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Enhanced Short-term System Marginal Price (SMP) Forecast Modelling Using a Hybrid Model Combining Least Squares Support Vector Machines and the Genetic Algorithm in Peninsula Malaysia

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Abstract: Forecasting SMP is critical in power systems, allowing market participants and grid operators to make more informed decisions. SMP prediction faces nonlinearities, volatility, and intricate factor interactions. Meanwhile, several existing methodologies exhibit inaccuracies in their predictions. Furthermore, when used across multiple circumstances, single forecasting algorithms have lower accuracy. This paper presents a novel forecasting model that combines Least Squares Support Vector Machines (LSSVM) and the Genetic Algorithm (GA) for (i) parameter optimization, and (ii) parameter optimization and input selection, for accurate SMP prediction. Furthermore, the performance of LSSVM-GA was observed through daily and weekly forecasts. GA optimizes the LSSVM parameters and forecast inputs concurrently to ensure the best possible performance. Historical data from the Single Buyer (SB) has been employed to train and evaluate this model. Correlation Analysis aids feature selection, boosting model generalization. Multiple forecast input combinations were examined to identify the most important forecasting features. The proposed daily forecast model exhibited a 3.54% performance improvement compared to the SB daily forecast model. Likewise, the proposed weekly forecast model outperformed the Single Buyer (SB) forecast by 1.19%. As per the results, the hybrid algorithm shows great potential as a viable option for generating precise forecasts of electricity prices.

Keywords: *Electricity price forecasting, Genetic algorithm, Least squares support vector machine, System Marginal Price (SMP)*

1. Introduction

The SMP is a fundamental indicator in electricity markets that represents the short-term cost of producing an additional unit of electricity at any given time. SMP forecasting is critical to the efficient operation of modern electricity markets, assisting market participants, grid operators, and policymakers in making informed decisions to optimize power generation, trading, and consumption. The prediction enables electricity generation firms to optimize generator output and the SMP by considering production expenses for profit maximization. Concurrently, electricity consumers utilize price predictions to strategize and regulate their usage, especially during anticipated increases in electricity prices.

Significant progress has been made in developing sophisticated SMP forecast models in recent years, leveraging advances in machine learning and optimization techniques to improve accuracy and robustness. Nonetheless, forecasting electricity prices proves more challenging than predicting electricity loads due to the inherent price volatility. Several factors contribute to the problem's complexity in the context of SMP forecast modelling. These include the non-linear and volatile nature of electricity prices, the impact of various exogenous variables such as weather conditions and demand patterns, and the dynamic interactions within the electricity market.

Previous studies used statistical models (SM) for price forecasting; for example, an autoregressive model with Dirac and Student's t-distributions was used to forecast intraday electricity prices in Germany [1]. Other SM methods include regression [2], transfer function (TF) [3], autoregressive integrated moving average (ARIMA) [4]–[7], and autoregressive moving average (ARMA) with generalized autoregressive conditional heteroskedastic (GARCH) [8]. Nonetheless, a notable drawback of the SM is its demand for a substantial degree of time series stability. To address these issues, researchers have turned to advanced computational methods in order to capture intricate patterns and relationships within historical SMP data.

As a result, recent advances in SMP forecast modeling have been made possible using various techniques such as ensemble methods, hybrid models, support vector regression, deep learning, and online machine learning. Artificial intelligence techniques like artificial neural networks (ANN) and support vector machines (SVM) do not necessitate high stability and have the capability to generate precise and consistent predictions by leveraging training data [9]. A comprehensive comparison of SVM, k-

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nearest neighbors (KNN), and ensemble-based methods has been reported to analyze SMP in the Turkish electricity market [10]. The ensemble-based method outperforms the other methods in terms of accuracy.

Many researchers have reported on the development of neural network (NN) models [3–10]. The deep neural network stands as a prominent NN approach that has drawn attention and been employed for electricity price prediction. [11]–[15]. Meanwhile, the multilayer perceptron (MLP), nonlinear autoregressive exogenous (NARX), and ARIMA models have been compared [16]. Overall, the forecast errors examined in the Korean energy market exhibit relatively minor magnitudes, following the sequence of ARIMA, MLP, and NARX.

