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A NOVEL METHOD OF BFOA-LSSVM FOR ELECTRICITY PRICE FORECASTING

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ABSTRACT

Forecasting price has now become an 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 increase the utility's profit and energy efficiency. This paper proposes a novel method of Least Square Support Vector Machine (LSSVM) with Bacterial Foraging Optimization Algorithm (BFOA) to predict daily electricity prices in Ontario. The selection of input data and LSSVM's parameters held by BFOA are proven to improve accuracy as well as efficiency of prediction. A comparative study of the proposed method with previous researches was conducted in term of forecast accuracy. The results indicate that (1) the LSSVM with BFOA outperforms other methods for same test data; (2) the optimization algorithm of BFOA gives better accuracy than other optimization techniques. In fact, the proposed approach is less complex compared to other methods presented in this paper.

Keywords: electricity price forecasting, least square support vector machine, bacterial foraging optimization algorithm.

INTRODUCTION

Electricity price forecasting is important for all market participants in deregulated electricity market to provide a better bidding strategy. In addition, the company that has ability to forecast future prices can reduce the risk of under-estimating or over-estimating the revenue from the generators. The supply and prices can be reviewed and adjusted based on the production cost to gain an optimum profit. Meanwhile, consumers use the price forecast to manage the consumption especially during spike occurrences.

However, forecasting electricity price is more challenging compared to predicting the load or demand. This is due to the volatility of price where unexpected spikes may occur at any point of series. Sudden disruption at generation and transmission sites, imbalance between supply and demand, as well as weather condition, are common factors influencing fluctuation in price. Other aspects may also affect electricity price, such as bidding policy and operating reserve price. Many methods have been explored by previous researchers to predict electricity price such as Time series (TS), Fuzzy Logic (FL), Neural network (NN) and Support vector Machine (SVM). TS approaches have been proven able to give satisfactory result (Conejo, Plazas, Espinola, & Molina, 2005; Contreras, Espinola, Nogales, & Conejo, 2003) for stable market. However, generally, they are more appropriate for linear problem whilst price series is a non-linear pattern.
Other popular methods are NN and FL (Aggarwal, Saini, & Kumar, 2008; Catalão, Mariano, Mendes, & Ferreira, 2007; Lin, Gow, & Tsai, 2010; W. A.R, Rahman, Z, & Ahmad, 2013), which can handle nonlinear relationship in price pattern. However, the problem of neural networks are 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 occur where the developed model cannot predict well with the presence of unseen data during testing phase; consequently producing large error. Furthermore, NN usually spends more time during training process, especially when more training data, hidden neurons and hidden layers are added. The prediction accuracy may also become inconsistent for each run of simulation.

However, most of the methods that have been explored by previous researchers are able to predict well during normal condition or without spike occurrences but when the spikes exist, the forecast error become large. Some researchers use more complex approaches with multiple procedures in order to predict spike values accurately. SVM is another technique which has been reported as a better method than TS and NN in terms of model complexity, accuracy and efficiency (Xu, Dong, & Liu, 2003; Yan & Chowdhury, 2013, 2014). SVM has good generalization and do not need huge data set to learn the relationship of input and output. An improved SVM; so called the Least Squares Support Vector Machines (LSSVM) is used in this paper as forecast engine as it has two main advantages over the original SVM. The advantages are, (1) SVM applies a quadratic equation during the training stage, while LSSVM applies linear formulations; (2) SVM only selects the ones with non-vanishing coefficients as support vectors while LSSVM considers all training data as support vectors (Yan & Chowdhury, 2013).

However, stand-alone LSSVM may not produce excellent forecast accuracy. Instead of using empirical

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search or heuristic method, many researchers apply optimization algorithms to select the significant inputs or optimize the parameters of forecast engines. Among the meta-heuristic approaches are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Tabu Search (TS), and Simulated Annealing (SA). These techniques explore the search space more thoroughly to find an optimum solution. However, the newly meta-heuristic algorithms like Biogeography-Based Optimization (BBO), Firefly (FF), Cuckoo Search (CS), Spiral Dynamics Inspired Optimization (SDA), and Bacterial Foraging Optimization Algorithm (BFOA) were found to perform better than those meta-heuristic approaches in terms of fast convergence, simplicity in programming, accuracy, and flexibility (Jhankal & Adhyaru, 2011; Korani, 2008; Mahapatra, 2013).

