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NEXT-HOUR ELECTRICITY PRICE FORECASTING USING LEAST SQUARES SUPPORT VECTOR MACHINE AND GENETIC ALGORITHM

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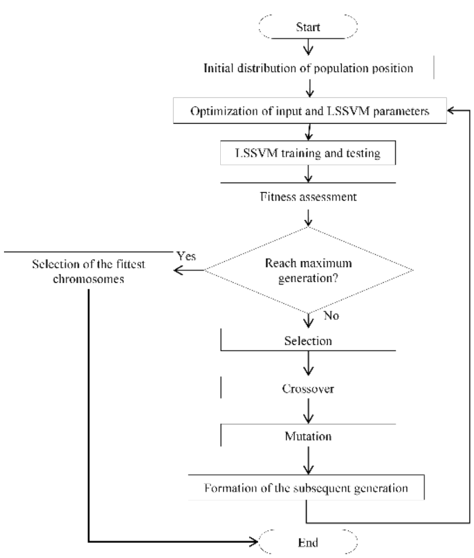
Graphical abstract



Abstract

Predicting the price of electricity is crucial for the operation of power systems. Short-term electricity price forecasting deals with forecasts from an hour to a day ahead. Hourly-ahead forecasts offer expected prices to market participants before operation hours. This is especially useful for effective bidding strategies where the bidding amount can be reviewed or changed before the operation hours. Nevertheless, many existing models have relatively low prediction accuracy. Furthermore, single prediction models are typically less accurate for different scenarios. Thus, a hybrid model comprising least squares support vector machine (LSSVM) and genetic algorithm (GA) was developed in this work to predict electricity prices with higher accuracy. This model was tested on the Ontario electricity market. The inputs, which were the hourly Ontario electricity price (HOEP) and demand for the previous seven days, as well as 1-h pre-dispatch price (PDP), were optimized by GA to prevent losing potentially important inputs. At the same time, the LSSVM parameters were optimized by GA to obtain accurate forecasts. The hybrid LSSVM-GA model was shown to produce an average mean absolute percentage error (MAPE) of 8.13% and the structure of this model is less complex compared with other models developed in previous studies. This is due to the fact that only two algorithms were used (LSSVM and GA), with the load and HOEP for the week preceding the forecasting hour as the inputs. Based on the results, it is concluded that the proposed hybrid algorithm is a promising alternative to produce good electricity price forecasts.

Keywords: Genetic algorithm, least squares support vector machine, Next-hour, electricity price forecasting

1.0 INTRODUCTION

Electricity price forecasting is vital for those involved in the electricity market as it serves as a guide and reference for electricity pricing strategies. In terms of day-ahead predictions, next-hour forecasting is beneficial for a successful bidding strategy, where the bidding amount can be revised or changed before the operation hours. In addition, electricity generation companies can adjust the output of electricity generators if they can predict the price of electricity. The amount and price of electricity supply can be adjusted primarily based on production costs in order to maximize profits. Price forecasts are also used by electricity consumers to plan and manage electricity consumption, especially when electricity prices are expected to soar.

However, predicting electricity prices is more challenging than predicting electricity loads due to the price volatility. There are several controllable factors that influence the price volatility such as the electricity load, climate, and fuel prices. However, there are also uncontrollable factors such as the bidding strategies and supply-demand imbalances. Supply-demand imbalances result from contingent demand throughout peak hours, failures in import and export transactions, and errors in predicting energy output by non-dispatchable generators.

To date, only a few studies have been carried out pertaining to next-hour electricity price forecasts. This is because most energy markets use a two-settlement market structure (day-ahead and real-time) in contrast to a single (real-time) settlement mechanism. Most previous studies used time series (TS) and neural network (NN) approaches for hourly price forecasting. For example, a TS model called multivariate adaptive regression splines (MARS) was designed and tested on the Ontario energy market [1]. Another study [2] was also carried out to forecast intraday electricity prices in Germany using an autoregressive model, which incorporated Dirac and Student's t-distributions. However, a significant drawback of the TS model is that it requires a high time series stability.

