FEATURE SELECTION AND PARAMETER OPTIMIZATION WITH GA-LSSVM IN ELECTRICITY PRICE FORECASTING

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Abstract. Forecasting price has now become essential task in the operation of electrical power system. Power producers and customers use short term price forecasts to manage and plan for bidding approaches, and hence increasing the utility's profit and energy efficiency as well. The main challenge in forecasting electricity price is when dealing with non-stationary and high volatile price series. Some of the factors influencing this volatility are load behavior, weather, fuel price and transaction of import and export due to long term contract. This paper proposes the use of Least Square Support Vector Machine (LSSVM) with Genetic Algorithm (GA) optimization technique to predict daily electricity prices in Ontario. The selection of input data and LSSVM's parameter held by GA are proven to improve accuracy as well as efficiency of prediction. A comparative study of proposed approach with other techniques and previous research was conducted in term of forecast accuracy, where the results indicate that (1) the LSSVM with GA outperforms other methods of LSSVM and Neural Network (NN), (2) the optimization algorithm of GA gives better accuracy than Particle Swarm Optimization (PSO) and cross validation. However, future study should emphasize on improving forecast accuracy during spike event since Ontario power market is reported as among the most volatile market worldwide.

1. Introduction

In deregulated electricity market, forecasting electricity price is more challenging compared to predicting the load or demand [1] due to the volatility of price series with unexpected price spikes at any point of series. Sudden disruption at generation and transmission sites, imbalance between supply and demand, as well as weather condition, are the common factors influencing fluctuation in price series. Other aspects may also affect price series, such as bidding policy and operating reserve price [2]. Therefore, many methods have been explored by previous researchers to forecast electricity price. Time series models have been proven able to give satisfactory result [2]–[6] for stable market, but generally they are more appropriate for linear problem whilst price series is a non-linear pattern.

Other popular methods are Neural Network and Fuzzy Logic, which can handle nonlinear relationship in price pattern [7]–[19]. The MAPE of 16% for weekdays and 20% for weekends are mentioned in literature in [12] and 8-21% in [14] when applying neural network and fuzzy inference, while the regression model in [7] produced MAPE of 10-28%. However, neural network always face the issues of over-fitting and under-fitting, where the network might only remember all training

examples including noises and outliers rather than catching the relationship between input and output.

Hence, generalization problem often occurs where the developed model cannot predict well with the presence of unseen data during testing phase; consequently producing large error. Meanwhile, neural network usually spends more time during training process, especially when more training data, hidden neuron and hidden layer are added [17]. In addition, the prediction accuracy may be unstable or change for each run of simulation.

Support vector machine is another technique which has been reported as a better method than time series [20] and neural network [1]–[4], [21]–[31] in terms of model complexity, accuracy and efficiency. In [32], Chaotic Least Squares Support Vector Machine (CLSSVM) was combined with Wavelet Transform (WT) and Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model to handle high volatility price series with the average error of 2.7% for PJM market and 2.58% for Spanish market. The hybrid method of rolling time series and LSSVM yielded MAPE of 2.26%; outperforming BPNN (4.11%) and ARMAX-AR-GARCH (2.72%) in [3]. Same goes for GA-LSSVM method in [26] method which produced MAPE of 4.2-9.7%; surpassing other techniques for all seasons.

On the other hand, the inclusion of optimization approach could improve the performance of forecasting. Literature in [33] applied modified relief and mutual induction to select input feature, and yielded MAPE of 4.55% (PJM), 5.22% (Spanish) and 17-19% (Ontario). Meanwhile, Modified Levenberg Marquardt with fuzzy c-mean (FCM) was applied to group daily load in [11], producing MAPE of 5.5-8.4% when applying Correlation Analysis for feature selection. Other literatures applied mutual information (MI) and Discrete Wavelet Transform (DWT) techniques for feature selection and Chaotic Gravitational Search Algorithm (CGSA) to reduce Gaussian noise and find the parameters of LSSVM [34], correlation analysis as feature selection and PSO as parameter selection of LSSVM [35], Self-Organizing Map (SOM Neural Network) to group data according to their similarities and PSO as parameter selection of LSSVM [1], correlation analysis as feature selection and GA as parameter selection for SVM [30], Maximum Likelihood Estimation (MLE) to choose parameters for SVM [36], cross validation