The BFOA was found to search food quicker than other optimization methods (Prabaakaran, Jaisiva, Selvakumar, & Kumar, 2013) and shows a great performance rather than other meta-heuristic optimization approaches like GA (A.V.S.Sreedhar Kumar, V.Veeranna, 2013; Hoo & Han, 2012; Jhankal & Adhyaru, 2011; Majhi, Panda, Majhi, & Sahoo, 2009; Sakthivel, Bhuvaneswari, & Subramanian, 2010), PSO (Hoo & Han, 2012; Karnan & Krishnaraj, 2012; Majhi *et al.* 2009; Sakthivel *et al.* 2010), ACO (Karnan & Krishnaraj, 2012), and SA (Hoo & Han, 2012) in many fields. In fact, the application of BFOA in electricity price forecasting is not reported yet. Thus, the hybrid method of LSSVM and BFOA is proposed in this paper to improve forecasting performance for short term electricity price forecasting. The inclusion of BFOA as feature selection and LSSVM's parameter selection gives more efficient and accurate result with lesser complexity than other optimization methods. The developed models are also applicable for Malaysia when the deregulated electricity market exists in future..

DESCRIPTION OF SVM, LSSVM AND BFOA

Support vector machine (SVM) and least squares support vector machines (LSSVM)

SVM as presented by Vapnik (Vapnik, 1998), is a supervised learning model that supports data analysis and pattern recognition for classification and estimation. Assume that an empirical data is set as Equation (1)

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

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

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

Support Vector Regression functions to solve for quadratic programs which involve inequality constraint. However, SVM has high computational problem where the optimization problem is defined as Equation (3)

$$\begin{gathered}\min \frac{1}{2}\|w\|^2 + C\sum_{k=1}^{N}(\xi_k + \xi_k^*) \\ \text{where } \xi \text{ is slack variable} \\ \text{subject to} \begin{Bmatrix} y_k - \langle w, \phi(x_k)\rangle - b \le \varepsilon + \xi_k \\ \langle w, \phi(x_k)\rangle + b - y_k \le \varepsilon + \xi_k^* \\ \xi_k, \xi_k^* \ge 0 \end{Bmatrix}\end{gathered} \tag{3}$$

While the ε-insensitive loss function is represented as Equation (4)

$$|y - f(x,w)|_\varepsilon = \begin{Bmatrix} 0, \text{if } |y - f(x,w)| \le \varepsilon \\ |y - f(x,w)| - \varepsilon, \text{otherwise} \end{Bmatrix} \tag{4}$$

Thus, LSSVM as suggested by Suykens and Vandewalle (Suykens, Gestel, De Brabanter, Moor, & Vandewalle, 2002) can solves this problem with linear Karush-Kuhn Tucker (KKT) equations, rather than using quadratic programming approach. The optimization problem is then denoted as Equation (5)

$$\begin{gathered}\min\ J(w,e) = \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma\sum_{k=1}^{N} e_k^2 \\ \text{subject to } ; \\ y_k = \{\langle w, \phi(x_k)\rangle + b + e_k, k = 1,..., N \le \varepsilon + \xi_k\}\end{gathered} \tag{5}$$

Where $e_k \in R$; are error variables and $\gamma \ge 0$ is a regularization constant that limits the trade-off between the fitting error minimization and smoothness of the estimated function. The Lagrangian is defined as Equation (6)

$$\begin{gathered}L(w,b,e;\alpha) = J(w,e) - a; \text{ where} \\ a = \sum_{i=1}^{N}\alpha_i\{y_i[w^T\varphi(x_i) + b] - 1 + e_i\}\end{gathered} \tag{6}$$

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. Hence, by using equality instead of inequality constraints, the LSSVM representation for estimation is developed as Equation (7)

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

In contrast with SVM, LSSVM applies the least square loss function rather than ε-insensitive loss function. Therefore, LSSVM is less complicated, more robust for more complex data and more efficient than SVM. Meanwhile, LSSVM can tackle the hidden pattern of nonlinear price series with shorter training time.