In place of TS models, the combination of intelligent prediction models is a favourable alternative to improve the accuracy and efficiency of electricity price forecasts. Artificial intelligence (AI) methods such as artificial neural network (ANN) and support vector machine (SVM) do not require high stability and these models can obtain accurate and stable predictions through the training data [3]. The development of NN models have been reported by many researchers [3–10]. One of the methodologies of NNs is deep neural network, which has gained popularity rapidly and has been applied to predict electricity prices [4], [5]. In [6], the Levenberg-Marquardt backpropagation algorithm was applied on the Ontario energy market. Meanwhile, in [7], recurrent neural networks and excitable dynamics were developed and evaluated on the Ontario, New South Wales, Spain, and California energy markets. A hybrid model (autoregressive-moving average model with exogenous input model (ARMAX)), adaptive wavelet neural network (AWNN), and generalized autoregressive conditional heteroskedasticity (GARCH) have been applied by Wu and Shahidehpour [8] on the Pennsylvania–New Jersey–Maryland (PJM) energy market. Meanwhile, an expectation-maximization technique for recurrent neural networks (RNN-EM) was established by Mirikitani and Nikolaev [9].

On the other hand, load and price forecasts have been modeled using wavelet transform (WT) as a pre-processing technique and long short term memory (LSTM) [10]. Entropy and mutual information (MI)-based feature selection has also been proposed to further improve the accuracy of forecasting. Moreover, load and price forecasting have also been demonstrated by Heydari et al. [11]. The initial process involved the decomposition of both signals (load and price series) via variational mode decomposition (VMD) before the number of inputs was optimized by neural network gravitational search algorithm (NNGSA). The forecasting process was then implemented after the generalized regression neural network (GRNN) parameters were optimized by the GSA. In contrast to previous works, Lee and Wu [12] proposed a similar day approach to predict electricity prices in the PJM energy market. The days were selected by four distance models: Euclidean norm, Manhattan distance, cosine coefficient, and Pearson correlation coefficient. The prediction outputs were then obtained through similar day regression (SDR) and similar day-based ANN (SDANN).

However, ANNs suffer from a number of drawbacks such as the local minima problem, slow convergence speed, and differences in the structure selection. SVM algorithm is widely used in place of ANNs owing to these disadvantages. Halu et al. [13] proved that the SVM model outperformed other models for Greek and Hungarian energy markets. Meanwhile, to capture linear and non-linear trends, a least squares support vector machine (LSSVM) model with self-adaptive kernel functions and GARCH time series was developed by Ghasemi-Marzbali [14]. Pre-processing was first carried out using WT before input selection was implemented by MI. An improved virus colony search algorithm (VCS) has also been used to optimize LSSVM parameters. Other studies have used LSSVM as the main forecasting technique to predict electricity prices and loads. In [15], dyadic wave transformation (DWT) and modified MI (MMI) have been used for pre-processing and feature selection, respectively, while modified GSA has been used as the optimization algorithm.

Based on the literature review, most of the available models can predict electricity prices reliably under normal conditions. However, the forecasting error increases during a price spike. Therefore, in this work, a new approach has been developed to predict next-hour electricity prices using a hybrid LSSVM-GA model. The prediction inputs and LSSVM parameters are optimized concurrently by the GA. This method has been proven to improve the prediction accuracy compared with other methods when tested on the Ontario energy market. This hybrid model can facilitate the process of bidding for electricity prices and improve the operation of power systems.

2.0 METHODOLOGY

2.1 SVM and LSSVM

The main forecasting engine applied in this study is LSSVM, which is an improved SVM model, in order to reduce the computational load. SVM is capable of reducing overfitting and the local minima trap [16], as well as effectively manage a high-dimensional input space [17]. SVM, on the other hand, necessitates a significant amount of processing. To reduce the SVM computational load, the LSSVM model was developed. LSSVM improves computational speed by solving a linear equation system over a quadratic programming problem (QP) [17], [18]. The Karush-Kuhn-Tucker (KKT) linear system is simpler than the QP system. LSSVM also retains the characteristics of SVM, with a high generalization level.

