planning for the utility company. Load forecasting electric tool helps to make important decisions, including decisions relating to the purchase and electric power generation, load switching, and infrastructure development. Expectations of pregnancy are extremely important for energy suppliers, solidarity and financial situations, and other participants in the electric power generation, transmission and distribution, and markets. And expectations of pregnancy can be divided into three categories: short-term outlook, which is usually from one hour to one week, and forecasts medium which is usually from one week to one year, and long-term forecasts that are longer than a year. Expectations for different time horizons important for different processes within the company benefit.

2. IMPORTANT FACTORS FOR FORECASTS

For short-term load forecasting should consider several factors, such as time factors, weather data, and potential customer classes. Medium-term outlook and long-term take into account the load historical data and weather, and a number of clients in different categories, Devices in the region and their characteristics, including age, economic and demographic data and expectations, and appliance sales data, and other factors. Time factors include time of year, and day of the week and hours of the day. There are significant differences in pregnancy between weekdays and weekends. The load on different days of the week also can behave differently. For example, it may be adjacent Mondays and Fridays for the weekend, they have structurally different amounts from Tuesday to Thursday. Is this is particularly true during the summer. The holidays are more difficult to predict because of the holidays and a relatively rare occurrence. Weather conditions affect the pregnancy. In fact, the Weather forecast parameters are the most important factors in pregnancy expectations in the short term. Can be considered as different weather variables to predict pregnancy. Temperature and humidity are the most commonly used predictors of pregnancy.

3. LITERATURE REVIEW

To accurately forecasting the electric load we can save the electricity as well as can distribute the efficient and limited energy sources. When the load forecasting of the electricity is not accurate it may increase the cost for operating the forecasting. For instance, when the electric load is over estimated it results unnecessary reservation of the spinning, inefficient distribution of the energy, the limited energy sources are wasted moreover, the excess supply owning by the international network is not acceptable. In comparison, when the electric load forecasting is under estimating it results in failure to provide sufficient reservation and produce high costs for the peaking units due to which the industrial and economic developments are discouraged. In order to achieve the future electric load demands, it require efficient electricity load planning, secure operation field in both the regional and national systems [5].

The demand for the electricity is usually modeled in terms of the weather variables(Hor et al., 2005; Cancelo et al., 2008). However, for the short term forecasting, the univariate methods are considered as sufficient as the weather variable smoothly changes in short time frames. Likewise, to ensure the robustness, the weather-based online systems require default procedures(Bunn, 1982). According to the recent empirical study(Taylor, 2008a), a univariate method can better perform than the multivariate method up to four hours ahead, however, by combining the forecasting of these two methods can achieve the best performance up to a day ahead. This implies that univariate can play a vital role for short term load forecasting (Soares and Medeiros, 2008) [7].

In order to best utilize the electric energy demands and resolve the conflict between supply and demand, load forecasting is extremely dire to plan the operational electric power systems and relevant research purposes as well.Short term load forecasting (STLF) is an essential part of load forecasting for its controllable, random, real-time,non-linear and dynamic factors influenced on it. As per characteristics of STLF, the neural networks are gaining an increased attention for dynamic and non-linear behavior of the system having strong robustness, fault tolerance, wavelet transform, grey system and support vector machine to achieve and face the demands and needs for higher accurate STLF [3].

Presently, artificial intelligence techniques have been implied in order to increase the electricity load forecasting demands and performance. Moreover, Rahman and Bhatnagar have presented knowledge based expert system (KBES) approach to achieve better load forecasting for the electricity, which can construct new rules based on the gathered information like daily temperature, previous day load, day type etc. Using this approach attained through training rules, the information received then transformed to the mathematical equations.Park et al. has established a three layer back propagation neural network to solve the problems of daily forecasting problems. The features extracted from the daily load are computed from temperature indices: peak, average and lowest load, while the output is the peak load.This model performs well for time series model and regression computed over the mean absolute percent error (MAPE). Initially the SVMs have been applied for pattern recognition problems; however, with the development of intensive loss function by Vapnik, SVMs are increasingly used in non-linear regression problems as well as times series forecasting (Cae et. al.) [1].

