

Particle Swarm Optimization for Least Square Support Vector Machine in Medium-Term Electricity Price Prediction

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Abstract: Predicting electricity price has now become an important task for planning and maintenance of power system. In medium-term forecast, electricity price can be predicted for several weeks ahead, up to a few months or a year ahead. It is useful for resources reallocation where the market players have to manage the price risk on the expected market scenario. However, the research on medium-term price forecast have also exhibited low forecast accuracy due to the limited historical data for training and testing purposes. Therefore, an optimization technique using Particle Swarm Optimization (PSO) for Least Square Support Vector Machine (LSSVM) was developed in this study to provide an accurate electricity price forecast with optimized LSSVM parameters. After thorough database mining in English language, no literature has been found on parameter optimization using LSSVM-PSO for medium-term price prediction. The model was examined on the Ontario power market which was reported as among the most volatile market worldwide. Monthly average of Hourly Ontario Electricity Price (HOEP) for the past 12 months and month index were selected as the input. The developed LSSVM-PSO showed higher forecast accuracy with lower complexity than the existing models.

Keywords:

1. Introduction

Electricity price prediction is essential for those involved in the electricity market in terms of providing better maintenance scheduling, expanding investment and making long-term planning. However, predicting electricity prices is a challenging task due to the uncertainty of electricity prices. Hence, research in electricity price forecasting has covered various fields such as science, engineering, and statistics. This led to the development of various model structures and approaches. However, most of these approaches have a focus on short-term electricity price forecasts, from one hour forward to the next day. In contrast, the method of predicting electricity prices for the medium-term is less explored. In addition, the medium-term prediction of electricity prices is more difficult than the short-term forecasts due to partial access to data [1]–[4]. Medium-term forecasts usually require data from a year ago [2], [5]. Therefore, medium-term price forecasts are unable to extract the latest electricity price trends.

Some scholars have discovered that the Neural Network (NN) technique is less appropriate for medium-term forecasting because NN requires huge data sets to train neural networks [6], [7]. Several Time Series (TS) models for medium-term electricity price forecasts have been developed by researchers for example regression models [8], generalized least squares model [9] and Autoregressive Moving Average Exogenous (ARMAX) model [10]. However, the TS method estimates future prices based on past data such as load and price data. Therefore, the forecast error will increase significantly when significant declines occur and increases loads and prices [7].

In the meantime, the Support Vector Machine (SVM) approach has been discovered by other researchers by combining SVM and ARMAX [11]. A comparison between SVM-ARMAX and single SVM was also shown. The SVM-ARMAX hybrid model showed better results than the single ARMAX model when they were tested in the Pennsylvania-New Jersey-Maryland (PJM) market. The same authors also used SVM to classify and predict electricity prices by four price zones [12]. Likewise, the advantage of SVM was demonstrated by Torbaghan et al. [6] in which the SVM models performed better than other hybrid models. Other researchers also proved that the performance of the SVM model developed was higher than other models such as NN and Radial Basis Function (RBF) [13]. Moreover, the latest findings showed by Ziel and Steinert were promising [14] with the forecast for every hour for several months up to three years. This study differed slightly from norm in terms of forecast output as it predicts every hour, rather than predicting for a monthly average. The model detects the probability of a price increase and was tested on the European Power Exchange (EPEX) electricity market for Germany and Austria.

Previous research however, did not emphasize on selecting appropriate forecast input and network parameters to improve the prediction accuracy. LSSVM and PSO approaches in other fields have shown promising improvement in accuracy for forecasting. Throughout the authors' review, there has been no literature on LSSVM and PSO approaches in medium-term electricity price forecasts. Therefore, this study develops medium-term

electricity pricing forecast techniques through LSSVM and PSO hybrid model. This model was observed to provide improved predictive error than previous models.

