Operating Reserve Forecasting in a Wind Integrated Power System using Hybrid Support Vector Machine-Fuzzy Inference System

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Abstract- In a restructured power system, Ancillary services (AS) are required to balance load generation mismatches and to meet unforeseen contingencies. Operating Reserve is a major part of AS which is highly uncertain to forecast, mainly due to the unpredictability of customer needs, over or under production of Energy and unpredictability in the integration of renewable energy sources. In this work, wind integration is considered as a factor to forecast operating reserve. The increase of wind integration into power system needs larger quantities of operating reserve. This demands an increase in the cost of generation and emissions. Forecasting the Operating Reserve Ancillary Service helps the system operators (SO) to plan scheduling of generators in advance and also in better bidding environment. Forecasting tools like feed-forward networks, Time series models were used to forecast load and Electricity price in the past. In this paper a hybrid method consisting of Support Vector Machines (SVM) and Fuzzy Interface System (FIS) is used to forecast Operating Reserve in Day-ahead market. Case studies using CAISO and ERCOT ISOs are presented. The SVM-FIS method is found to be better forecasting tool to predict the operating reserve Ancillary Service.

Keywords Renewable energy, Wind, Ancillary services, forecasting, support vectors, fuzzy inference system.

1. Introduction

A Balancing and scheduling are two major components of power markets. Order No. 888 of Federal Energy Regulatory Commission has initiated a separate market for Ancillary services which strive for the balance of the system. Thus pricing and scheduling of these services became a major issue in power markets. California Independent System Operator (CAISO) is first to implement Separate Ancillary Service Market followed by NYISO, MIDWEST ISO, ERCOT and PJM markets. Reserve is one of the Ancillary Service which these ISOs schedule in their markets. CAISO uses a fixed amount of Energy as up and down reserve to adjust the disturbances in load, generation schedules. NYISO sets reserve requirement based on weekday or weekend, hour of day, and season. MIDWEST ISO schedules the reserve based on conditions that prevail before Day-ahead market closes. ERCOT the largest wind integrated ISO in United States, sets the reserve based on usage as 30 days of same month of previous year and also considers adjustment based on wind capacity. PJM schedules Reserve as 1% of the peak load and 1% of the valley load. For simplicity in calculations of Ancillary Service requirement these SOs opted for deterministic method. This deterministic method is easy to implement. However, it does not consider variations in load and contingencies in the system. Though the quantity of AS is very small, they play a major role in maintaining the system balance and security. SO has to schedule the AS to balance the differences in load and generation. Operating reserve is one such AS which has a major participation in mitigating such differences.

Numerous researchers proposed operating reserve scheduling by using robust, probabilistic, stochastic and chance constraint optimisation methods [1-5]. Objective of minimising generalised social cost and uncertainty in price elasticity of demand is done using a robust optimisation technique to solve an optimal unit commitment decision is proposed in [1]. Probabilistic method based on Weibull Probability density function that incorporates wind generation uncertainty to clear the Energy and Spinning reserve market jointly was proposed in [2]. [3] determined the Operating Reserve requirement and its pricing by formulating loss of load cost in capacity bidding process by using probabilistic method. Cross-Entropy Method has been proposed in [4] to assess the probabilistic spinning reserve in PJM interconnection. A hybrid stochastic and interval optimisation method to include wind and load uncertainties has been attempted in [5] to trace solution to a transmission constrained Unit Commitment.

The renewable energy like wind integration raises a major concern to power market participants for its uncertain nature. To balance intermittent nature of wind, markets have to purchase larger quantities of AS and also need to pay huge prices in acquiring them. Dynamic Reserve Strategy is presented in [6] to incorporate wind uncertainties into unit commitment in-order to reduce cost of generation and operating reserve requirement. In [7] dynamic scheduling of operating reserve in Energy and Ancillary service Markets is presented by considering Wind power integration. [6-7] incorporated wind generation output into the system which has probabilistic characteristics in nature. These studies have not considered the system topologies like line limits. Economic Dispatch (ED) is one of the widely used methods to optimally schedule Energy and Spinning Reserves. [8] attempted ED problem to incorporate wind uncertainties into the scheduling of thermal generators. However, in these studies, limitations in predictability of wind power fluctuations affect the actual operating reserve requirement by the power system. Few researchers have proposed scheduling energy storage devices [9][10] and demand response [11][12] resource to provide operating reserve in the grid. Methods like Economic dispatch, Optimal power flow and Unit commitment will assist the operator for minimum amount of Operating reserve required by the power system to improve efficiency and reliability.