Conversely, load and price predictions have been structured by applying wavelet transform (WT) as a preliminary process, coupled with the utilization of long short-term memory (LSTM) [17]. Entropy and the utilization of mutual information (MI) for feature selection have also been put forth as methods to enhance the precision of forecasting. Additional research has documented multi-horizon predictions for electricity load and price utilizing a hybrid deep learning approach that incorporates bidirectional long short-term memory (BiLSTM) and a multi-head self-attention mechanism. This technique is applied to forecast locational marginal price (LMP) and system load on a daily scale [18]. Moreover, an ensemble empirical mode decomposition (EEMD) algorithm is employed to extract concealed characteristics from the time series of load and price.

Furthermore, Heydari et al. [19] demonstrated load and price forecasting. The initial step encompassed applying variational mode decomposition (VMD) to both signals (load and price series), followed by optimizing the number of inputs through the NN gravitational search algorithm (NNGSA). Subsequently, the forecasting procedure was executed, with the parameters of the generalized regression neural network (GRNN) being optimized by the GSA.

Differing from prior research, Lee and Wu [20] introduced a similar day strategy to predict electricity prices in the PJM energy market. Four distance models were used to choose the days: the Euclidean norm, the Manhattan distance, the cosine coefficient, and the Pearson correlation coefficient. The forecasting outcomes were then derived using similar day regression (SDR) and similar day-based ANN (SDANN). Another investigation detailed the creation of a day ahead SMP prediction model utilizing an artificial neural network (ANN) algorithm. This model integrated both long-term historical data and short-term historical data, while employing the k-fold cross-validation optimization algorithm [21]. The Pearson correlation coefficient was utilized to identify the short-term input variable. The selection of the long-term variant to compute the Similar-Days Index was accomplished using the discrete Frechet distance, combined with insights into the season and day type.

However, ANNs have a few limitations, including challenges like the local minima issue, sluggish convergence speed, and disparities in structure selection. These shortcomings have led to the frequent substitution of ANNs with the SVM algorithm. This shift is supported by the work of Halu et al. [22], who demonstrated the superiority of the SVM model over alternative approaches in the Greek and Hungarian energy markets. demonstrated that the SVM model outperformed other models in the Greek and Hungarian energy markets. Meanwhile, Ghasemi-Marzbali [23] created a LSSVM model with self-adaptive kernel functions and GARCH time series to capture linear and non-linear trends. WT and MI were used for pre-processing and input selection, respectively. The optimization of LSSVM parameters was achieved through an enhanced virus colony search algorithm (VCS). Meanwhile, LSSVM has been used as the primary forecasting technique in other studies aimed at predicting electricity prices and loads. For instance, dyadic wave transformation (DWT) and a modified version of MI (MMI) were employed for pre-processing and feature selection respectively. These steps were followed by the utilization of a modified gravitational search algorithm (GSA) for optimization purposes.

All the studies mentioned have shown that these methodologies have the potential to enhance the accuracy and reliability of short-term SMP forecasts. These advancements are critical in facilitating efficient decision-making and contributing to the overall sustainability of the power system as electricity markets continue to evolve. Under normal conditions, most available models can predict electricity prices with high accuracy. During a price spike, however, forecasting error increases. Consequently, this study introduces a novel methodology for forecasting SMP on daily and weekly basis. This approach involves a hybrid LSSVM-GA model, wherein the parameters of the LSSVM and the inputs for forecasting are optimized using a GA.

The following are the main contributions of this work:

1) Correlation Analysis is used to investigate the relationship between the input variables and the SMP. The data for this analysis was obtained from the Single Buyer (SB) website. To ascertain the most influential input for short-term SMP prediction, simulations were executed using nine distinct combinations of inputs. The input variables include historical day-ahead prices from the past three days and one week earlier, demand forecasts, and monthly generation mix forecasts.
2) A LSSVM-GA based SMP forecast model is proposed, with two types of optimizations performed: (i) LSSVM

parameter, and (ii) LSSVM parameter and forecast input. Both simulation results show that optimizing only the LSSVM parameters yields higher accuracy than optimizing both the LSSVM parameters and the forecast input. This means that optimizing or reducing forecast inputs may result in insufficient input and thus inaccurate forecasting.

3) Daily and weekly SMP forecasts have been proposed. The proposed models were tested on the Peninsula Malaysia energy market and were shown to improve prediction accuracy when compared to the SB forecast. Hence, this hybrid has the potential to streamline the electricity price bidding process and enhance the efficiency of power system operations.