2.Theory of main forecast engine and optimization algorithm

2.1.SVM and LSSVM

SVM is a supervised learning model capable of data classification and estimation created by Vapnik [15]. In the early phases, SVM was applied for classification. Later, it was improved with the addition of a solution to the calculation of nonlinear functions. SVM solves quadratic equations and can reduce local minimum problems [16] in very large input dimensions [17]. Even so, the main drawback of SVM is the complexity of its computing. Thus, Least Squares Support Vector Machine (LSSVM) was designed to decrease the SVM computational load [7], [18]. LSSVM has a linear equation system of Karush-Kuhn-Tucker (KKT) compared to Quadratic Programming (QP) in SVM [17], [19]. KKT is simpler and can increase the calculation speed compared to QP. LSSVM also retains the advantages of SVM which has a great generalization capability which can ultimately reduce errors.

2.2.PSO

PSO was proposed by Eberhart and Kennedy [20] to mimic the natural habits of group of birds or a school of fish during foraging activities. In contrast to Genetic Algorithm (GA), PSO does not produce offspring from parents. In PSO, these bird populations only develop their natural habits while searching for food and moving closer to the target. When individuals of a swarm search for food, they will spread and move around randomly. Once the source of food is found, it will be announced to its neighbours to approach the source of food too. Hence, each bird flies to the destination with its velocity and find food from its new location. These processes are repeated until the swarm approaches a preferred location. As a result, every bird learns from its own exposure during local search. It also takes experience from other birds through global search [21]. During searching progression, each particle has three important parameters: current location, the best previous location, and flying velocity. The parameters are represented as in equation (1):

$$\left. \begin{aligned} \text{Current location, } X_i &= (x_{i1}, x_{i2}, \dots, x_{iS}) \\ \text{Best previous location, } P_i &= (p_{i1}, p_{i2}, \dots, p_{iS}) \\ \text{Flying velocity, } V_i &= (v_{i1}, v_{i2}, \dots, v_{iS}) \end{aligned} \right\} (1)$$

The best location P_g of the best particle g is considered as the best fitness of all particles. Meanwhile, the velocity of every particle, V_i is calculated based on the location of the best particle g as shown by equation (2):

$$\text{New } V_i = \omega \times \text{current } V_i + c_1 \times \text{rand}() \times (P_i - X_i) + c_2 \times \text{Rand}() \times (P_g - X_i) (2)$$

where c_1 and c_2 are positive constants, which is also known as a learning factor. Typically, the values of $c1$ and $c2$ are 2 while $\text{rand}()$ and $\text{Rand}()$ are random functions with the output in the range of 0 to 1. ω is an inertia weight, which controls the effect of the prior velocities on the recent velocity. It is important in balancing global search and local search. Meanwhile, it was recommended by Shi and Eberhart [22] to reduce the value of ω gradually in the range of [1.4–0.5]. Hence, the new location that is associated with the new velocity is computed as presented in equation (3):

$$\begin{aligned} \text{New location } X_i &= \text{current location } X_i + \text{New } V_i; \\ V_{\max} \geq V_i &\geq -V_{\max} \end{aligned} (3)$$

where V_{\max} is the maximum velocity limit for a particle. Therefore, it can be concluded that the core elements in PSO are the dimension of population and generation, V_{\max} ; and ω [21]. The overall flowchart of PSO algorithm is presented in Figure 1.

3.Modelling of LSSVM-PSO

The developed model was examined on the Ontario Electricity Market. The average monthly price for the 12 months before the month to be predicted and the month index were selected as the input [23]. The month index refers to the month to be predicted, represented by a value of 1 to 12 to represent January through December. Training data is 59 months; from January 2005 to October 2009; while the forecast period is from November 2009 to October 2010. Therefore, each training and test sample had 13 inputs and one output which is the forecasted price of a month ahead. Figure 2 shows the flow chart of the LSSVM-PSO model which combines the LSSVM optimization, training, and testing processes. During the optimization, the PSO optimizes the values of the

LSSVM parameters, namely gamma (γ) and sigma (σ) simultaneously. Optimized LSSVM parameters are trained in LSSVM until the optimum fitness or Mean Absolute Percentage Error (MAPE) values are obtained.