Bacterial foraging optimization algorithm (BFOA)

There is a bacteria namely E.coli, which is present in human's intestines that has unique foraging activities

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during locating and ingesting nutrient or food. BFOA mimics this mechanism by applying four main steps during foraging; that are chemotaxis, swarming, reproduction, and elimination-dispersal. In chemotaxis step, bacteria searches for nutrient to maximize the energy intake while foraging by taking small steps (chemotaxis) and interacts with other bacteria by sending attractant signal to form a swarm; or repelent signal to move individually. They tumble or swim to find nutrient but avoid dangerous places. Hence, suppose that $\theta^i(j,k,l)$ is the *i*-th bacterium position at *j*-th chemotactic, *k*-th reproduction, and *l*-th elimination-dispersal step, the position of each bacterium after having swimming or tumbling can be defined as Equation (8)

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{8}$$

Where *C*(i) is the size of the step taken during tumbling or swimming, and Δ is a vector in the random direction where the elements lie in position of [-1,1]. The objective function or actual cost for each location of bacterium *i* is calculated and represented as *J(i,j,k,l)*.

During swarming step, a bacterium that has uncovered good sources of nutrients during its search may attract other bacteria to form a swarm. On the other hand, the repellent signal can be released to ensure that the bacteria do not get too close to each other. The cell-to-cell attraction and repellent of E.Coli swarm can be denoted as Equation (9)

$$\begin{aligned} J_{cc}(\theta, P(j,k,l)) &= \sum_{i=1}^{S} J_{cc}(\theta, \theta^i(j,k,l)) \\ &= \sum_{i=1}^{S}[-d_{att}\exp(-w_{att}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)] + a \\ a &= \sum_{i=1}^{S}[-h_{rep}\exp(-w_{rep}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)] \end{aligned} \tag{9}$$

Where Jcc is the objective function value to be added to the current objective function that will reduce the final objective function, S is the total number of bacteria, and p is the number of variables to be optimized.

When food is sufficient and the temperature is suitable, the healthiest or well performed bacteria increase in length and split at the middle to form duplication of itself that contributes to the next generation while the least healthy bacteria dies. This activity is known as reproduction. Hence, BFOA applies this phenomenon by sorting the best objective function in increasing order and keeps half of the population's size to reproduce while the other half is eliminated. The most fit bacteria is split into two identical copies. The last step is elimination-dispersal where chemotactic process may be liquidated and the bacteria proceed to new positions when sudden environmental changes exist. The flow of BFOA applied in this work is shown in Figure-1.

THE PROPOSED HYBRID METHOD

Ontario power market

Ontario power market was conducted by Independent Electricity System Operator (IESO) which plays important roles in power system operation, forecasting short term demand and supply of electricity, and managing the real time spot market electricity price. HOEP; an hourly average of MCP is used by most market participants in Ontario.

Ontario was reported as one of the most volatile market in the world (Zareipour, Bhattacharya, & Cañizares, 2007) and hence gives a big challenge for price forecaster. Moreover, electricity price in Ontario is more volatile than the other three adjacent markets; New England, PJM, Midwest and New York; as Ontario is a single-settlement market which implement real-time market while the neighboring markets apply two-settlement system (day ahead and real time).

Consequently, single-settlement system has less efficiency than two-settlement system (Arciniegas Rueda & Marathe, 2005) and affects all market participants. Single-settlement system is exposed with unpredictable events such as sudden weather changes, generation outages and demand underforecast; where error in load forecast during peak hours may cause expensive generation units to be dispatched and hence producing spikes in electricity price. Besides, import and export failures can also lead to price volatility. The capacity of import and export are fixed and are scheduled 1 hour before the dispatch hour. Hence, failure in import trades may force the expensive units to be dispatched, causing spikes in electricity prices. Meanwhile, failure in export dealings may result to low prices when certain generation units are not dispatched. Moreover, low or high prices may exist when the energy output of non-dispatchable generators are not forecasted accurately.