to select parameters for SVM and SOM to cluster input data [37], GA and PSO as well as Quantum inspired Particles Swarm Optimization (QPSO) for similar day method [38], Rough Set as data selection and PSO as parameter selection of SVM [29], Principal Component Analysis (PCA) and K-Nearest Neighbor (KNN) as data selection [22], GA to select parameters for SVM [25] and LSSVM's parameters [39], [26] Artificial Fish Swarm Algorithm (AFSA) [28] and Independent Component Analysis (ICA) as feature selection [27].

2. Fundamental of SVM, LSSVM, GA and PSO

This section introduces the fundamental of SVM, LSSVM, GA and PSO in terms of their theories and concepts.

2.1 SVM and LSSVM

Support Vector Machine (SVM) as presented by Vapnik [40] is a supervised learning model that supports data analysis and pattern recognition for classification and estimation.

Assume that an empirical data is set as

$$[(x_1, y_1),....,(x_m, y_m)] \in X \times \Re; X = \Re^d \qquad (1)$$

where X represents the space of the input patterns. For linear functions f,

$$f(x) = \langle w, x \rangle + b \text{ where } w \in X, b \in \Re \qquad (2)$$

Support Vector Regression functions to solve for quadratic programs with ε-insensitive loss function which involves inequality constraint. Hence, SVM has high computational problem where the optimization problem is defined as

$$\min \frac{1}{2}\|w\|^2 + C\sum_{k=1}^{N}(\xi_k + \xi_k^*) \text{ where } \xi \text{ is slack variable}$$

$$\text{subject to} \begin{cases} y_k - \langle w, \phi(x_k) \rangle - b \le \varepsilon + \xi_k \\ \langle w, \phi(x_k) \rangle + b - y_k \le \varepsilon + \xi_k^* \\ \xi_k, \xi_k^* \ge 0 \end{cases} \qquad (3)$$

while the ε-insensitive loss function is defined as

$$|y - f(x,w)|_\varepsilon = \begin{cases} 0, \text{if } |y - f(x,w)| \leq \varepsilon \\ |y - f(x,w)| - \varepsilon, \text{otherwise} \end{cases} \quad (4)$$

Thus, Least Squares Support Vector Machines (LSSVM) as suggested by Suykens and Vandewalle [41] can be used to solve this problem with linear Karush-Kuhn Tucker (KKT) equations, instead of using quadratic programming approach. The optimization problem is then denoted as

$$\min J(w,e) = \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma\sum_{k=1}^{N} e_k^2$$
$$\text{subject to } y_k = \left\{\langle w, \phi(x_k)\rangle + b + e_k, k=1,...,N \leq \varepsilon + \xi_k\right\} \quad (5)$$

where $e_k \in R;$ are error variables and $\gamma \geq 0$ is a regularization constant that limits the trade-off between the fitting error minimization and smoothness of the estimated function [42]. The Lagrangian is defined as

$$L(w,b,e;\alpha) = J(w,e) - \sum_{i=1}^{N}\alpha_i\{y_i[w^T\varphi(x_i)+b]-1+e_i\} \quad (6)$$

where $\alpha_i \in R$ are the Lagrange multipliers; agreeing to Wolfe's duality theory. The α_i in SVM is positive but it may be negative or positive for LSSVM [43]. Hence, by using equality instead of inequality constraints, the LSSVM representation for estimation is developed as

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x,x_k) + b \quad (7)$$

In contrast with SVM, LSSVM applies the least square loss function rather than ε-insensitive loss function. Therefore, LSSVM is less complicated [41], [44], more robust for more complex data and more efficient than SVM [43], [45]. The parameters for SVM usually involves C, ε and σ, while LSSVM has only σ and γ [4], [25], [30], [32], [46].