The optimization process is initiated by assigning random location and velocity for each particle in the D -dimension. The associated location of each particle is a basis for LSSVM training to produce fitness function for each particle. The best previous location of the particle is denoted as P_{best} , while the best particle among all the particles in the swarm is referred to as G_{best} . Based on the location of the best particle, the new velocity is updated for each particle. Meanwhile, the new location of each particle is also calculated based on the new velocity. Therefore, all particles have new updated locations, until a global optimal location is found.

The optimization process is completed when the predetermined number of generations has been reached. On the other hand, the search can also stop when a good MAPE value is obtained. However, when there is no improvement in MAPE for several generations, the search process should be stopped. To obtain a good PSO configuration, an analysis of the number of generations and populations was performed. This analysis was conducted to observe the influence of the number of generations and populations on the accuracy of the optimization.

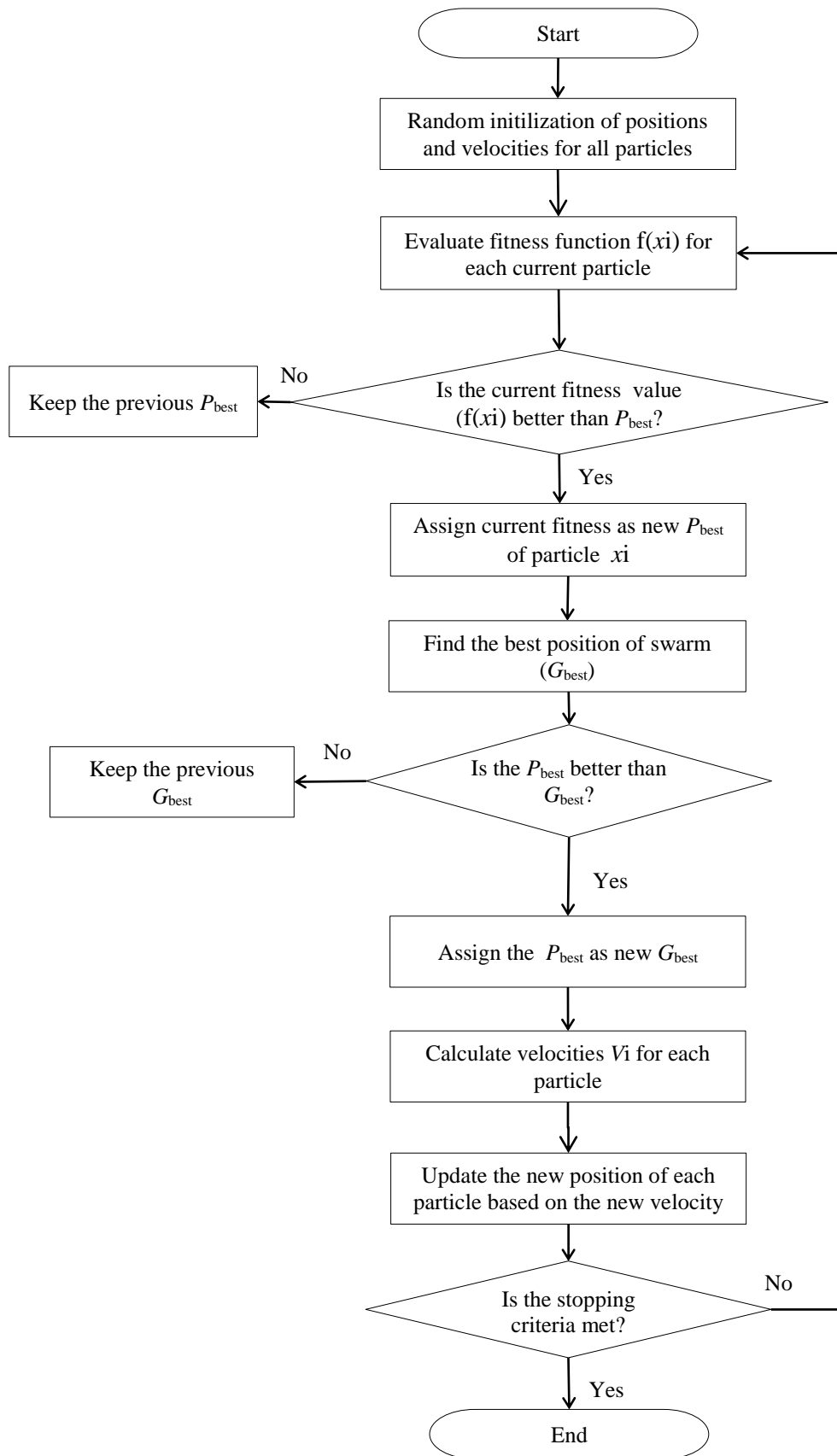


Figure 1. Flowchart of PSO.