Forecasting OR helps in balancing the uncertainties in wind generation in Day-ahead market. Forecasting helps in optimal bidding strategies for generators to participate in the market for optimising their profit. It also helps in scheduling demand response and other balancing mechanisms. Reserves are classified differently in various markets. The two major classifications of Operating reserves are Spinning Reserve (SR) and Non-Spinning Reserve (NSR). SR gives balance to sudden changes in the system and NSR provides balancing and reduction of cost paid towards uncertainties.

In literature many forecasting tools were proposed for Electricity load forecasting, price forecasting [13-14] and wind speed forecasting [15-16] for short and long term periods in Hour-ahead and Day-ahead markets. Not much research work has been reported in Ancillary services forecasting. [17] designed a two stage forecasting model using Adaptive Wavelet Neural Networks consisting of Load and Operating reserve for forecasting of operating reserve in Hour-ahead and Day-ahead markets. However, considering Wind generation as variable in operating reserve has a significant effect on the market operations. [18] attempted the Spinning Reserve forecasting using iterative training which uses Levenberg-Marquadt learning algorithm and real coded genetic algorithm. However, it elevated SR requirement only, whereas Non-Spinning reserve also has a significant effect in reducing the total cost paid to AS. A Stochastic hybrid method consisting of modified grey model to forecast OR requirement and markov chain model to improve the forecasting accuracy was proposed in [19].

The present work considers Operating Reserve (OR) forecasting with System load and wind generation as inputs. These variables for forecasting OR has never been considered in the literature. Load and Wind generation are considered as inputs to predict Day-ahead OR requirement. A hybrid method with Support Vector Machines (SVM) and Fuzzy Interface System (FIS) is proposed in this paper which eliminates the local minimum problem in ANN and requirement of high-level decomposition in Wavelets. SVM is previously used for Electricity load and price forecasting. The paper is organized as follows. Section 2 presents the SVM-FIS model. Section 3 describes the operation of AS market. Section 4 provides the data analysis for forecasting operating reserve. Section 5 presents the problem modelling. Section 6 gives the conclusion and future work.

2. Support Vector Machine-Fuzzy Inference System (SVM-FIS)

Support Vectors (SV) have a good number of applications in classification and regression problems. SVs use supervised learning to analyse the data [20]. The modified SVs are being used in regression analysis. SVs have an advantage of avoiding overfitting and local minimum [21] over Multilayer Neural Networks (MLNN) [22]. They require less tuning of parameters in training from the data. It is successfully applied for forecasting Market Clearing price (MCP) in electricity markets [23]. Due to their high level of generalisation SVs are widely used for forecasting Electricity Load [24-28] and price [23,29-30]. In this section Support Vector Machines and Fuzzy inference system are explained, followed by hybrid method SVM-FIS method.

2.1. Support Vector Machines

The general structure of SVM model with N inputs, bias b and single output is shown in Fig. (1). The structure of SVM is similar to feed forward MLNN. However, activation functions in hidden layer of MLNN are replaced with a kernel function ‘K’ in SVMs.

SVM uses a hyperplane to map the input with the output. SVs are formed from most relevant input features related to variables to be forecasted. Kernels transfer the nonlinear data in problem input space into a linear regression in feature space. SVM uses quadratic formulation to solve optimisation algorithm. Support vector regression involves non-linearly mapping original input data x_i with the higher dimensional feature space y_i in the training data containing N samples. The regression problem thus forms a function that can be used to forecast new values accurately.

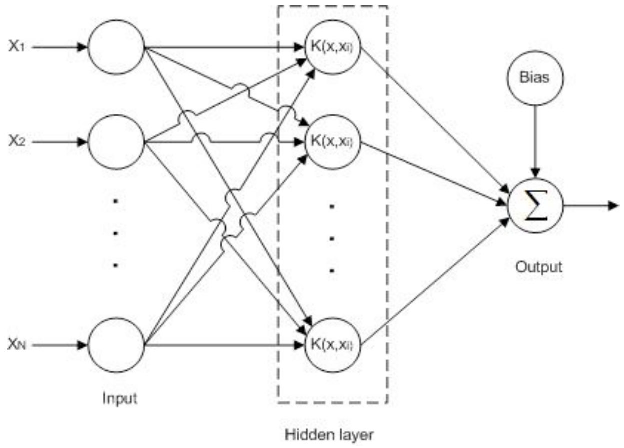

Fig. 1. General structure of SVM

The function from SVM regression is given as

$$y_i = f(x_i) = (\omega.\psi(x_i)) + b \tag{1}$$

Where ω denotes weight vector, ψ denotes non-linear mapping function from input to high dimensional feature space and b is the threshold value. To maximise the mapping of input data into feature space following optimisation function f is minimised as given in Eq. (2).