2.2 Genetic Algorithm (GA)

Genetic algorithm (GA) is one of Evolutionary Algorithms (EA) approaches, where the optimization approaches are based on population [47]. EA has common processes of mutation, crossover, natural selection, reproduction and

recombination [48]. Other methods in EA family are Evolution Strategy (ES), Genetic Programming (GP) and Evolutionary Programming (EP). In a GA, a population of candidate solutions, which is known as individuals or creatures, should have a set of chromosomes for each of candidate solution. The chromosomes can be mutated and changed. Usually, the solutions are denoted as a binary string which is 0 or 1, but other encodings are also permitted [49].

Typically, the evolution begins by generating random individuals from a population, where at each phase, individuals are randomly chosen as parents. Children are then produced and the processes are repeated. Consequently, an ideal solution is achieved and the fitness of every individual in each generation is calculated. The fitness is an objective function that is used to measure the performance of each chromosome. In this study, the fitness function is represented Mean Absolute Percentage Error (MAPE). The algorithm is usually terminated when the generation reaches its maximum value or an acceptable fitness value is obtained. Second generation population is then generated from the selected solutions, where normally a new solution imitates many of its parent's characteristics.

2.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) was introduced by James Kennedy and Russell Eberhart. PSO mimics the social behavior of a group of migrating birds or fish trying to reach unknown destination in the search space by changing its velocity. PSO does not produce children as GA does. Each individual in a group will randomly move around to find food and announce the source of food to its neighbors so the neighbors will approach the same location. The best fitness with the best co-ordinate for each particle is called as personal best, *pbest*. Meanwhile, each particle also gets to know the fitness of those in its neighborhood and uses the position or *gbest* of the ones with the best fitness to adjust the particle's velocity. Hence, the new position for each particle is its old position plus the new velocity or as following equation:

$$v_{id}^{k+1} = v_{id}^k + c_1 r_1^k(pbest_{id}^k - x_{id}^k) + c_2 r_2^k(gbest_d^k - x_{id}^k)$$
$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (8)$$

where v_{id}^k and x_{id}^k are the velocity of particle i at k times and the position, respectively, $pbest_{id}^k$ is the position of individual i at its best position at k times, $gbest_d^k$ is the position of the group at the best position. The speed of the particle is capped to $-v_{dmax}$ and v_{dmax} to limit the searching space. c_1 and c_2 denote the speeding figure that can adjust the velocity of the particle [50], while r_1 and r_2 represent random fiction.

3. Research Design

This section discusses the selection of input data and accuracy measure. The inputs were chosen based on significant impact on price forecasting that had strong correlation with price characteristics.

3.1 Input Selection and Data Normalization

Data from 10–23 January 2010 of Ontario power market; two weeks prior to the testing period, was selected as the training data with 74 input features which comprised of:
1. the maximum load on the day before target day; $L_{max(d-1)}$
2. day type of target day (-1 for weekend and 1 for weekday)
3. 24-hour loads on target day
4. 24-hour Hourly Ontario Electricity Price (HOEP)(s) on the day before target day
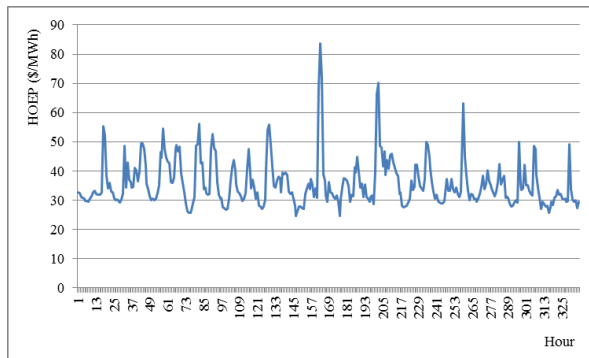5. 24-hour generation's prices on the day before target day

Fig. 1: HOEP of 10–23 January 2010 for training purpose

Figure 1 shows the HOEP series used for training purpose. The testing data was selected from 25–31 January 2010. The training and testing data were normalized to prevent the domination of very large value in the data [2]. The data was normalized between [-1, 1] as in formula (9):

$$x_n = \frac{x_j - \left[\dfrac{x_{max} + x_{min}}{2}\right]}{\left[\dfrac{x_{max} - x_{min}}{2}\right]} \qquad (9)$$

where x_n is normalized value, x_j is the raw sample value, x_{max} and x_{min} are the maximum and minimum value of each feature in the samples.