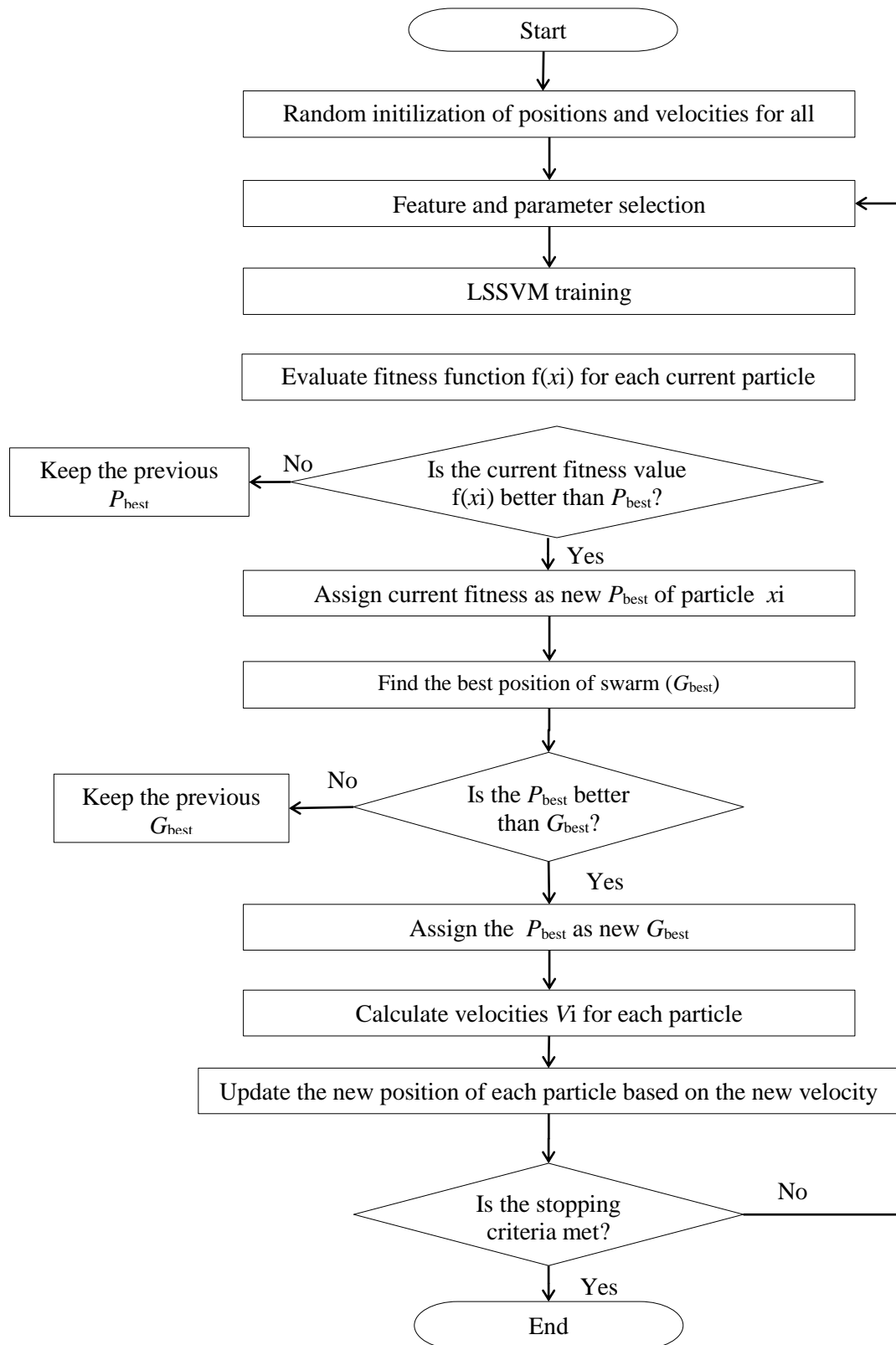


Figure 2. Flowchart of hybrid LSSVM-PSO.

4..Result

The performance of the model was assessed through Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) as shown in equation (4) and equation (5), respectively:

$$MAPE = \frac{100}{n} \times \sum_{i=1}^n \frac{|P_{actual} - P_{predict}|}{P_{actual}} \quad (4)$$

$$MAE = \frac{1}{n} \times \sum_{i=1}^n |P_{actual} - P_{predict}|(5)$$

where P_{actual} is the true value and $P_{predict}$ is the prediction value. The size of sample is represented by n .

4.1. Analysis on the size of population and generation

Table 1 shows the influence of the number of generations and populations on the forecast accuracy. From these 4 cases, it can be concluded that if the size of the population and generation is smaller, the MAPE and MAE also become lower. This is due to the size of the training data and the number of predictive inputs which are moderate. Hence, the small size of the population and generation is also sufficient, as concluded by Piotrowski et al. [12]. From the author's observations, most of the best PSO models utilize approximately 70-500 particles. This contradicts previous studies where the number of selected populations was often too small. This is because, a larger population size can increase the efficiency of PSO for more difficult and practical applications. This allows the PSO to perform optimizations in the appropriate space faster. However, for smaller applications, a slightly lower population size is recommended. Even so, some applications perform best when hundreds of particles are used.

Table 1. Analysis on number of population and generation

	Case 1	Case 2	Case 3	Case 4
No. of population	30	100	200	300
No. of generation	100	300	500	1000
MAPE	9.0248	13.7464	18.3334	26.7112
MAE	3.4993	5.6282	6.7081	8.9729

4.2. Performance of LSSVM-PSO model

By selecting the size of the population and generation in Case 1, LSSVM-PSO performance of medium-term forecasts is shown in Table 2. The gamma and sigma values for LSSVM were optimized by PSO. The regression value shown is also quite good indicating that the predicted HOEP is almost identical to the actual HOEP. MAPE and MAE values are also relatively low and outperform the MAPE produced by the other models as in Table 3.

Table 2. LSSVM-PSO model for medium-term forecast

No. of population	30
No. of generation	100
Sigma	27.3802
Gamma	651.0299
Regression	0.68
MAPE	9.0248
MAE	3.5