SVM configuration affects the SVM performance such as type of kernel function, kernel parameter and size of training sample. Thus the previous studies using SVM on wind forecasting are limited in which particular kernel function and particular parameter are picked for these studies. Kernel function to be chosen is very important for any particular application such as linear, polynomial and Gaussian kernel in order to investigate the accuracy of the load forecasting [8].

Support vector machine (SVM) algorithms have the capability to control the capacity of decision function and choose the kernel function accordingly according to the sparsity of the solution. SMS is basically structured on risk minimization factor that eventually yields high generalization performance. Besides, SVM have the ability to solve both linear and quadratic programming problems having always unique solutions and globally optimal unlike neural network which require nonlinear optimization that may get stuck at local minima [6].

Short-term load forecast (STLF) always remains a demanding issue for power operation systems. Various operating decisions are comprised on STLF including dispatch scheduling, reliability analysis, security maintenance and assessment plans for generators. In addition, load forecasting play a vital role in energy transaction in the competitive electricity market. The market profit, share and share holder value are greatly affected by the forecast error. The electricity load forecasting to the variability and nonstationarity of load series became difficult to forecast, especially in electricity market [4].

Load forecasting approaches based on the demands have been generally classified into the time series, kalman filtering technology, state space, artificial intelligence, regression models, fuzzy logic methods. Time series approach such as Box–Jenkins ARIMA model, predict the electricity load forecasting based on historical load data. On the other hand, Kalman filtering approach use random process for load forecasting using 3-10 historical data in order to establish the periodic load component of the depending variable such as load or temperature of power system. The regression model establishes cause and effect relationship between the independent variable such as climate factor, seasonal factor and social activities with the electricity load [2].

SVM developed by Vapnik 1998 is used in statistical machine learning and regression problems(Akay, 2009; Cherkassky& Ma, 2004; He, Wang, & Jiang, 2008; Lazaro, Santamarı´a, Perez-Cruz, &Artes-Rodrı´guez, 2005; Wu, Chau, & Li, 2008) as well as wind speed prediction(Mohandes, Halawani, Rehman, & Hussain, 2004; Salcedo-Sanz et al., 2009). Moreover, SVMr training are used for sequential minimal optimization algorithms(Smola&Scholkopf, 1998) [9].

In the last decade due to the rapid increase in the wind generation of electricity, the capacity of the wind power have been increased almost fourfold 24.3 GW to 203.5 GW. Short-term load forecasting are used in the power system planning for unit commitment and dispatch (1 hr to 72 hr), while Medium-term forecasting ranging from 3 days to 7 days used to plan maintenance of the wind farms, outage of thermal generation, unit commitment, storage operation and to schedule grid maintenance of the energy. The wind power predictions have been described both in theories and practices of meteorology and climatology specifically to wind power generation [10].

4. DATA ACQUISITION

Al-Khwarizmi Institute of Technology, The Punjab University Lahore, provide electricity hourly load demands of the complete year 2008 and July to December 2009 of one grid. The data was taken from a feeder in order to fulfill the maximum load requirementsfor this study. The data was accordingly separated for morning, day, evening and night hours. Likewise, load data season wise was separated. However, there was no special event data in the present study.

5. RESULT AND DISCUSSIONS

Electricity consumption on the basis of current and past, and is used to predict the electrical load to estimate the load electric power at a later time. For one day predict pregnancy and a one-week prediction pregnancy is to arrange a plan today schedule and plan the schedule for a week on the unit, which includes the decision unit GE to get out, and coordination between hydropower and electricity, heat and energy exchange in the connection, distribution of economic power load, and Inspection Equipment, etc. ultra-short-term prediction of pregnancy within 1 hour and is used to guide the distribution of economic output set startup and shutdown a range of meals, they are also used to monitor the safety, preventive and control critical to deal with the situation. At present, power plants, especially those in China, are in dire need of a very short pregnancy prediction, any expectation within one minute or one hour. Load forecasting instruction judge dispatchers download the very short term, both parts of the revolution enough at the right time in the near future, rotary parts is an important factor in determining the integrity of the system category. In addition, it helps dispatchers to adjust the distribution of power group, on and off from a move in the peak and trough packing, and it is also a must for automatic generation control (AGC) and the achievement of economic dispatch dynamically. Long-term, very short power load forecasting is the information that the energy market demands.