The subsequent sections of this paper are structured in the following manner. Section 2 summarizes the related SMP forecasting methodology, the proposed LSSVM-GA framework, and the pre-processing techniques used in this work. Section 3 contains the experimental evaluation of the SMP forecasting model, encompassing the correlation analysis and the outcomes of forecasting performance. The paper concludes in Section 4.

2. Methodology

2.1. SVM and LSSVM

LSSVM, an improved SVM model, was used as the primary forecasting engine in this study. SVM is capable of managing a high-dimensional input space effectively [24], reducing overfitting, and avoiding the local minima trap [25]. In contrast, SVM demands significant a substantial amount of processing. The LSSVM model was created to reduce the computational load on the SVM. Through the solution of a linear equation system within a quadratic programming problem (QP), LSSVM enhances computational speed [24], [26]. Notably, the linear Karush-Kuhn-Tucker (KKT) system is less intricate compared to the QP system. Furthermore, LSSVM maintains the distinctive attributes of SVM, encompassing its robust capacity for generalization.

2.2. GA

Holland [27] proposed GA, drawing from the concept of 'survival of the fittest' and emulating the natural progression through reproduction. GA achieves optimal solutions through iterative computations, driven by its three core processes: selection, crossover, and mutation. The fitness function is GA's objective function.

The process of GA optimization commences by establishing an initial distribution of chromosome positions within the population. This distribution then optimizes both prediction inputs and LSSVM parameter values. The LSSVM is subsequently trained and tested using the refined set of inputs and parameter settings. The fitness function or forecasting error, MAPE, is computed during the evaluation.

During the reproduction phase, the selection of the fittest individual, often referred to as a parent, takes place. Chromosomes possessing higher fitness values are more likely to contribute to the subsequent generation through offspring creation. Chromosomes with superior fitness engage in gene exchanges via crossovers and mutations to form the offspring's chromosome. Maintaining a constant population number, highly robust parent chromosomes engage in crossovers with others in the population. This exchange results in the swapping of genetic segments between the two genotypes. Typically, crossover rates fall within the range of 0.6 to 1.0 [28].

Following the crossover process, every parental chromosome performs mutations to maintain a diverse set of solutions through slight, random alterations. Mutations are carried out at random, involving the conversion of bit "1" to bit "0" or vice versa. Mutations, unlike crossovers, are not an assured step in the process. However, they can avert chromosomes from becoming trapped within local minima by introducing a new genetic substance for evolutionary progress. Mutation rates are generally set below 0.1 [28], or 0.1 [29].

Fig. 1 depicts the processes that occur during GA optimization. Four primary factors, namely population size, generation size, crossover probability, and mutation probability, collectively influence the performance of GA. Setting a larger population size and generation can improve the chances of finding a global optimum. This entails employing hundreds of chromosomes or populations across thousands of generations. However, this advantage is balanced by an increase in computational time [28].

2.3. The Proposed LSSVM-GA Model

Fig. 1 displays the flowchart detailing the hybrid LSSVM-GA model for both daily and weekly forecast. The population and generation numbers were fine-tuned to achieve the best MAPE during the validation stage. Once convergence is reached, the optimization process will be terminated. The GA optimizes and streamlines the inputs for subsequent processing by the LSSVM. Simultaneously, the GA identifies the best numbers for the LSSVM parameters which are gamma (γ) and sigma (σ). The main objective function, or fitness function, of the model is the MAPE. Additionally, the Mean Absolute Error (MAE) is computed through a comparison of the forecasted and real SMP.

2.4. Data Interpretation and Correlation Analysis

The model's accuracy is evaluated using historical SMP data which publicly available via Single Buyer (SB) website. SMP historical data is examined to ensure that it is accurate, reliable, and covers a sufficiently long period to capture market conditions and patterns. Fig. 2 depicts the SMP series in Peninsula Malaysia from 2017 to 2022, demonstrating the price series' volatility over a few years. Demand patterns, fuel price dynamics, renewable energy integration, regulatory changes, and geopolitical events all have an impact on this variability. Throughout the year, periods of increased demand, such as during the peak summer months, can cause price increases. In contrast, the incorporation of renewable energy sources such as solar and wind may dampen price fluctuations. Volatility can be exacerbated by regulatory changes and unforeseeable events.