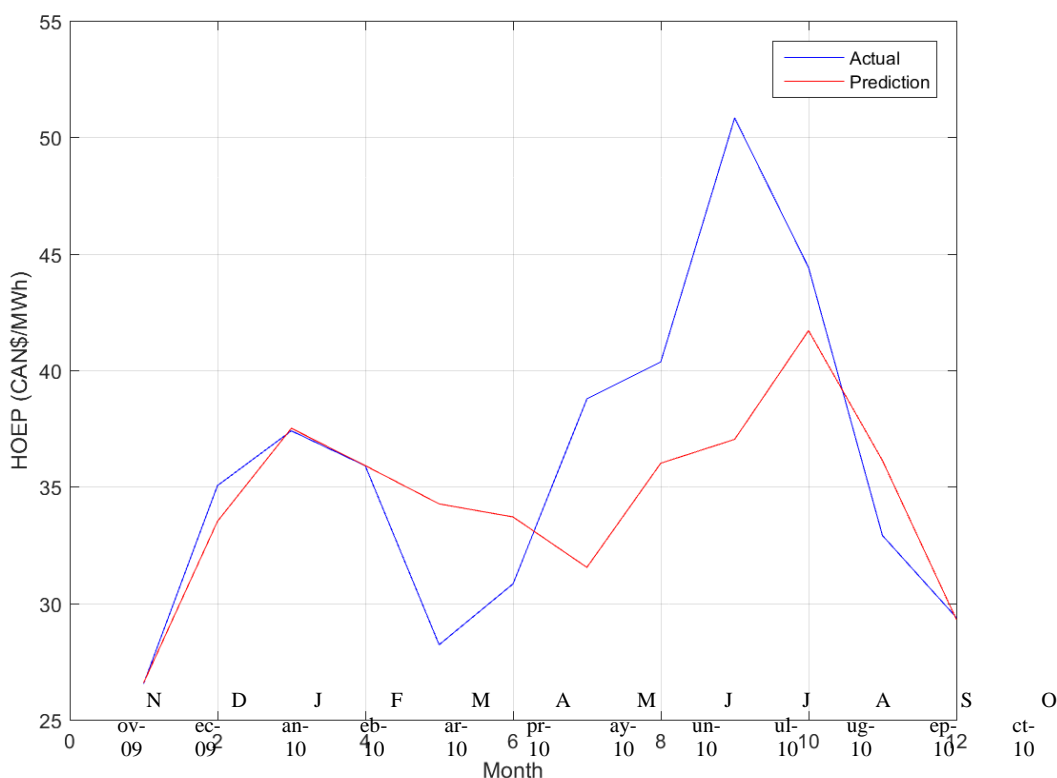


Figure 3. Actual and forecast prices of LSSVM-PSO.

The plot for the actual HOEP compared to the predicted HOEP is illustrated in Figure 3. In 2010, the summer period occurs between May to October. Based on the report by Ontario Energy Board [24], there was an increase in HOEP during this period compared to the previous year. However, in a closer look, the predicted monthly HOEP is approaching the actual reading except in March and July 2010.

Table 3. MAPE for medium-term forecasts in the Ontario electricity market.

Ref	Method	MAPE (%)
	LSSVM-PSO	9.02
[25]	LSSVM-BFOA	9.57
[23]	LSSVM-GA	9.43
	SVM	14.25
	RBF-NN	17.65
	WNN	32.99
	MA	32.58
[6]	SVM/SVM	12.97
	SVM/RBF-NN	13.2
	RBF-NN/RBF-NN	14.33
	RBF-NN/SVM	16.09
	Navigant Co.	33.04

For a fair comparison, this developed LSSVM-PSO model was compared to other methods available in Ontario for the same test period. A summary of the performance comparison for the developed models is shown in Table 3. From Table 3, the LSSVM-PSO hybrid model outperforms other models including the forecast model produced by Navigant Consulting Ltd. (Navigant). Navigant Company is operated by the Ontario Energy Board (OEB) which provides price forecasts for the Ontario electricity market.

Referring to LSSVM-BFOA [25] and LSSVM-GA [23], both methods have optimized the number of predictive inputs and the values of the LSSVM parameters. However, LSSVM-PSO only performs optimizations on LSSVM parameters. This indicates that the initial number of predictive inputs of 13 inputs may be sufficient and should not be further reduced. Inadequate input can reduce the accuracy of the prediction.