Smart Grid will in the future to achieve reliable operation of the power system and the economic benefit from its resources. This requires predict pregnancy in a wide range of yarns time, from minutes to several days. Carried predict loads integrated every hour outside for a day 1-1A week ago and is usually referred to predict short-term pregnancy (STLF). These projections are used each hour through energy management systems (EMS) for the development of operational plans for power plants and their generation units, and energy planning transactions in the market. It is also necessary for theSecurity Studies energy system, including the analysis and management of emergency loads.

In addition, the load-frequency control and dispatch functions for EMS economic require pregnancy forecasts in within a shorter lead time, from one minute to several tens of minutes. And they are referred to and expectations of pregnancy for a very short time (VSTLF). These projections, integrated with information about transactions Wheeling decision, and the availability of transmission, and the generation cost, the spot market pricing of energy, spinning reserve requirements imposed by the independent system operator, and is used to determine the best strategy for the benefit of resources. Very short-term Load forecasting has become much greater importance in today's liberalized energy industry.

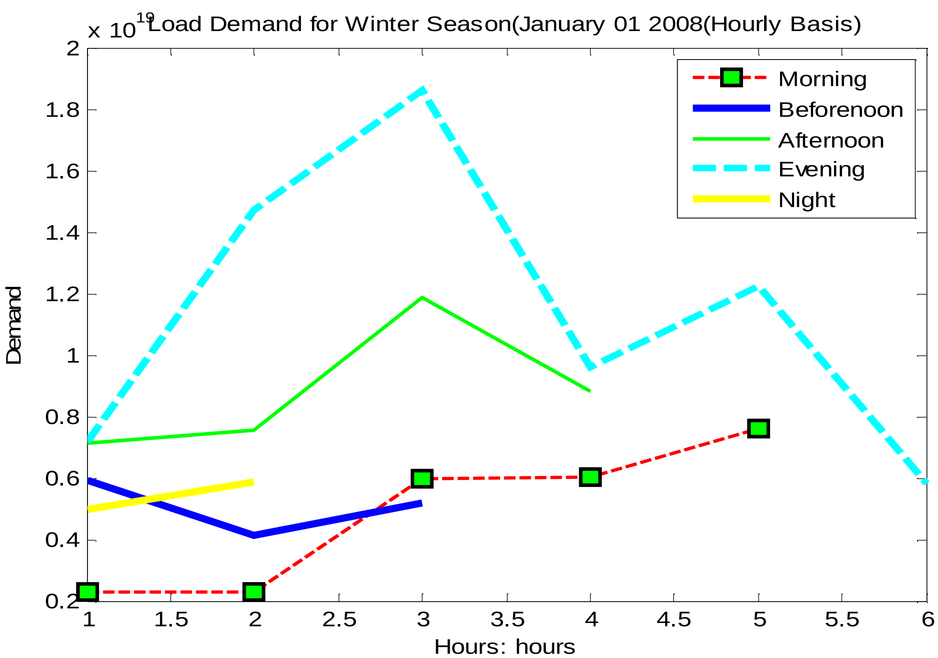

Figure 1: Load Demand Winter Season January 01, 2008

In the above figure 1, load demand is plotted for January 01, 2008, morning hours, before noon, after noon, evening and night hours. The load data collected from s grid station shows that electricity demands are different during different hours of the day. Thus it is pertinent to supply the load demands accordingly during different hours of the day. This comes in Very Short term Load Forecasting (VSTLF) and Short Term Load Forecasting (STLF) that is load demands for every next hour and next few minutes of the day. This will help us to know the minimum requirements of load demands of electricity during different hours of the day. The figure 1 shows that load demand during morning and night hours is more in winter seasons. Thus supply shall accordingly be made as required which will smooth the system and avoid to load-shedding.