$$\text{Min } f = \frac{1}{2}\|\omega\|^2 + C*(\sum_{i=1}^{N}(\xi_i + \xi_i^*)) \tag{2}$$

Where ξ_i and ξ_i^* are the slack variables and determine the cost of error computed as the distance of training data points. These are above and below the target hyper-plane. The function is subjected to the following constraints (3)

$$\begin{aligned} & y_i - (\omega.\psi(\mathrm{x_i})) - \mathrm{b} \le \varepsilon + \xi_\mathrm{i}, \\ & (\omega.\psi(\mathrm{x_i})) + \mathrm{b} \text{ -} \mathrm{y_i} \le \varepsilon + \xi_i^*, and \xi_\mathrm{i}, \xi_i^* \ge 0, \end{aligned} \tag{3}$$

In eq.(3) ε is the precession with which the training takes place.

The optimisation function f is computed by solving the dual optimisation problem using Lagrange multipliers.

$$\begin{aligned} LM(\omega,\xi,\xi^*,\lambda,\lambda^*,\alpha,\alpha^*) = {} & \frac{1}{2}\|\omega\|^2 + C*(\sum_{i=1}^{N}(\xi_i + \xi_i^*)) \\ & - \lambda_i * \sum_{i=1}^{N}(-y_i + (\omega.\psi(\mathrm{x_i})) + \mathrm{b} + \varepsilon + \xi_\mathrm{i}) \\ & - \lambda_i^* * \sum_{i=1}^{N}(y_i - (\omega.\psi(\mathrm{x_i})) - \mathrm{b} + \varepsilon + \xi_i^*) \\ & - \sum_{i=1}^{N}(\alpha_i * \xi_i + \alpha_i^* * \xi_i^*) \end{aligned} \tag{4}$$

In eq. (4) $\lambda, \lambda^*, \alpha, \alpha^*$ are the Lagrange multipliers and C is constant that determine the trade-off between the function f and the amount up to which deviations larger than ε are tolerated. The partial derivatives of eq.(4) with respect to ω,b,ξ_i, and ξ_i^* are

$$\frac{\partial LM}{\partial \omega} = 0, \frac{\partial LM}{\partial b} = 0, \frac{\partial LM}{\partial \xi_i} = 0, \frac{\partial LM}{\partial \xi_i^*} = 0, \tag{5}$$

$$\begin{aligned} & \omega = \sum_{i=1}^{N}(\lambda_i - \lambda_i^*).\psi(x_i) \\ & \sum_{i=1}^{N}(\lambda_i - \lambda_i^*).\psi(x_i) = 0 \\ & C - \lambda_i - \alpha_i = 0 \\ & C - \lambda_i^* - \alpha_i^* = 0 \end{aligned} \tag{6}$$

The Lagrangian relaxation optimisation is done by reducing dual gap between eq. (4) and the dual function of eq. (4). The minimization of (4) is maximization of dual function which is given as in (7).

$$\max imize \begin{Bmatrix} -\frac{1}{2}\sum_{i,j=1}^{N}(\lambda_i - \lambda_i^*).(\lambda_j - \lambda_j^*).(\psi(x_i).\psi(x_j)) \\ -\varepsilon\sum_{i=1}^{N}(\lambda_i - \lambda_i^*) + \sum_{i=1}^{N} y_i.(\lambda_i - \lambda_i^*) \end{Bmatrix} \tag{7}$$

$$subjected\ to \sum_{i=1}^{N}(\lambda_i - \lambda_i^*) = 0, and \lambda_i, \lambda_i^* \in [0, C]$$

The necessary condition for the optimal solution of eq. (7) is that all the Lagrangian multipliers are equal to zero. Thus nonlinear SVM function can be rewritten as eq. (8).