2.2 GA

GA was introduced by Holland [19] based on the 'survival of the healthiest' principle and the mechanism of natural progression through reproduction. GA can locate the best solution through repeated computations. The objective function of GA is the fitness function. Selection, crossover, and mutation are the three core processes of GA.

The optimization mechanism begins with a random distribution of chromosome population positions, and following this, the prediction inputs and LSSVM parameter values are refined. The optimized number of inputs and LSSVM parameters were fed into the LSSVM for the training and testing processes. Following this, the fitness function or prediction error is calculated. Next, the most suitable individual (or parent) is selected during the reproduction process. Chromosomes with improved fitness values tend to produce offspring throughout the next generation. To imitate the likely survival, the healthiest chromosomes exchange genes through crossovers and mutations to form the child chromosome during the reproduction process. By maintaining the population size, very healthy parents perform crossovers with other parents in the population. During this process, fragments of the two genotypes are exchanged. Crossover rates are typically in the range of 0.6–1.0 [20].

After the crossover process, mutations are accomplished by each parent chromosome to preserve a variety of solutions by performing minor, arbitrary modifications. Mutations are performed randomly by converting bit "1" into bit "0" or bit "0" into bit "1". Unlike crossovers, mutations do not always occur. However, by presenting a new genetic substance for evolutionary development, mutations can prevent chromosomes from getting stuck in the local minima. Mutation rates are typically 0.001 [21] or less than 0.1 [20].

The processes that occur in GA optimization are shown in Figure 1. The four essential features influencing the performance of GA are the population size, total generation, crossover rate, and mutation rate. The probabilities of finding a global optimum can be improved by setting a greater population size and generation; that is, hundreds of chromosomes or populations and thousands of generations. However, this comes at the expense of higher computational time [20].

2.3 Proposed Hybrid LSSVM-GA Model

This work uses only open-source data from http://www.ieso.ca/. The relationship between the target price and other forecasting inputs was obtained through correlation analysis, as shown in [22]. From the analysis, the previous hourly Ontario electricity price (HOEP), demand, total market demand (TMD), and pre-dispatch price (PDP) indicated a strong relationship with the targeted HOEP. To minimize the computational time, only HOEP and demand for the previous seven days, along with the 1-h PDP, were used as the forecasting inputs. Moreover, the HOEP showed a high correlation with the most recent input and was less influenced over longer time intervals. Therefore, the inputs used were the HOEP for the previous seven days, demand for the previous seven days, and 1-h PDP. The corresponding initial number of inputs was 337.

Table 1 Training and forecasting periods

Test Week	Training (10 weeks)	Training (10 weeks)
Week 1 (Spring, low demand)	Feb 16–Apr 25	Apr 26–May 2
Week 2 (Summer, peak demand)	May 17–Jul 25	Jul 26–Aug 1
Week 3 (Winter, high demand)	Oct 4–Dec 12	Dec 13–Dec 19

The test data consisted of three weeks, each reflecting one of the three major seasons of the year, as indicated in Table 1. Each test week was trained with sample data for 10 weeks or 70 days prior to the forecasting week. Each training sample consisted of 337 inputs fed into the GA during the optimization process.
Figure 1 shows the flow chart of the hybrid LSSVM-GA model. The population and generation numbers were initially set at 50 and 1000, respectively. The optimization process will be terminated once convergence is reached. The GA optimizes and reduces the number of inputs to be further processed by the LSSVM. At the same time, the GA finds the optimal value of the LSSVM parameters, i.e., gamma (γ) and sigma (σ). The main objective function (or fitness function) of this model is the MAPE. The mean absolute error (MAE) was also determined from the forecasted and actual HOEP.