Table 1: Performance Using 10 folds Cross Validation

Performance Using 10 fold CV

Load Data for Months:	Training/Testing	CV Approach:	Accuracy:	Error:
Nov. Dec.	2008/2009	10 fold CV:	99.8633 %	0.0013671
Nov. Dec.	2009/2008	10 fold CV:	99.7266 %	0.0027341
July to Dec	2009/2008	10 fold CV:	99.8415 %	0.0015851
July to Dec	2008/2009	10 fold CV:	99.9547 %	0.0004529

The Table 1 computes the performance using 10 fold cross validation for Nov. Dec. data 2008 as training and 2009 as testing and vice versa as well as data of July to Dec.2008 and 2009 accordingly. The accuracy and error computed in each case is shown in the table 1.

Real time forecasting system performance is measured on similar load situations as well as on different load situations in working days, weekends and seasonal demands.

Various techniques are appliedinvolving Support Vector Machine (SVM) kernels, Linear Discriminant Analysis (LDA), QuadraticDiscriminant Analysis (QDA), the re substitution error is calculated in each case. It is noticed that SVM Radial Base Function Kernel using 10 fold cross validation gives the best performance of 99 %, however, other techniques also have almost similar results as shown in Table 1 and Table 2.

In order to analyze the performance indexes, the actual and predicted values are computed using Mean Square Error (MSE), Relative Error (RE) and Mean Absolute Percentage Error (MAPE). The performance of forecasting effect using RE is computed using following formula.

$$RE(t) = \frac{w(t) - \overline{w}(t)}{w(t)} \times 100\ \% \qquad (1)$$

Where,$w(t)$ is actual value and $\overline{w}(t)$ is the forecasting value.

The most commonly used aggregative indicator in power systems is MAPE, used to evaluate the forecasting performance of whole predicting process in a more comprehensive way.

Mathematically,

$$MAPE = \frac{1}{N}\sum_{t=1}^{n} \left| \frac{w(t) - \overline{w}t)}{w(t)} \right| \qquad (2)$$

Where, N is the sample number.

Support Vector Machine (SVM), kernels applied on load forecasting data are polynomial, Gaussian, Highly Radial Base Function and Multi Quadratic. Beside it, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) techniques are applied. The MAPE

Calculated in each case is shown in table 2. The results show that SVM MQ gives 99.53 % performance of actual and forecasting data for Nov. Dec. 2008 and 2009 than other kernels.

Table 2: Performance using Re Substitution Error

Data for the month	Technique	Error Value	Error Type
Nov.Dec.2008 and 2009	10 fold CV	0.0014	RSE
	Stratified 10 fold CV	0.0027	-do-
	LDA	0.01	-do-
	QDA	0.01	-do-
	10 fold CV	$1.7203e^{-024}$	MSE
	SVM poly	0.7967	RE
	SVM Polynomial	0.0088	MAPE
	SVM Gaussian	0.0148	-do-
	SVM HRBF	0.0216	-do-
	SVM MQ	0.0047	-do-

SVM: Support Vector Machine, CV: Cross Validation, RSE: Re-substitution Error, MSE: Mean Square Error, RE: Relative Error, MAPE: Mean Absolute Percentage Error, HRBF: Highly Trained Radial Base Function, MQ: Multi Quadratic Kernel

The forecasting performance measured using RE and MAPE as shown in table 2. The figure 2 shows the corresponding plot of actual and forecasting values during November and December 2008 and 2009 where 2008 values are used as actual and 2009 as forecasting values. The corresponding RE and MAPE are computed which are 0.7967 and 0.0047 least in case MQ kernel respectively. The RE and MAPE are computed using SVM kernel which gives above 99 % of performance accuracy. The similar results are to be obtained for other seasons, working and non-working days.

Table 3: Electricity Load Demands of Working and Non-Working Days.