$$\begin{aligned} & \mathrm{y_i} = \mathrm{f(x_i)} = \sum_{1=1}^{\mathrm{N}}(\lambda_i - \lambda_i^*)\langle\psi(x),\psi(\mathrm{x_i})\rangle + \mathrm{b} \\ & b = \mathrm{y_t} - \langle\omega,\psi(\mathrm{x_i})\rangle \pm \varepsilon \quad for\ \lambda_i, \lambda_i^* \in [0,\mathrm{C}] \end{aligned} \tag{8}$$

Input samples for which $(\lambda_i - \lambda_i^*) \neq 0$ were taken as support vectors. To map input data into feature target plane SVM uses a kernel function. So the modified eq.(8) with a kernel function K is give in eq. (9).

$$\mathrm{y_i} = \mathrm{f(x_i)} = \sum_{1=1}^{\mathrm{N}}(\lambda_i - \lambda_i^*)K(x,\mathrm{x_i}) + \mathrm{b} \tag{9}$$

Gaussian function shown in eq. (10) is used as the kernel function in this paper.

$$K(x,\mathrm{x_i}) = \exp(-\frac{\|x - x_i\|^2}{2\sigma^2}) \tag{10}$$

SVM has the advantage of structural risk minimization to adopt best patterns for approximation purpose. Steps involved in obtaining support vectors from input samples are as follows.

Step 1: Regression curve is obtained from input samples of wind and load with least error ε with the target y_i i.e., operating reserve.

Step 2: For all samples with $(\lambda_i - \lambda_i^*) \neq 0$, support vectors are extracted.

Step 3: Non-linear function ψ given in eq. (8) is used to map x_i into a feature space by using a kernel function K given in eq.(10).

Step 4: The final output $f(x)$ is calculated using eq. (9).

2.2. Fuzzy Inference System

Fuzzy inference system is set of IF....Then rules of the form

$$Q_i : IF\ X_1\ is\ A_1^i \text{ and } X_2 \text{ is } A_2^i \text{ ...and } X_N \text{ is } A_N^i \text{ then } Y \text{ is } B^i\ for \text{ all } i = 1,2...M \quad (11)$$

Where X_l $(l=1,2,...N)$ and Y are the input and output variable of FIS respectively. A_l^i, and B^i are the linguistic variables. The membership functions of A_l^i, and B^i are given as $\mu_{A^i_l}(X_l)$, $\mu_{B^i}(Y)$ respectively. The overall equation for FIS is given by the eq.(12) as

$$f(X) = \frac{\sum_{i=1}^{M} Y_i \left(\prod_{l=1}^{N} \mu_{A_l^i}(X_l)\right)}{\sum_{i=1}^{M} \left(\prod_{l=1}^{N} \mu_{A_l^i}(X_l)\right)} \quad (12)$$

Where f: $Q^n \rightarrow Q$, $\mu_{A^i_l}(X_l)$ is the Gaussian membership function, and Y is the point in the output space at which $\mu_{B^i}(Y)$ achieves its maximum value.

The eq. (12) can be written as

$$f(X) = \sum_{i=1}^{M} Y_i * P_i$$

$$Where\ P_i = \frac{\sum_{i=1}^{M} Y_i \left(\prod_{l=1}^{N} \mu_{A_l^i}(X_l)\right)}{\sum_{i=1}^{M} \left(\prod_{l=1}^{N} \mu_{A_l^i}(X_l)\right)} \quad (13)$$

The right-hand side of eq. (13) resembles the right-hand side of eq. (1) for b=0. This linear equation can uniformly approximate future value which is given on arbitrary accuracy.

2.3. SVM-FIS

In order to relate eq. (9) and (13) a Gaussian Kernel function and Gaussian membership function are used respectively and also the bias term b in eq.(9) is considered to be zero (b=0) then

$$f(x) = \sum_{i=1}^{t} (\lambda_i - \lambda_i^*) \exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right) \quad (14)$$

$$f(x) = \frac{\sum_{j=1}^{t} Y_i \exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right.}{\sum_{j=1}^{t} \exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right.} \quad (15)$$

$$f(x) = \sum_{j=1}^{t} Y_i\, exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right. \quad (16)$$

The center of Gravity (COG) of membership function is taken as

$$Y_i = (\lambda_i - \lambda_i^*) \quad (17)$$

Eq. (9) and eq. (13) are similar in representation. However, drawback of this representation is that, fuzzy losses its normalisation which in turn affects the generalisation property of fuzzy and also interpretability is difficult during modification. Alternatively, the kernel function of SVM is set as eq.(18).