In contrast, two-settlement market clears market demand 24 hours before dispatch hour so that the market participants have ample period to manage their supply and demand (Zareipour, Bhattacharya, *et al.* 2007). When spike occurs due to unpredictable events, only minor cluster of market participants that involved in real-time market will be affected.

Volatility of price series in Ontario can be seen in (Azmira & Siah, 2014) where in general, electricity prices are correlate with demand behavior and season. However, there were certain periods where the prices did not follow the demand pattern. In fact, 1-hour-ahead and 3-hour-ahead PDPs show large deviation with HOEP within year 2002 to 2005 as reported in (Zareipour, Cañizares, & Price, 2007). Hence, the selection of significant inputs is important to produce more reliable forecast model.

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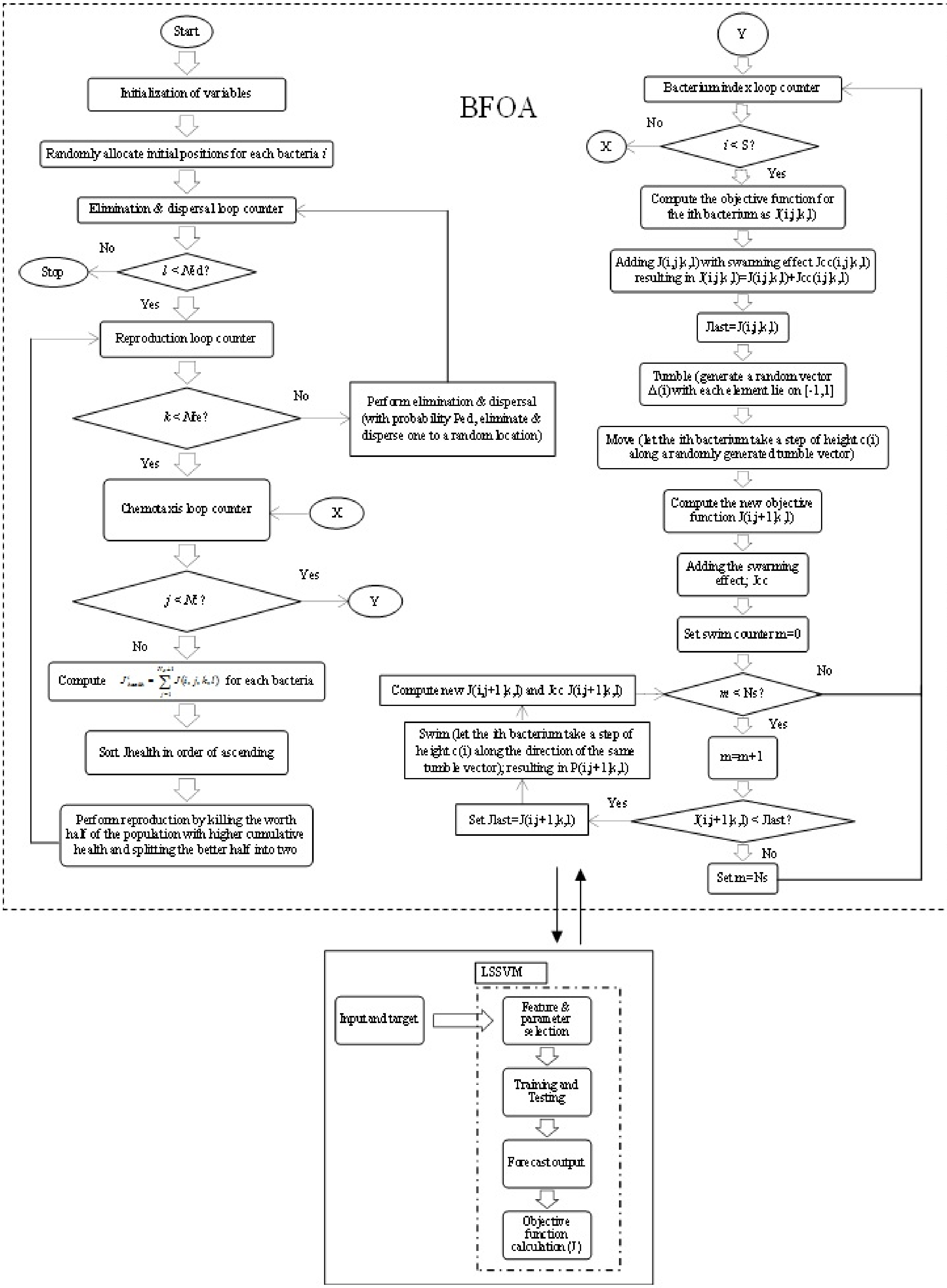