Electricity Demand Season Wise, Working Days, Non-Working Days

Seasons	Max.Demand	Min.Demand	Avg.Demand
Nov.,Dec.2008	2865	890	1642.188
Working Days	2865	890	1659.8672
Nonworking Days	2432	945.76	1706.9027
Nov.Dec.2009	2695	786	1557.5273
Working Days	2695	786	1590.2216
Non Working Days	2311	800	1472.9069

The Table 3 above shows the electricity demands of working and non-working days during the winter season November& December 2008 and 2009. The maximum,minimum and average demand is computed. The results in the table shows that the demand during both 2008 and 2009 of working days is more than that of non-working days in Nov. Dec. As maximum demand of electricity of working days during 2008 is 2865 MW while in 2009 it is 2695 MW. However, it is 2432 MW and 2311 MW during non-working days accordingly. The same prediction can be achieved for other seasons of working and non-working days.

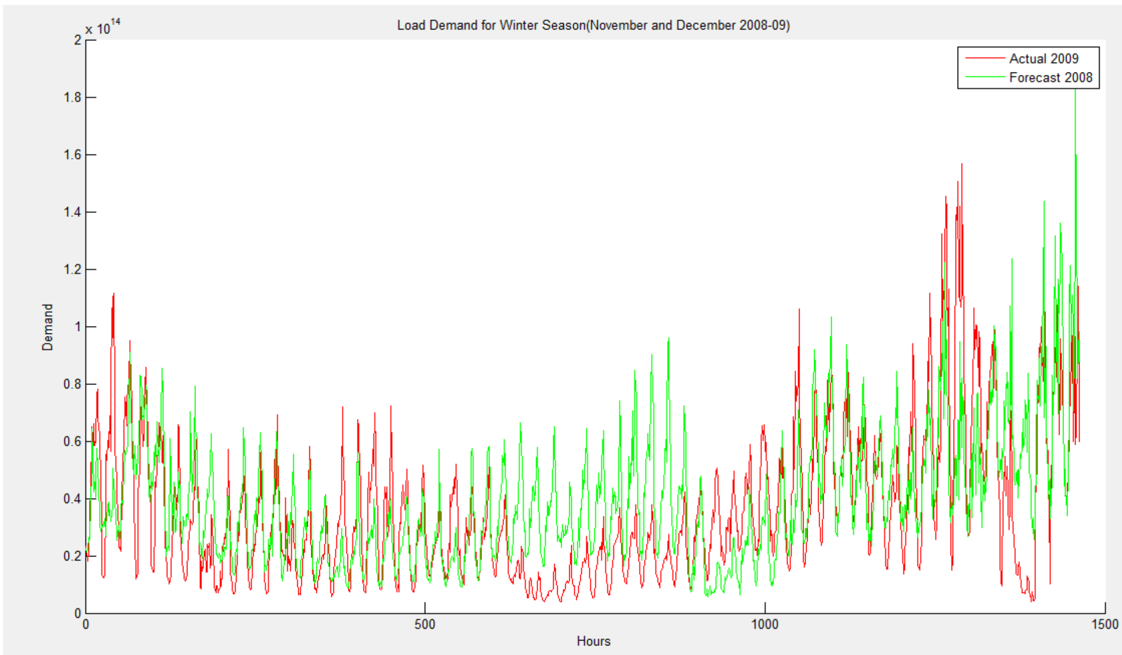

Figure 2: Actual and predicted value plot of November and December 2008 and 2009

The table 3 shows the maximum, minimum and average demands of load. The figure 3 below shows the load demand in graphical form for first week working days of January 2008. The varying amplitude shows the different demands during morning, before noon, afternoon, evening and night as well as load demands during working days in a week in January.