5. Conclusion

Electricity price prediction is an important aspect in the operation and scheduling of power systems. Thus, medium-term forecasts are beneficial in maintenance scheduling, allocation of resources and investment expansion. It is also important for energy market members in deciding to buy or sell energy. SVM has proven to have the ability to find the global in larger spaces with higher speed and accuracy. Previous work in medium-term electricity price forecasts have shown plausible accuracy using LSSVM with room for improvement. Therefore, the hybrid methods of LSSVM and PSO was developed in this project to further improve the medium-term electricity price forecasting. PSO as an optimization algorithm optimizes LSSVM parameters which in turn allows LSSVM to better predict monthly electricity prices. The optimization process is accomplished through foraging activities during local search and from global search. The percentage of forecast error generated is lower than other existing models in the Ontario Electricity Market.

There are many methods that have been explored and developed for medium-term electricity price forecasts. Each model has its own strengths and weaknesses. Due to the various and complex factors that affect the monthly and annual price patterns, sometimes the Artificial Intelligence (AI) method is also not able to predict well. To overcome this problem, different approaches have been combined against NN or SVM such as using optimization algorithms to reduce the number of inputs and select the optimal network parameter values. Therefore, research needs to be continued to explore new approaches in line with current price patterns and the energy market. It is hoped that the forecast error can be reduced and in turn improve the forecast performance. This is because an accurate forecasting not only benefits in terms of low penalties but also improves performance on power grid maintenance and operational scheduling.

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References

1. X. Yan and N. a. Chowdhury, "Mid-term electricity market clearing price forecasting utilizing hybrid support vector machine and auto-regressive moving average with external input," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 64–70, Dec. 2014, doi: 10.1016/j.ijepes.2014.05.037.
2. X. Yan and N. a. Chowdhury, "Mid-term electricity market clearing price forecasting: A multiple SVM approach," *Int. J. Electr. Power Energy Syst.*, vol. 58, pp. 206–214, Jun. 2014, doi: 10.1016/j.ijepes.2014.01.023.
3. X. Yan and N. A. Chowdhury, "A comparison between SVM and LSSVM in mid-term electricity market clearing price forecasting," in 2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), May 2013, pp. 1–4, doi: 10.1109/CCECE.2013.6567685.
4. X. Yan, S. Member, and N. a Chowdhury, "Mid-term Electricity Market Clearing Price Forecasting Using Multiple Support Vector Machine," *J. energy*, vol. 2015, pp. 1–5, 2013.
5. N. a. Chowdhury, "Electricity market clearing price forecasting in a deregulated electricity market," in 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems, Jun. 2010, no. 1, pp. 36–41, doi: 10.1109/PMAPS.2010.5528949.
6. S. S. Torbaghan, A. Motamedi, H. Zareipour, and L. A. Tuan, "Medium-term electricity price forecasting," in 2012 North American Power Symposium (NAPS), Sep. 2012, pp. 1–8, doi: 10.1109/NAPS.2012.6336424.
7. T. Ahmad, H. Zhang, and B. Yan, "A review on renewable energy and electricity requirement forecasting models for smart grid and buildings," *Sustain. Cities Soc.*, vol. 55, p. 102052, Apr. 2020, doi: 10.1016/j.scs.2020.102052.
8. S. S. Torghaban, H. Zareipour, and L. A. T. L. A. Tuan, "Medium-term electricity market price forecasting: A data-driven approach," in North American Power Symposium (NAPS), 2010, 2010, pp. 1–7, doi: 10.1109/NAPS.2010.5618960.