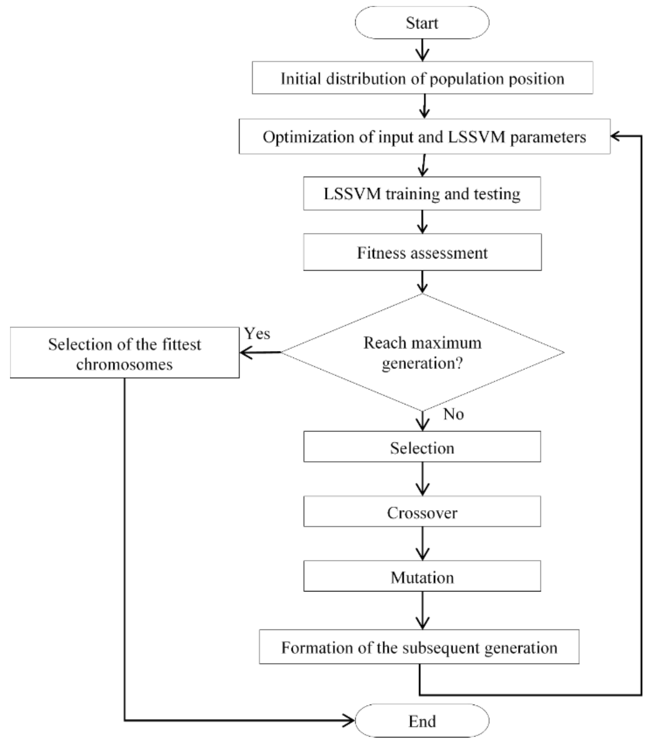


Figure 1 Flow chart for the hybrid LSSVM-GA model

3.0 RESULTS AND DISCUSSION

The MAPE and MAE (calculated from Eq. (1) and Eq. (2)) were used to assess the accuracy of the established model. The actual HOEP value and its forecasted value at hour *t* are represented by P_{actual} and $P_{forecast}$, respectively, whereas N represents the number of hours for a week.

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

$$MAE = \frac{1}{N} \times \sum_{t=1}^{N} \left|P_{actual_t} - P_{forecast_t}\right| \tag{2}$$

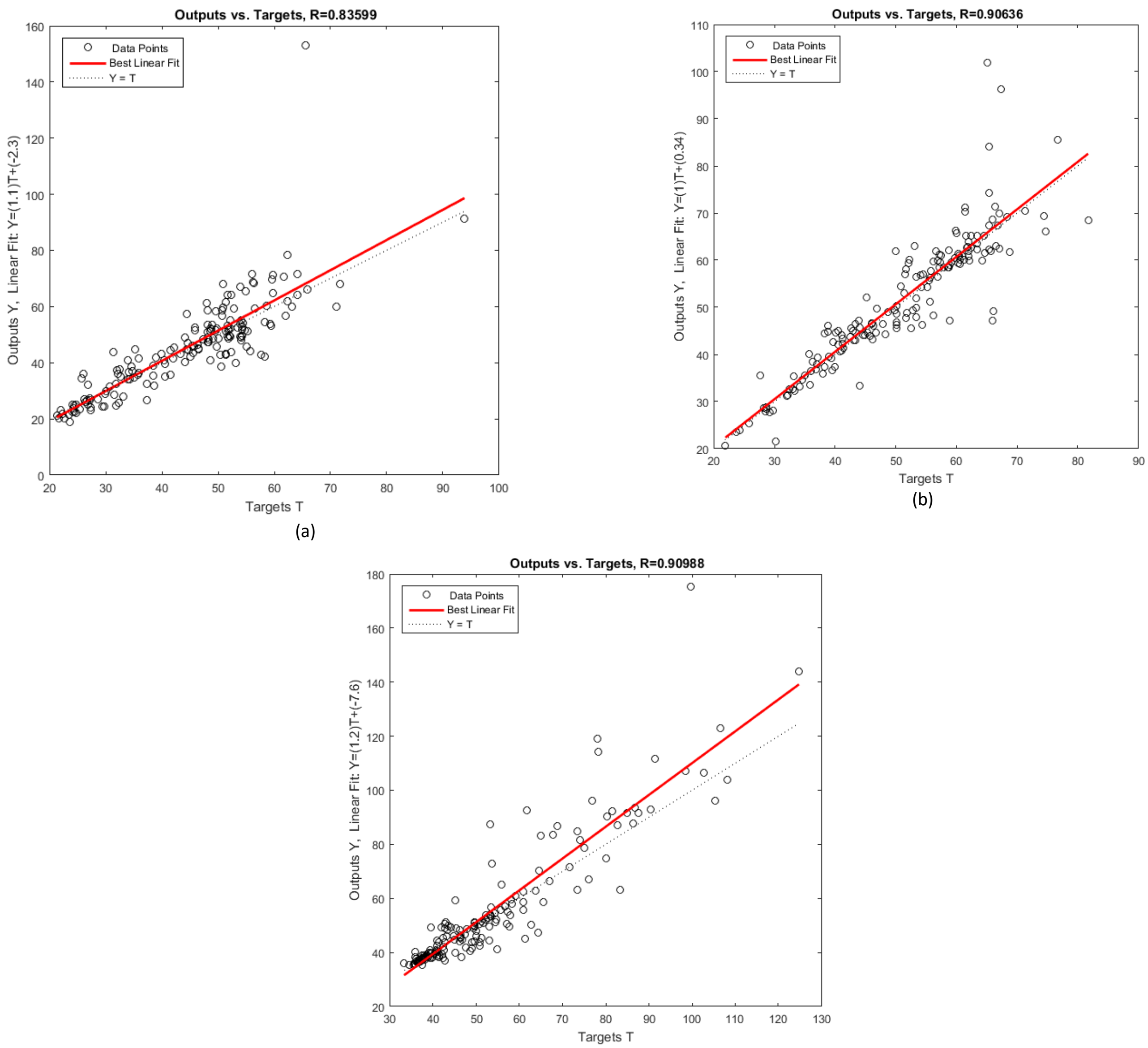
Table 2 shows the performance of the LSSVM-GA model for next-hour electricity price forecasting.