3.2 Error Evaluation Function

Weekly Mean Absolute Percentage Error (WMAPE), Weekly Mean Absolute Error (WMAE) and regression value (R) were applied to measure the performance of forecast results. Regression value measures the correlation between actual value was used to measure the correlation between the actual value and forecast value as the closest value of 1, indicating strong correlation where the forecast result was able to follow the actual value very closely. The MAPE and MAE formulas were defined as:

$$MAPE = \frac{100}{N} \times \sum_{t=1}^{N} \frac{\left|P_{actual_t} - P_{forecast_t}\right|}{P_{actual_t}} \qquad (10)$$

$$MAE = \frac{1}{N} \times \sum_{t=1}^{N} \left|P_{actual_t} - P_{forecast_t}\right| \qquad (11)$$

where P_{actual} and $P_{forecast}$ are the actual and forecast HOEP at hour t, respectively, while N is the number of hours in a week.

4. Results and Discussion

This section presents the simulation results of LSSVM and Neural Network. All simulations were held in Matlab. LSSVMlab was chosen as LSSVM toolbox while Matlab's built-in toolbox for Neural Network, GA and PSO were used for during training and testing phases. The LSSVM approach with optimization techniques of GA and PSO were

compared with the stand alone LSSVM. The Neural Network model was also being compared with the LSSVM models to prove the accuracy of LSSVM.

4.1 LSSVM

Cross validation technique was applied to search the gamma (γ), and sigma (σ) values. The range of searching was set for [exponential (-25, 25)] for both gamma and sigma. Table 1 shows some of the LSSVM's results when using cross validation for different values of gamma and sigma. The best MAPE was found to be 13.0871% when gamma=2 and sigma=32. Table 2 shows the simulation time was 1.56 minutes while the regression (R) was 0.478.

Table 1: MAPE for LSSVM

Sigma (σ)	Gamma (γ)				
	2^1	2^1	2^3	2^4	2^5
2^1	13.1256	13.1928	13.2808	13.5880	14.0289
2^2	13.2864	13.4042	13.5569	13.7386	13.9808
2^3	13.3012	13.5097	13.7608	14.1209	14.5080
2^4	13.1851	13.4071	13.7067	14.0907	14.5762
2^5	**13.0871**	13.2155	13.4808	13.8542	14.3294

Table 2: Forecast accuracy measures of LSSVM, LSSVM-GA, LSSVM-PSO and NN

Model	Selected input	WMAPE	WMAE	Simulation time (minutes)	Regression (R)
LSSVM	all 74 inputs	13.0871	5.6575	1.5567	0.4780
LSSVM-GA	31	**10.6072**	**4.3801**	20.1895	**0.7651**
LSSVM-PSO	31	10.8019	4.3989	20.2592	0.7643
Neural Network	all 74 inputs	15.7813	6.8281	1.4853	0.3943

4.2 LSSVM with GA and PSO

Genetic Algorithm and Particle swarm optimization (PSO) were applied to select significant input features and the parameters for LSSVM. The population size and generation were fixed to 100 and 300, respectively, for both GA and PSO. The crossover fraction for GA was 0.5, while each of the two parameters of LSSVM was represented by ten bits. The result in Table 2 shows that only 31 inputs were selected for LSSVM-GA and LSSVM-PSO compared to 74 inputs for

LSSVM and NN. The gamma and sigma for GA were 24.7851 and 164.0292, while the gamma and sigma for PSO were 55.0387 and 293.2622. The selected inputs were:

- HOEP at hour 9, 11, 12, 14, 18, 20 and 21 on the day before target day
- Forecast load at hour 1-20 on target day
- Generation's price at hour 1, 4, 6 and 19 on the day before target day

It was observed that LSSVM-GA performed better than LSSVM-PSO and other models in terms of WMAPE, WMAE and regression (R). In fact, the result achieved was better than that of proposed model in [38] for the same market model and test period. The average MAPEs for the three cases in [38] were 11.79% (SVM-GA), 11.98% (SVM-PSO) and 11.11% (SVM-QPSO; Quantum Inspired Particles Swarm Optimization QPSO).