The developed model also refers to the Energy Commission's Corporate Green Energy Programme Guidelines (CGPP), which were issued on November 7, 2022. It includes NEDA application guidelines covering NEDA participant categories, SMP, NEDA governing documents, and the NEDA registration process. According to the NEDA application guidelines, SMP is primarily influenced by fuel price, system demand, and generation system condition. However, fuel price information is private and not available to the public. As a result, before developing the short-term forecast model for SMP in Malaysia, Correlation Analysis was performed using data provided by SB via https://www.singlebuyer.com.my/about.php?id=1 to investigate the correlation relating the input features and the desired output. Individual correlations between SMP on the targeted day and the six input variables were investigated:

i. Past day-ahead prices for the preceding three days and one week ($SMP_{d-1}, SMP_{d-2}, SMP_{d-3}, SMP_{d-7}$).

ii. The demand forecast for the upcoming day (D_d).

iii. The day-ahead forecasts of monthly generation mix (total for solar, hydro, gas, and coal) (G_d).

2.5. Data Splitting

The subsequent task within the preprocessing phase involves choosing data for training, validation, and testing. The training set aids the model in learning patterns, while the validation set fine-tunes parameters, and the testing set assesses real-world performance. Splitting correctly prevents overfitting (model fitting noise), ensures generalization, and aids in the detection of model bias or instability. Improper splitting can result in inaccurate forecasts because of biased training, over-optimization, or an inability to generalize. The following options are available for creating a subset of the dataset:

a. 80% for training, 10% for validation, and 10% for testing.

b. 70% for training, 15% for validation, and 15% for testing.

c. 60% for training, 20% for validation, and 20% for testing.

Table 1 shows the data selection for training, validation, and testing for daily and weekly SMP forecasts. Additionally, Table 3 shows ten different sets of input for daily forecast models. The daily forecast training sample spans 184 days, from June to November 2021. The daily forecast generates a half-hourly SMP of 48 points for the day ahead. The testing sample has a total of 28 days, so the forecasted output dimension comprises 28*48 points. In the case of weekly forecast, each input sample covers a week of historical SMP preceding the output. The weekly forecast model also generates half-hourly SMP for 7 days ahead, resulting in 336 columns for both input and output.

Table 1. Data splitting for short term SMP forecasting.

Data splitting	Daily forecast	Weekly forecast			
Training	June – Nov 2021	3 April, 2017	-	17 May, 2020	(161 weeks)
Validation	Jan-22	18 May, 2020	-	23 May, 2021	(53 weeks)
Testing	Feb-22	24 May, 2021	-	29 May, 2022	(53 weeks)

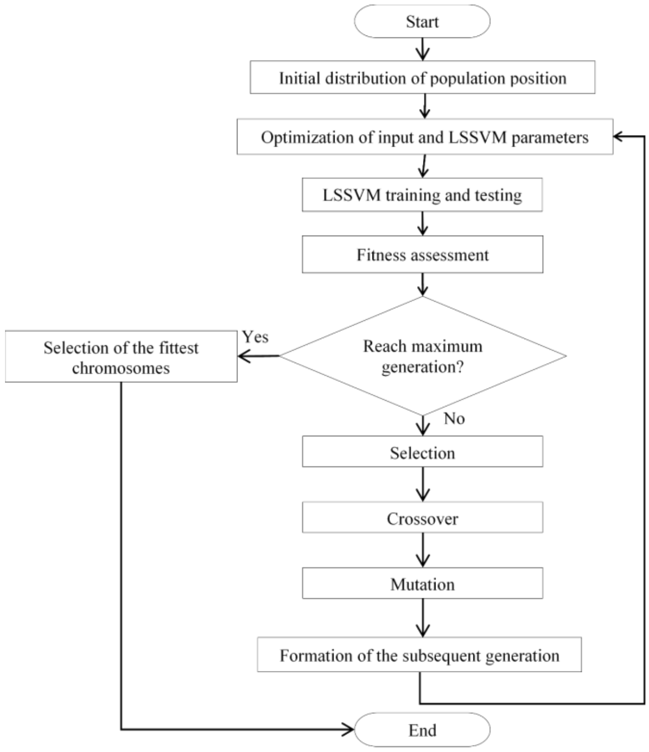


Fig. 1. Flowchart for the hybrid LSSVM-GA model for both daily and weekly forecasts.