9. C. Nunes, A. Pacheco, and T. Silva, "Statistical models to predict electricity prices," in 2008 5th International Conference on the European Electricity Market, May 2008, pp. 1–6, doi: 10.1109/EEM.2008.4579004.
10. X. Yan and N. a. Chowdhury, "Mid-term electricity market clearing price forecasting: A hybrid LSSVM and ARMAX approach," *Int. J. Electr. Power Energy Syst.*, vol. 53, pp. 20–26, Dec. 2013, doi: 10.1016/j.ijepes.2013.04.006.
11. X. Yan and N. a. Chowdhury, "Hybrid SVM & ARMAX based mid-term electricity market clearing price forecasting," in 2013 IEEE Electrical Power and Energy Conference, EPEC 2013, 2013, pp. 0–4, doi: 10.1109/EPEC.2013.6802978.
 - A. P. Piotrowski, J. J. Napiorkowski, and A. E. Piotrowska, "Population size in Particle Swarm Optimization," *Swarm Evol. Comput.*, vol. 58, p. 100718, Nov. 2020, doi: 10.1016/j.swevo.2020.100718.
12. Mohamed and M. E. El-Hawary, "Mid-term electricity price forecasting using SVM," in 2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), May 2016, pp. 1–6, doi: 10.1109/CCECE.2016.7726765.
13. F. Ziel and R. Steinert, "Probabilistic mid- and long-term electricity price forecasting," *Renew. Sustain. Energy Rev.*, vol. 94, pp. 251–266, Oct. 2018, doi: 10.1016/j.rser.2018.05.038.
14. V. N. Vapnik, *Statistical Learning Theory*. New York: Wiley, 1998.
15. G. Xie, S. Wang, Y. Zhao, and K. K. Lai, "Hybrid approaches based on LSSVR model for container throughput forecasting: A comparative study," *Appl. Soft Comput.*, vol. 13, no. 5, pp. 2232–2241, May 2013, doi: 10.1016/j.asoc.2013.02.002.
16. H. Wang and D. Hu, "Comparison of SVM and LS-SVM for Regression," in 2005 International Conference on Neural Networks and Brain, 2005, no. 5, pp. 279–283.
17. J. A. K. Suykens and J. Vandewalle, "Least Squares Support Vector Machine Classifiers," *Neural Process. Lett.*, vol. 9, no. 3, pp. 293–300, 1999, doi: 10.1023/A:1018628609742.
18. S. Li and L. Dai, "Classification of gasoline brand and origin by Raman spectroscopy and a novel R-weighted LSSVM algorithm," *Fuel*, vol. 96, pp. 146–152, Jun. 2012, doi: 10.1016/j.fuel.2012.01.001.
19. R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science, 1995, pp. 39–43, doi: 10.1109/MHS.1995.494215.
20. E. Elbeltagi, T. Hegazy, and D. Grierson, "Comparison among five evolutionary-based optimization algorithms," *Adv. Eng. Informatics*, vol. 19, no. 1, pp. 43–53, Jan. 2005, doi: 10.1016/j.aei.2005.01.004.
21. Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in 1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98TH8360), 1998, pp. 69–73, doi: 10.1109/ICEC.1998.699146.
22. Azmira et al., "An Optimization Method of Genetic Algorithm for LSSVM in Medium Term Electricity Price Forecasting," *J. Telecommun. Electron. Comput. Eng.*, vol. 10, no. 2, pp. 99–103, 2018.
23. Ontario Energy Board, "Monitoring Report on the IESO-Administered Electricity Markets," 2015. [Online]. Available: http://www.ontarioenergyboard.ca/OEB/_Documents/MSP/MSP_Report_20120427.pdf.
24. A. W. A. Razak, N. N. A. N. Ibrahim, I. Z. Abidin, Y. K. Siah, A. A. Z. Abidin, and T. K. A. Rahman, "A hybrid method of least square support vector machine and bacterial foraging optimization algorithm for medium term electricity price forecasting," *Int. J. Integr. Eng.*, vol. 11, no. 3, pp. 232–239, 2019, doi: 10.30880/ijie.2019.11.03.024.