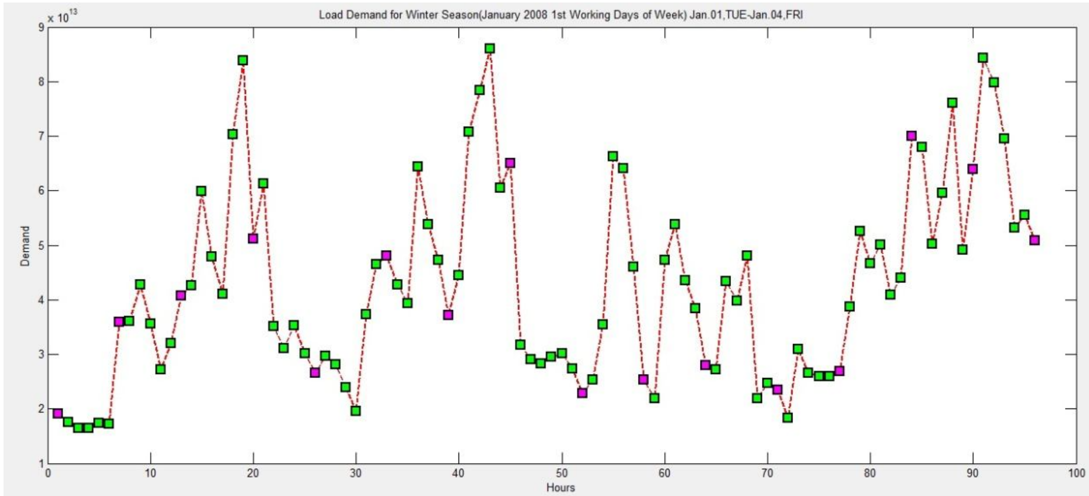

Figure 3: Load Demand for January 1st working days 2008

6. CONCLUSION

Support Vector Machine (SVM) kernels are used for Short Term Load Forecasting (STLF) on data. The results are computed and performance is measured using 10 fold cross validation, re-substitution error, Mean Square Error, Relative Error and MAPE. The results obtained from SVM are compared with LDA and QDA. SVM kernel gives higher performance of 99%. The SVM kernel approach is suggested for STLF in seasonal demands and can have the adaptability on different load situations such as working days and non-working days. Moreover, STLF can help in generation dispatch, capacity switching, load management program, feeder reconfiguration, voltage control and automatic generation control (AGC). In addition, it will help to establish operational plans for power stations and their generation unit and to plan market energy transaction and load management.

7. FUTURE WORK

For Medium Term and Long Term Forecasting data required is meteorological information such as temperature, wind speed, illumination, special events and data from different locations.

Medium term forecasting

Data required description of appliances used by customers, customer behavior, size of house, age of equipment, technology change and population dynamics used in end use application. In addition, other factors required are economic factors such as per capita income, employment level and electricity pricing.

Long term Forecasting

Forecasting on population growth, economic development, industrial construction and technology development

REFERENCES

[1] Pai, Ping-Feng, and Wei-Chiang Hong. "Support vector machines with simulated annealing algorithms in electricity load forecasting." *Energy Conversion and Management* 46.17 (2005): 2669-2688.

[2] Pai, Ping-Feng, and Wei-Chiang Hong. "Forecasting regional electricity load based on recurrent support vector machines with genetic algorithms." *Electric Power Systems Research* 74.3 (2005): 417-425.

[3] Amjady, N., and F_ Keynia. "Short-term load forecasting of power systems by combination of wavelet transform and neuro-evolutionary algorithm." *Energy* 34.1 (2009): 46-57.

[4] Hong, Wei-Chiang. "Chaotic particle swarm optimization algorithm in a support vector regression electric load forecasting model." *Energy Conversion and Management* 50.1 (2009): 105-117.

[5] Huang, Wei, YoshiteruNakamori, and Shou-Yang Wang. "Forecasting stock market movement direction with support vector machine." *Computers & Operations Research* 32.10 (2005): 2513-2522.

[6] Gao, Ciwei, et al. "Price forecast in the competitive electricity market by support vector machine." *Physica A: Statistical Mechanics and its Applications*382.1 (2007): 98-113.

[7] Taylor, James W. "Triple seasonal methods for short-term electricity demand forecasting." *European Journal of Operational Research* 204.1 (2010): 139-152.

[8] Zhou, Junyi, Jing Shi, and Gong Li. "Fine tuning support vector machines for short-term wind speed forecasting." *Energy Conversion and Management* 52.4 (2011): 1990-1998.

[9] Salcedo-Sanz, Sancho, et al. "Short term wind speed prediction based on evolutionary support vector regression algorithms." *Expert Systems with Applications* 38.4 (2011): 4052-4057.

[10] Foley, Aoife M., et al. "Current methods and advances in forecasting of wind power generation." *Renewable Energy* 37.1 (2012): 1-8.