Figure-1. Flowchart of the proposed hybrid BFOA-LSSVM model.

The proposed hybrid method flowchart

To demonstrate the performance of proposed hybrid model, price series of Ontario power market in 2004 is selected for training and testing. The data are available at http://www.ieso.ca/. The training and testing data were normalized between [-1, 1] as in Equation (10) to prevent the domination of very large value in the data.

$$x_n = \frac{x_j - \left[\dfrac{x_{\max} + x_{\min}}{2}\right]}{\left[\dfrac{x_{\max} - x_{\min}}{2}\right]} \tag{10}$$

From the equation, x_n is normalized value, x_j is raw sample value, x_{max} and x_{min} are the maximum and minimum value of each feature in the samples. As a comparison with previous researchers, six forecast models are developed to represent the whole year of 2004. Each model is trained with ten weeks data prior to the forecasting week as shown in Table-1.

Table-1. Training and testing period.

		Training	Testing
Spring low point	Week 1	Feb 16 -Apr 25	Apr 26-May 2
	Week 2	Feb 23 -May 2	May 3-9
Summer peak demand	Week 3	May 17 - July 25	July 26 - Aug.1
	Week 4	May 24 - Aug 1	Aug 2 - 8
High demand winter	Week 5	Oct 4 - Dec 12	Dec 13 - 19
	Week 6	Oct 11 - Dec 19	Dec 20 - 26

Table-2. BFOA parameters.

		S	N_c	N_s	N_{re}	N_{ed}	p_{ed}
Spring low point	Week 1	22	15	5	100	3	0.25
	Week 2	18	15	5	50	3	
Summer peak demand	Week 3	16	15	5	50	3	
	Week 4	18	15	5	50	3	
High demand winter	Week 5	10	15	5	70	3	
	Week 6	16	10	5	15	6	

Figure-1 shows the flowchart of the proposed hybrid model, combining the optimization process and LSSVM training and testing. The inputs used for training the LSSVM network are the previous day HOEP; Pt-1, …, Pt-24, forecasted load on the forecast day; Lt, …, Lt+24, maximum load on previous day; Lmax(d-1), day type of forecast day (-1 for weekend and 1 for weekdays), and generation's price on previous day; Gt-1, …, Gt-24 . All the 74 inputs are optimized by BFOA where only significant inputs are selected to be fed into LSSVM network. On the other hand, BFOA optimizes parameters of LSSVM which are gamma, γ and sigma, σ.

Table 2 shows the BFOA parameters for all 6 models representing 6 weeks where S is number of bacteria, Nc is number of chemotactic steps, Ns is number of steps taken during swimming, Nre is number of reproduction steps, Ned is number of elimination-dispersal steps, and ped is probability of elimination-dispersal. These parameters must be chosen properly. Too small value of Nc may trap the bacteria into local minima while Ns must be smaller than Nc. The length of unit walk, C(i) is selected in the range [0,1] and is set to be constant. Too small value of C(i) may lead to slow convergence while high value of C(i) may cause failure in searching local minima. The value of ped =0.25 is selected since too large value may increase computational time due to extensive search.