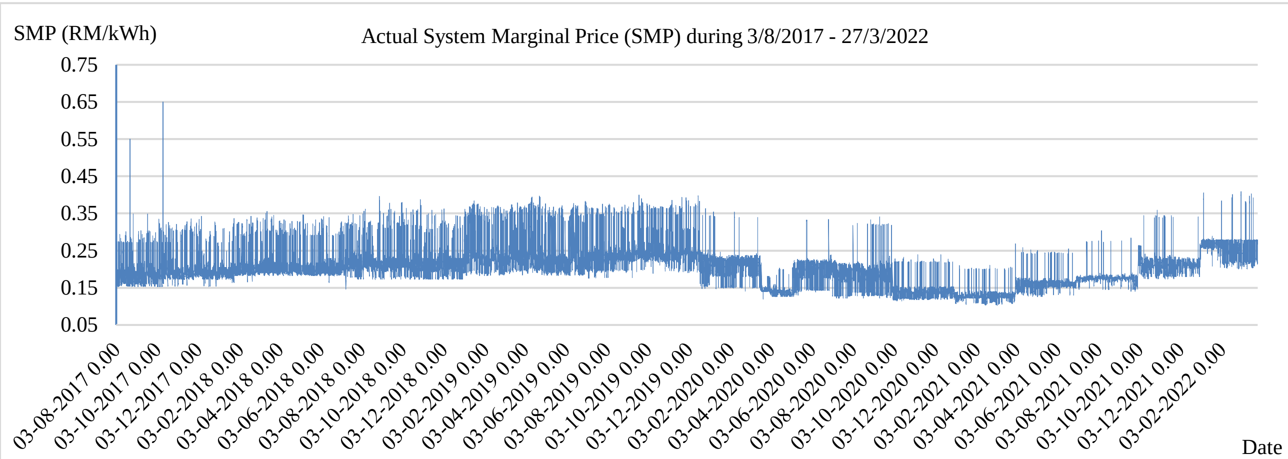


Fig. 2. SMP series for 2017 till 2022

2.6. Accuracy Measure

The accuracy of the developed model was assessed using MAPE and MAE, computed using Equations (1) and (2). MAPE measures the average percentage difference between predicted and actual values, highlighting proportional forecasting errors. The average absolute difference between predicted and actual values is calculated using MAE, which indicates the magnitude of errors. In these equations. SMP_{actual} denotes the real SMP value, $SMP_{forecast}$ represent its forecasted value at hour t, whereas N stands for the total number of hours.

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

$$MAE = \frac{1}{N} \times \sum_{t=1}^{N} \left|SMP_{actual_t} - SMP_{forecast_t}\right| \quad (2)$$

3. Results and Analysis

3.1. Correlation Analysis

Table 2 shows the correlation between the input variables and future SMP observed between April 2 and May 31, 2021.

Table 2. Correlation analysis between the input variables and future SMP

Variable 1 (Target)	Variable 2 (Input)	Correlation coefficient
	SMP_{d-1}	0.467
	SMP_{d-2}	0.318
	SMP_{d-3}	0.345
SMP_d	SMP_{d-7}	0.367
	D_d	0.473
	G_d	0.46

The correlation coefficient derived from the correlation analysis ranges between 0.318 and 0.473, which is generally considered to be a medium correlation. However, since the forecast SMP for the following trading day is published every day at 5 p.m., the SMP on the day before the forecast day (SMP_{d-1}) may not be the input variable. As a result, except for (SMP_{d-1}), all the inputs in Table 2 are considered forecast inputs for the daily forecasts.

3.2. Proposed Hybrid LSSVM-GA Model for Daily Forecast

In order to develop daily forecast model using LSSVM-GA, two types of optimizations were performed:

i. network parameters

ii. network parameters and input selection

LSSVM-GA performance was also evaluated using nine different input combinations to determine the most important input for short-term SMP forecasting. Table 3 shows that optimizing only the LSSVM parameters

Table 3. MAPE for different sets of input for daily forecast models.