$$K(x_i, x) = \frac{\exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right)}{\sum_{j=1}^{t} \exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right)} \quad (18)$$

SVMs output is calculated using eq. (19)

$$f(x) = \frac{\sum_{j=1}^{t} (\lambda_i - \lambda_i^*) \exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right)}{\sum_{j=1}^{t} \exp\left(-\tfrac{1}{2}\left(\frac{x_i - x}{\sigma_i}\right)^2\right)} \quad (19)$$

In order to check the equivalence of eq. (14) and (19), set center of gravity of membership functions to $(\lambda_i - \lambda_i^*)$. However, eq.(19) is possible if we know number of support vectors formed. In this case it is 't'. The operational principle of SVM approach involves nonlinear mapping of input samples into a higher dimension feature space. A linear optimal hyperplane with lowest error measure to each class is obtained within the feature plane. Support Vectors are extracted as the center of gravity of membership functions such that the extracted fuzzy rules can separate the different data sets with smallest error measures. Fuzzy equivalent of Support Vector machine is shown in the fig. (2).

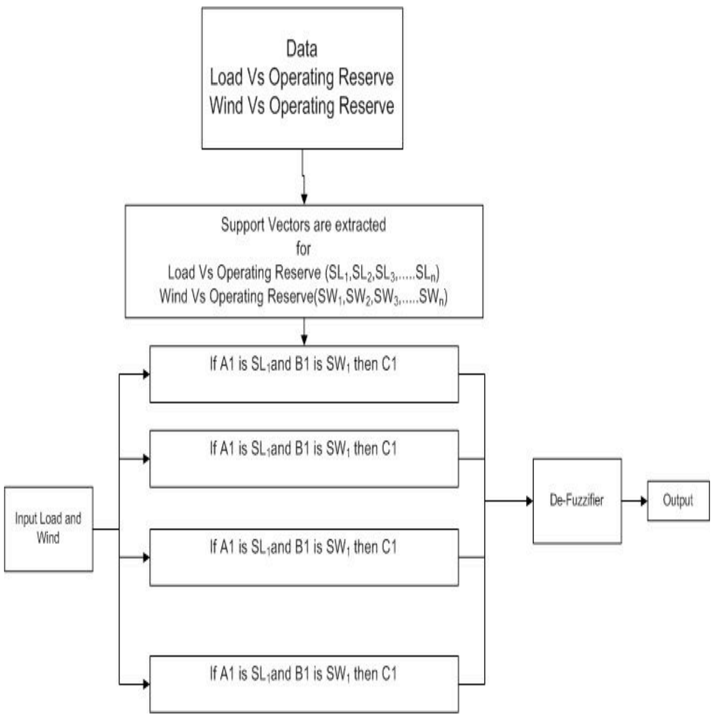

Fig. 2. Fuzzy equivalent of SVM

2.4. Training

The Algorithm for the proposed method to train with samples is given below

Step 1: Initialize ε, C and σ for SVM.

Step 2: Using algorithm given in Subsection 2.1 find support vectors (SVs) x_i

Step 3: Estimate Y_i in eq. (16) using Recursive Least Square Estimation (RLSE) [31].

Step 4: update σ using gradient descent algorithm [32] until error is minimized.

Step 5: Go to step 2, repeat until error is minimized.

In order to get near perfect forecasting accuracy choosing different parameters in SVM-FIS model is necessary. In order to do so, a cost function is necessary. This is usually a Mean Square Error (MSE) function.

3. Operation of AS Market

3.1 In California ISO (CAISO):

California was the first ISO to design a competitive AS market. It is successfully providing the essential operating reserve including regulation reserves to all the market participants in contingencies [33]. CAISO uses Day-ahead and Hour-ahead markets to meet the Ancillary services requirement. A Day-ahead market is worked out in this paper to show the Operating reserve forecast.

3.2 In ERCOT ISO:

ERCOT ISO is integrated with more wind energy. In 2011 ERCOT's total wind generation reached 25% of total system load, thus making it as the largest wind producer in North America [34]. AS studies on ERCOT gives a greater insights to the problem considered in this work. Hourly wind Generation for the year 2014-15 is shown in fig. (3).