During swarming phenomenon, the attractant depth (dattract) and attractant width (wattract) are selected as 0.1 and 0.2; respectively. If the values are large, the bacteria will tend to build as a swarm while too small values will cause the bacterium to search nutrients on its own. Meanwhile, the Nre should not be too small because it may cause premature convergence. As in general, increasing the size of S, Ned, Nre, and Nc may increase the computational complexity, simulation time, but perhaps leading for better optimization progress where bacteria have more searching space.

Results and Discussion

Forecast accuracy is measured by Mean Absolute Percentage Error (MAPE) as Equation (11):

$$MAPE = \frac{100}{N} \times \sum_{t=1}^{N} \frac{\left|P_{actual\,t} - P_{forecast_t}\right|}{P_{actual\,t}} \tag{11}$$

where Pactual and Pforecast are the actual and forecasted HOEP at hour t, respectively, while N is the number of hours in a week. Table-3 shows the comparison between the proposed method and other methods by previous researchers in Ontario with the same testing periods.

It can be concluded in general that the proposed approach surpasses other methods with the average MAPE for those six test weeks is 13.11% while the best MAPE produced by previous researchers was 15% (Shayeghi & Ghasemi, 2013). In addition, the LSSVM+BFOA performs the best for Week 1, 4, and 6 as compared with other approaches.

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Table-3. Comparison for Ontario market in 2004.

Method		Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Average
(Shayeghi & Ghasemi, 2013)	LSSVM+CGSA+WT	14.3	14	14	14	14.1	14.5	15
(Aggarwal et al., 2008)	Heuristic	21.7	17.8	22.92	37.77	24.6	24.55	24.89
	IESO	23.78	25.26	10.41	16.22	22.06	23.51	20.21
	MLR	16.26	19.23	17.69	20.55	16.73	18.54	18.17
	NN	16.56	19.34	17.45	20.27	17.03	19.69	18.39
	Wavelet+NN	15.21	18.62	17.91	18.72	16.61	18.02	17.51
(Zareipour et al., 2006)	ARIMA	15.9	18.6	13.6	21.5	15.4	20.8	17.6
	TF	15.6	18	12.3	18.3	14.8	17.5	16.1
	DR	15.9	18.1	13	19	14.7	18.5	16.5
	IESO	39.7	30.3	36.9	31.6	60.2	37.3	40
	NN							18.8
Proposed method		12.85	14.07	11.57	11.25	15.13	13.78	**13.11**

Meanwhile, the MAPEs obtained by the proposed model during summer peak demand (Week 3 and Week 4) are lower than other weeks, and the MAPE during Week 5 shows the worst performance. The price series in 2004 is illustrated by Figure-2. Figures-3-4 show the plot of actual and forecasted prices by the proposed hybrid method of LSSVM+BFOA for Week 1 and Week 3; respectively. As in general, the proposed method can predict well for most of the time during normal condition, except for spikes events when unexpected circumtances occur.

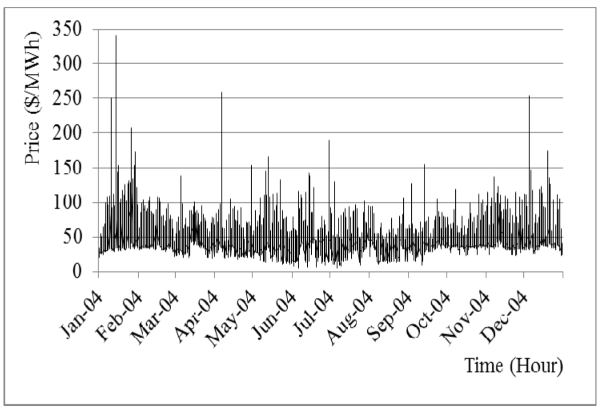

Figure-2. Price series in Ontario for year 2004.

The overall results presented by the proposed hybrid model of BFOA and LSSVM reveals a significant improvement for short term price forecasting due to its simplicity and reliability. This novel technique which never applied in electricity price forecasting is proven to give better forecast accuracy than other current approaches developed for highly volatile market such as Ontario power market. However, a special tehnique should be applied on spike value prediction to get better forecast accuracy.