Table 2 MAPE values for the hybrid LSSVM-GA model

Test Week	Total optimized input	MAE	MAPE	Regression
Week 1 (Spring, low demand)	129	4.91	10.09	0.83
Week 2 (Summer, peak demand)	143	3.16	6.46	0.91
Week 3 (Winter, high demand)	113	7.04	7.84	0.91

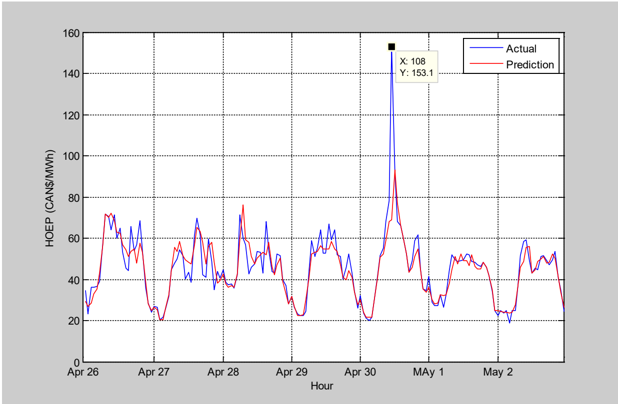
The GA optimizes the total input based on scenarios that are unique for every training sample. The lowest MAPE was achieved for Week 2 whereas the highest MAPE was obtained for Week 1. Regression is the correlation between the target and the output, and it ranges from 0 to 1. A regression value close to 1 represents a high correlation between the forecast and actual values, indicating high forecast accuracy.

Figure 2 depicts the regression plots for Weeks 1 through 3.