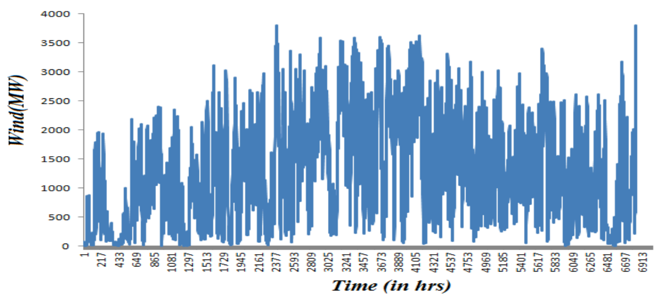

Fig. 3. Hourly wind Generation for the year 2014-15

4. Data Analysis for Forecasting Operating Reserve

Most of the Energy markets are using deterministic ways to assume the amount of AS required to balance the system adequacies. ISOs will predetermine the quantity of AS required in the Day-ahead and Hour-ahead markets. But due to increase in uncertainties of renewable energy sources integration, deterministic method fails to get exact amount of AS requirement. This leads to adversaries like running large thermal generators all the time, increase in emissions and prices.

The process of creating a proper design for the forecasting model starts with the analysis of data collected from the past recordings of forecasting variables. This process includes finding out the seasonality, and trends of such design. In this paper the OR requirements of CAISO [33] and ERCOT [34] for 8670 hours are recorded and analysed for the year 2014. The co-relation between hourly system load and operating reserve, wind generation and operating reserve are presented in fig.(4)-(5).

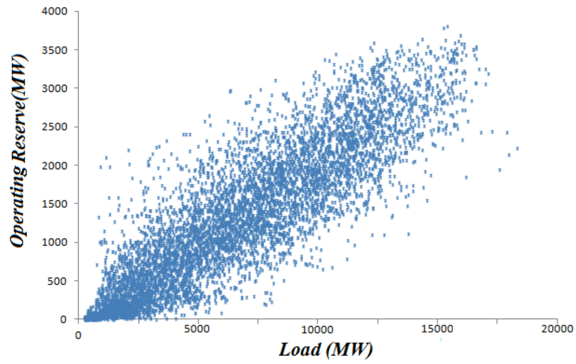

Fig. 4. Hourly load Versus Operating Reserve

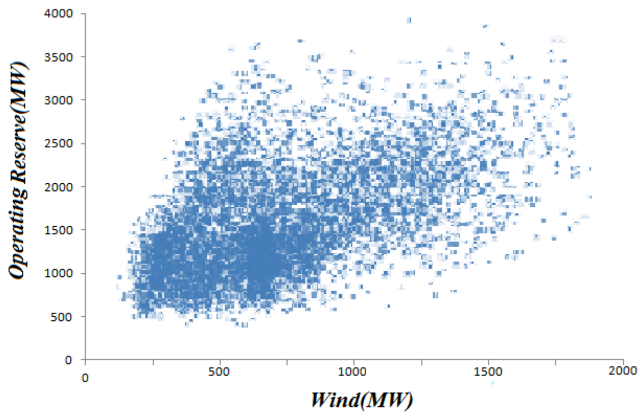

Fig. 5. Hourly wind Versus Operating Reserve

These variables are used to compute correlation within them using eq. (20).

$$\rho_{x,y} = \frac{\operatorname{cov}(x,y)}{\sigma_x \sigma_y} = \frac{\sum (x-\mu_x)(y-\mu_y)}{\sqrt{\sum (x-\mu_x)^2 (y-\mu_y)^2}} \tag{20}$$

The co-relation between hourly load and operating reserve is observed as 0.94, whereas wind generation and operating reserve is observed as 0.91 (Wind Generation is considered to be 40%). This shows that hourly load and wind generation have a considerable impact on OR requirement. Fig. (6) show the OR requirement, wind generation and system hourly load during the summer month of 2014. The figures reveal that the OR is more volatile in nature.