4.3 Neural Network

A neural network model (NN) was developed to compare the performance of LSSVM and NN. Three layers were applied for the NN model, which consisted of an input layer, a hidden layer with a hidden neuron and an output layer. All 74 inputs were fed into the input layer, where no feature selection was held. The output layer produced 24 outputs representing 24 hours. Tansig and purelin transfer function were used for hidden and output layer, respectively. Similar cross validation procedure as for LSSVM was performed to select the number of hidden neuron in the hidden layer. Table 2 shows that NN model produced the least of MAPE and MAE, at 15.7813% and 6.8281, respectively.
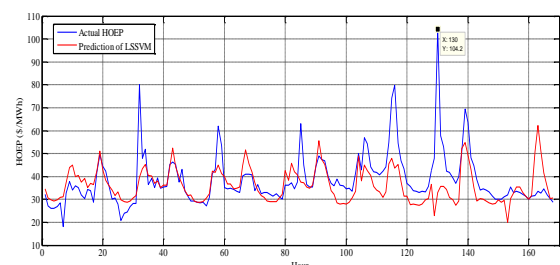
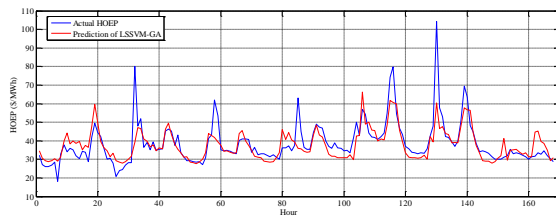

Fig. 2: Forecast and Actual HOEP by LSSVM

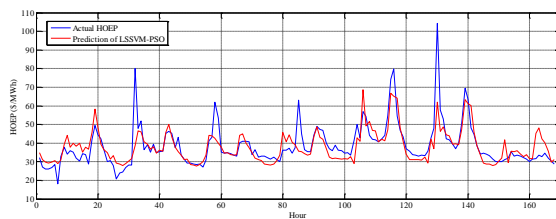Fig. 3: Forecast and Actual HOEP by LSSVM-GA

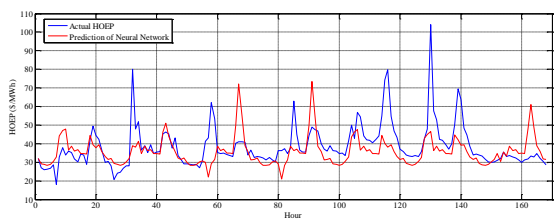Fig. 4: Forecast and Actual HOEP by LSSVM-PSO

Fig. 5: Forecast and Actual HOEP by Neural Network

Figure 2-5 show plots of forecast versus actual HOEP for all models. The first day on testing period was a winter day, hence the forecast models were not able to follow the spike closely. Similar situation happened at point 130 or 10 a.m. on Saturday, 30 January 2010 where the actual HOEP was $104.2/MWh, while the average HOEP for this test data was $38.44/MWh. However, Figure 2 and 3 show that LSSVM-GA and LSSVM-PSO could track the actual data better than the other two models. All of the models were developed on a PC with 6GB of RAM memory and Intel Core i5 2.5GHz processor, while the simulation time of about 20 minutes for LSSVM-GA and LSSVM-PSO was reasonable for day-ahead system operation and decision making.

Conclusion

A hybrid LSSVM and GA for day-ahead electricity price forecasting in Ontario has been proposed and evaluated. The performance of LSSVM-GA model was compared with those of LSSVM, LSSVM-PSO, NN and another published approaches by a recent research, which apply the same training and testing data [38]. The performance measure was accessed through weekly MAPE, MAE and regression (R). Ontario was found as among the most volatiles power market in the world [51] nonetheless, our hybrid model has shown that the forecast accuracy is also acceptable and better than that obtained by single LSSVM and NN, or other techniques [38]. However, the accuracy on spike areas is quiet low; thus, this issue can be focused on in the future research, research while considering other influential factors such as spot market price and spinning reserve market price [2].

Acknowledgments

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