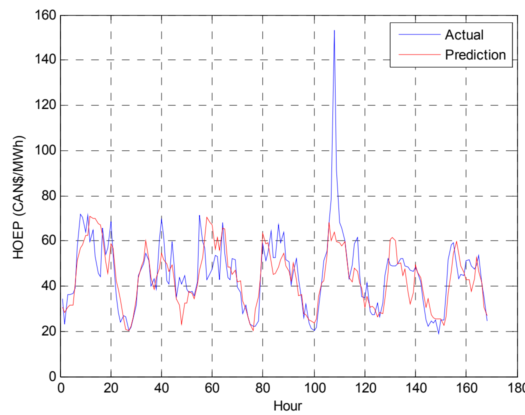

Figure-3. Actual vs. prediction HOEP for week 1.

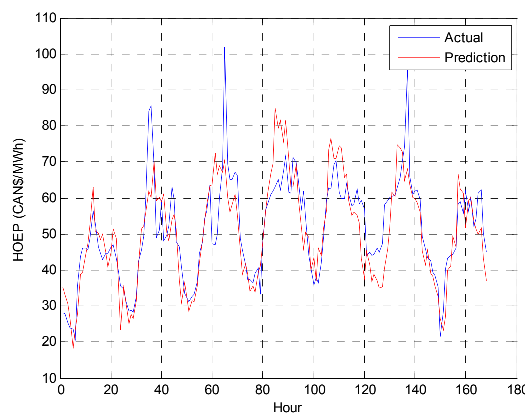

Figure-4. Actual vs. prediction HOEP for week 3.

CONCLUSIONS

Electricity price forecasting is an essential task in power system operation and planning. Short term forecast model would be useful for both producer and consumer in developing bidding strategies or negotiation skills either in the pool market or through bilateral contracts. An accurate forecast model enables the power producer at generation sites to review and change the bids of supply and prices prior to the dispatch day or hour. Hence, the output from the generators can be managed based on the price forecast to gain a maximum profit. Meanwhile, consumers can use the developed model to manage and maximize their consumption or hedge themselves against price spike occurrences.

This work contributes to the field of electricity price forecasting by developing a novel hybrid method of Least Square Support Vector Machine and Bacterial Foraging Optimization Algorithm to predict short term electricity prices. LSSVM is selected as forecast engine rather than SVM due to its efficiency, accuracy, and simplicity. Meanwhile, the BFOA performs optimization process by selecting only significant features to be fed into the LSSVM and optimizing parameters for LSSVM.

These optimization processes are accomplished by eliminating species with poor foraging and selecting species with successful foraging. There are four main activities during foraging namely chemotaxis, swarming, reproduction, and elimination-dispersal where each step play an essential role to bring the solution approaching global minima. During chemotaxis, the cost function is calculated for each movement of tumbling and swimming. However, each bacterium will try to move towards increasing concentrations of foods which having lower value of cost function. The next step will further improves the cost function where during swarming process, each bacterium attracts other bacteria to move as a swarm and release repellent signal to mark a minimum space among the bacteria.

The next step of reproduction ensures only the healthiest bacteria with good cost function are survived and reproduce for the next cycle of foraging by sorting bacterial population in order of ascending accumulated cost function. Half of the bacteria which are the healthiest bacteria are split into two to form replica of them while the other half are dies. The last step of elimination-dispersal may avoid the bacteria of being trapped into the local minima where some bacteria are eliminated and replaced by new bacteria with a predefined probability ped. The new bacteria will be located at random position to imitate dispersal process via wind in real word.

The application of BFOA in electricity price forecasting is not reported yet but it is proven to give better accuracy than other approaches presented in this paper. In fact, this hybrid method is less complex compared to other approaches proposed by other literatures presented in this paper. Moreover, the developed models tested on Ontario electricity market in year 2004 can be applied in Malaysia when the deregulated electricity market exists in future. Despite of this, short term planning and forecasting is highly risky in Ontario and moving towards two-settlement market should improve forecast accuracy and reduce price volatility as well.

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