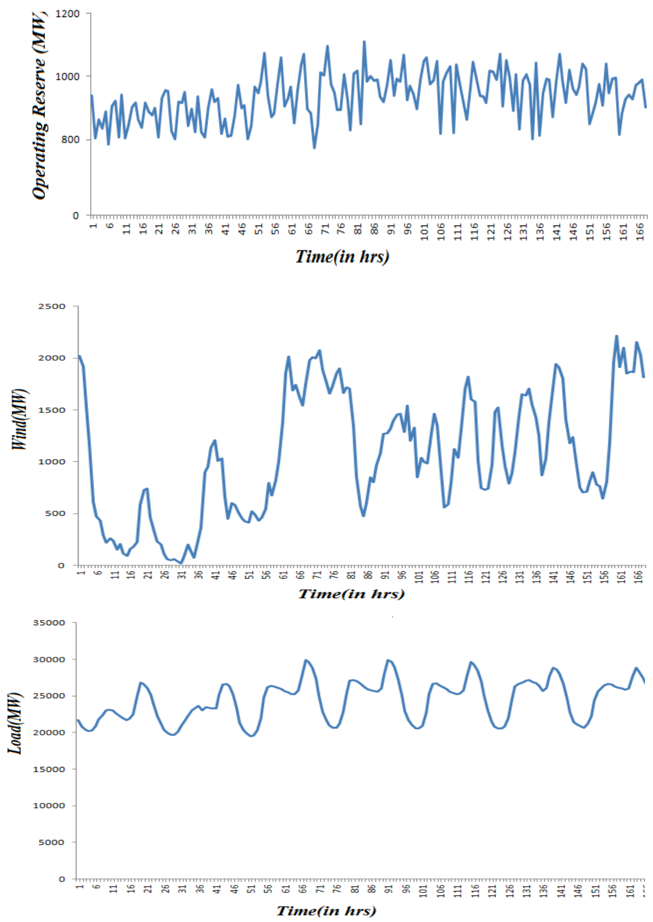

Fig. 6. Operating reserve, Wind and load Data for 168 hrs

5. Results and Discussion

The main objective of the forecasting tool is to obtain a pattern from historical data to forecast near perfect future values of desired quantity based on dependent variables. This paper proposes Operating Reserve Ancillary Service forecast in a day-ahead electricity market using wind generation and load forecast as dependent variables. Due to high volatile nature of wind generation and load forecast, power system has to provide huge quantity of operating reserve to maintain system under stable conditions.

5.1 Training and Testing data sets

Required day-ahead data sets of Wind, Load and Operating Reserve are acquired from open access systems of CAISO [33] and ERCOT [34]. The data sets of winter, summer for the year 2014 are used in case studies. For training, the data of 30 days prior to the forecast day are considered. To test the accuracy of the SVM-FIS forecasting model the last 7 days of winter and summer are considered. The testing data is not included in the training set to illustrate the efficiency of the proposed method.

5.2 Input variable selection

The base for any forecasting method lies with input selection. In literature, methods like correlation analysis and regression analysis are used to select the best input variables that will influence the outcome of the forecasting method. From the statistical analysis done in section 4, it is evident that load and wind are the two variables that influence the operating reserve. The SVM-FIS is involved in the following two steps

The forecasting will work as follows. In initial stage support vectors are formed for both input variables, i.e., system load and wind generation. In the later stage these support vectors are used to form the fuzzy rules to train the fuzzy inference system to the desired output, i.e., operating reserve in this case. The forecasting approach is shown in fig. (2). The hourly load, wind generation and operating reserve for a day-ahead market is obtained from CAISO and ERCOT.

Stage 1: Normalise the data and initialize $\varepsilon=0.001$, $C=500$ and $\sigma=0.1$ for SVM.

Stage 2: Obtain support vectors for the input variables Table.1

Table 1: Support Vectors for Wind and Load

Wind	Load
0.132186	0.613381
0.13328	0.781957
0.137716	0.56446
0.794627	0.772288
0.895241	0.977094

Stage 3: Estimate Y_i

Table 2: Support Vectors for Operating Reserve

Operating Reserve
0.589897
0.750183
0.543686
0.775426
0.975331

Stage 4: Update σ until error is minimised

Stage 5: Fuzzify the obtained Support vectors using Gaussian membership function. Fuzzy rules are given below. Input space (wind and Load) and Output space (Operating Reserve) are divided into five sets: Very Small (VS), Small (S), Medium (M), Large (L) and Very Large (VL).

Wind / Load	VS	S	M	L	VL
VS	VS	VS	VS	M	M
S	S	M	M	L	L
M	M	M	M	M	M
L	L	L	L	L	L
VL	VL	VL	VL	VL	VL

Stage 6: Normalise the test data (wind and load)

Stage 7: Obtain the output for the supplied test input and de-fuzzify the output to get desired output.

Stage 8: MAPE is calculated for output obtained and desired output.