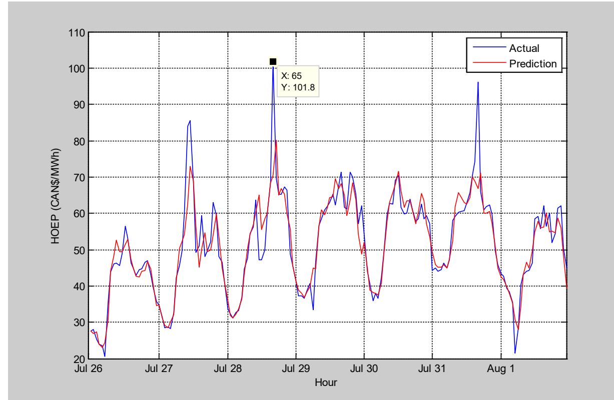


(c)

Figure 2 Regression plots obtained for the hybrid LSSVM-GA model for (a) Week 1, (b) Week 2, and (c) Week 3



(a)



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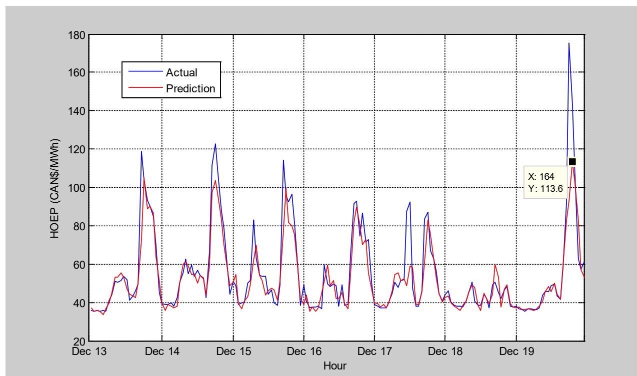
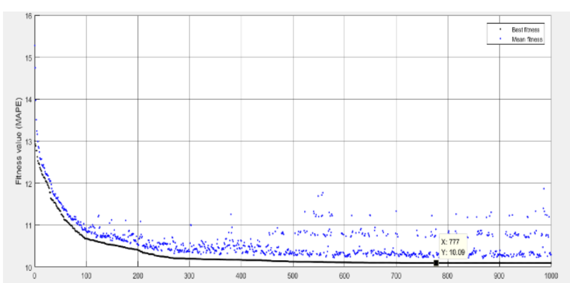
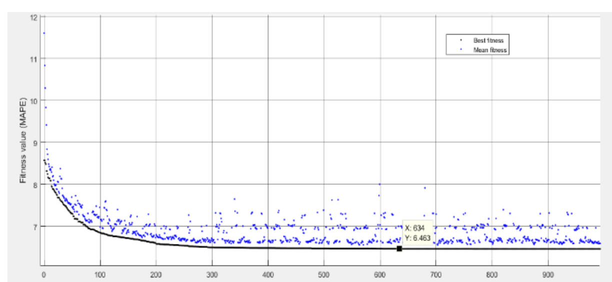


(c)

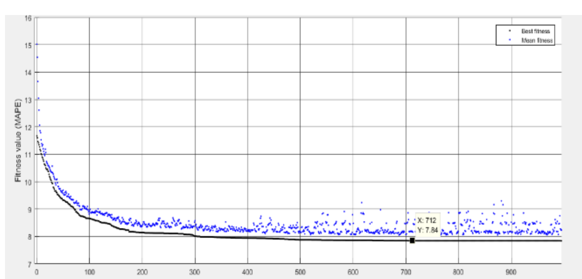
Figure 3 Comparison between the electricity price predicted by the hybrid LSSVM-GA model and the actual electricity price for (a) Week 1, (b) Week 2, and (c) Week 3



(a)



(b)



(c)

Figure 4 GA plots obtained for the hybrid LSSVM-GA model for (a) Week 1, (b) Week 2, and (c) Week 3

Figure 3 shows the actual and predicted prices from Week 1 to Week 3. It can be observed that, with the exception of the extremely high price spike, the forecasted price series is almost coincident with the actual price pattern. The most unstable day in Week 1 was April 30, 2004, as shown by the price curve in Figure 2(a). Meanwhile, compared with other weeks, Week 2 had the lowest MAPE as the least fluctuations were observed for this week. Similarly, multiple spikes were observed for Week 3, and it is evident that the LSSVM-GA is capable of accurately tracking the price fluctuations. This indicates that LSSVM-GA has good generalization with unseen data even in the presence of an unpredictable event.

Meanwhile, Figure 4 shows the GA plots for the three test weeks. It can be observed that convergence was achieved after 600–700 generations and thus, the simulation was terminated at this point.