Optimization	GA-LSSVM Number of Input	GA-LSSVM MAPE (%)	SB MAPE (%)
LSSVM parameters and number of inputs	241; (SMP_{d-2}, SMP_{d-3}, SMP_{d-7}, D_d, G_d, Day index)	9.18	
LSSVM parameters	241; (SMP_{d-2}, SMP_{d-3}, SMP_{d-7}, D_d, G_d, Day index)	8.42	
	240; SMP_{d-2}, SMP_{d-3}, SMP_{d-7}, D_d, G_d	8.95	
	192; SMP_{d-3}, SMP_{d-7}, D_d, G_d	8.9	
	144; SMP_{d-7}, D_d, G_d	12.9	10.63
	96; D_d, G_d	19	
LSSVM parameters	49; G_d, Day index	22	
	48; G_d	21	
	48; SMP_{d-2}	8.74	
	48; SMP_{d-1}	7.09	

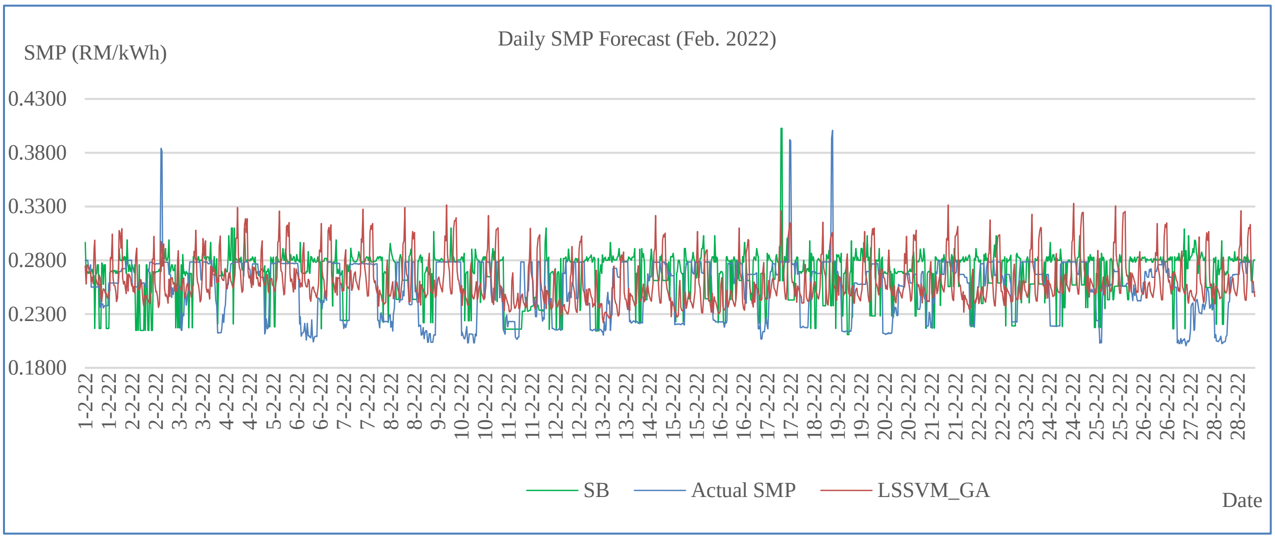


Fig. 3. A comparison of the daily forecasts generated by the LSSVM-GA and SB models to the actual SMP.

produces better accuracy than optimizing both the LSSVM parameters and the forecast input. Consequently, optimizing or reducing forecast inputs may result in insufficient input and, as a result, inaccurate forecasting. Therefore, only network parameters are optimized in the weekly forecast.

Meanwhile, the SMP was strongly correlated to the latest input and had a smaller impact across extended time spans. Finally, both types of optimizations outperformed SB's prediction, which had a MAPE of 10.63%. Fig. 3 depicts the time series of the actual and predicted SMP from the proposed LSSVM-GA and SB models.

3.3. Proposed Hybrid LSSVM-GA Model for Weekly SMP Forecast

by 1.19%.

3.4. The Overall Performance of the LSSVM-GA

Table 4 presents the total efficacy of the LSSVM-GA framework for daily and weekly SMP forecasts. The GA optimizes the entire input and LSSVM parameters based on the distinct circumstances present in each training sample. The relationship between the target and the output is denoted by regression, spanning a scale from 0 to 1. A regression value approaching one signifies a significant relationship between forecasted and actual values, reflecting a high level of forecast accuracy.