5.3 Forecasting results analysis

To show the efficiency of the proposed method, it is compared with methods proposed in Literature like Multilayer Feed-Forward Neural Network (MFNN)[17], Elman Network[35], ANFIS[36] and Hybrid methods like Adaptive Wavelet Neural Network(AWNN)[17], Particle Swarm Optimization–Adaptive Neuro-Fuzzy Inference System [37]. The same input training sets were considered for the above-mentioned methods. Comparison of MAPE for all the methods is given in Table III.

$$MAPE(\%) = \frac{1}{N}\sum_{h=1}^{N}\frac{\left|x_h^{act} - x_h^{for}\right|}{x_h^{act}} * 100$$

where x_h^{act} and x_h^{for} are the actual and forecasted value of OR(variable x) for hour h, respectively and N is the total number of observations given in table as Days considered. Fig (7) shows the comparison of OR during testing obtained with SVM-FIS with the original values in Day-ahead market.

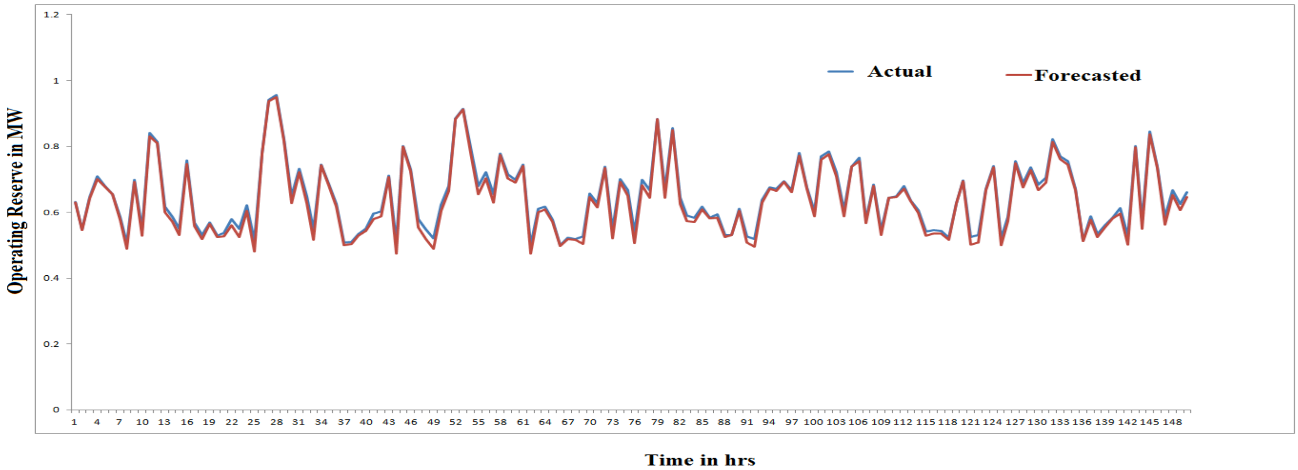

Fig. 7. Opearting reserve forecast using SVM-FIS

Table 3: Comparison of results

	MLNN	AWNN	GA Based	MLNN	PSO-ANFIS	Elman Network	ANFIS	ANFIS	SVM	SVM-FIS
	[17]	[17]	[18]	[17]	[37]	[35]	[36]	[36]		(Proposed)
	Without Wind			With Wind	With Wind	With Wind	Without Wind	With Wind	With Wind	With Wind
	Mean Absolute Percentage Error (MAPE (%))									
Operating Reserve	7.156	3.416	3.988	9.478	3.201	5.856	2.992	3.847	3.127	2.146
Iterations	-	-	-	26	17	52	6	15	12	4
Days considered for Training	30	30	30	30	30	30	30	30	30	30

6. Conclusion

The early researchers has explored Support vectors Machines and fuzzy logic methods individually for forecasting load and Electricity price. In this paper a hybrid approach using Support Vector Machines and Fuzzy Inference System is proposed for forecasting operating reserve in Day-ahead Market. The SVM-FIS inherits the advantage of structural risk minimization from support vector machines to adopt best patterns for approximation purpose and interpretation capability of Fuzzy Inference System. The proposed method applied to CAISO and ERCOT ISO is both novel and efficient. The hourly system load, wind and operating reserve (OR) requirements for day-ahead market is acquired from the California independent system operator (CAISO) and ERCOT controlled areas for the year 2014 have been used to verify the efficacy of the proposed method. The test results obtained through the simulation of the proposed method are compared with the methods given in the literature. Further comparison of various error indices for the proposed method reveals a good forecasting accuracy over other methods in the literature.

Conflict of Interest:

The authors declare that they have no conflict of interest.

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