The forecasting model was evaluated and compared with several models developed in previous studies [1, 7, 9] for the same test data and energy market, and the results are tabulated in Table 3. It can be seen that the hybrid LSSVM-GA model outperformed other models in terms of the prediction accuracy. In addition, the model structure produced in this study proved to be less complex compared with previous models. This is due to the fact that this model consists of one main prediction engine (LSSVM) and one optimization algorithm (GA). The optimization process is terminated when the predefined number of populations and generations are reached, or when the MAPE value is satisfied.

Table 3 Comparison of the average MAPE for different electricity price forecasting models tested on the Ontario energy market

Reference	Forecasting Model	Week 1	Week 2	Week 3	Average MAPE
Proposed work	LSSVM-GA	10.09	6.46	7.84	8.13
[7]	RNN-FHN-FFNN-ES	10.76	9.12	11.61	10.50
[9]	RNN-EM	15.09	10.52	15.78	13.80
	RNN-EKF	16.01	11.89	16.59	14.83
	MLP-EKF	16.83	12.64	16.77	15.41
	MLP-EM	15.48	11.87	16.78	14.71
[1]	MARS (Case 1)	13.3	9.4	12.9	11.87
	MARS (Case 2)	12.5	8.6	11.8	10.97
	IESO	23.78	10.41	22.06	18.75

RNN with excitable dynamics developed by Sharma and Srinivasan [7] appears to have a more sophisticated design methodology in order to address both spiky and non-spiky price zones. The RNN model was embedded with the Fitz-Hugh Nagumo (FHN) technique to manage spiky price regions. Furthermore, the feedforward neural network (FFNN) approach was designed to anticipate the RNN-FHN residual errors when forecasting stable (non-spiky) price regions. To improve the forecasting accuracy, the FFNN output was also integrated with the RNN-FHN model. Moreover, the feedforward and feedback weights of the RNN were trained using evolutionary strategies (ES) whereas the FFNN was trained using the backpropagation algorithm.

Meanwhile, the multivariate adaptive regression splines (MARS) model developed by Zareipour et al. [1] demonstrated higher MAPE than the proposed hybrid LSSVM-GA model. The MARS model for Case 1 was constructed using lagged values of the HOEP whereas the MARS model for Case 2 was generated using current and lagged values of the 2-h ahead PDP and 2-h ahead pre-dispatch demand (PDD). The results show that incorporating pre-dispatch data into the second scenario (Case 2) enhances the average weekly MAPE. This also serves as the foundation for the LSSVM-GA model developed in this study, which includes PDP as one of the inputs.

4.0 CONCLUSION

Accuracy is the main focus of forecasting. Good prediction models are characterized by low prediction errors and low complexity. Market players in the deregulated electricity industry use forecasts to analyze and adjust bids before the dispatch hours. Selection of forecasting inputs and network parameter settings is necessary for this task. Previous works on short-term electricity price forecasting have shown reasonable prediction accuracy using LSSVM with room for further improvement. Therefore, a hybrid LSSVM-GA model for next-hour electricity price forecasting was established in this work to further improve short-term electricity price forecasting. In this model, the GA optimizes the inputs and LSSVM parameters simultaneously by using the most recent inputs, namely, the HOEP and demand for the previous seven days, as well as 1-h PDP. The proposed hybrid LSSVM-GA model outperformed most of the other models with an average MAPE of 8.13% when tested on the same electricity market over the same period. This model can facilitate electricity market participants to achieve effective price and supply deals, maintain efficient operations, ensure efficient electricity consumption, and ultimately boost company profits. However, there is still a need to explore new approaches to suit current price patterns and the energy market. It is hoped that the forecasting error can be reduced, which will in turn, improve the forecasting performance. This is because accurate short-term forecasts will not only benefit others in terms of low penalties, but also improves the scheduling of daily operations. In fact, in the long term, more accurate forecasts can reduce the volatility of electricity prices. This in turn can reduce the long-term investment risk, which is highly dependent on electricity prices.

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