The optimal population and generation sizes are determined by the problem's complexity and the algorithm's

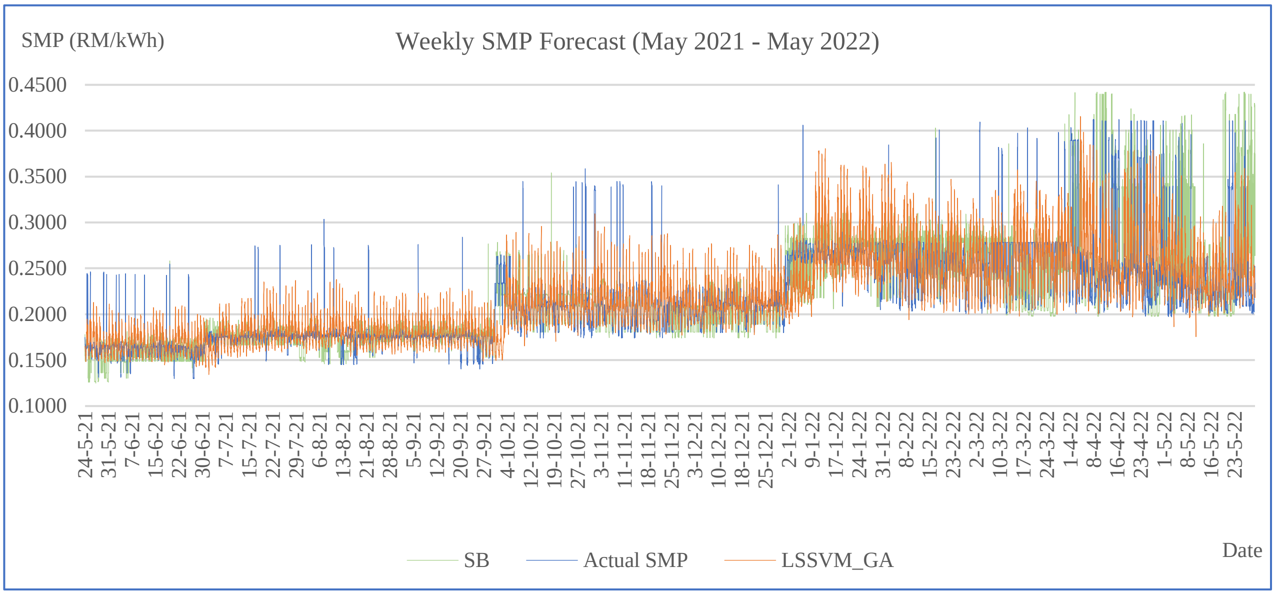


Fig. 4. A comparison of the Weekly SMP Forecasts generated by the LSSVM-GA and SB.

The weekly SMP forecast represents the SMP trend's behaviour for the entire year. The dataset spans a significant period and captures various operational scenarios and market conditions, providing a solid foundation for model training and validation. This modelling can also be used to make long-term predictions. The input for each sample is a week of historical SMP preceding the output. The forecasting model was tested and compared to the SB forecast and the actual SMP, with the results shown in Fig. 4.

It is important to acknowledge that the comparison with SB forecasts involves the collection of daily forecasts generated by SB over a one-week timeframe. The time series in Fig. 4 indicates that apart from an exceptionally sharp price spike, the projected price series closely mirrors the real price trend. The LSSVM-GA can capture price oscillations, demonstrating its ability to robustly generalize to new data even when confronted with unforeseen occurrences. The MAPE of the LSSVM-GA model was 8.55% when tested from May 2021 to May 2022, outperforming the SB forecast

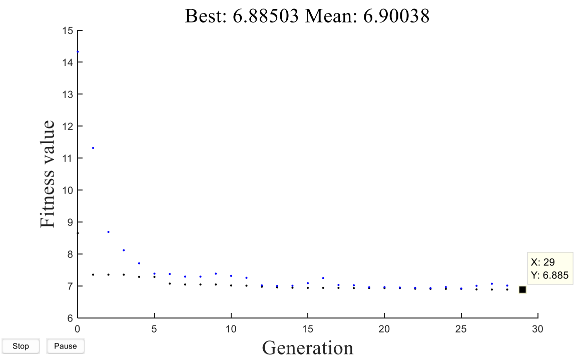
convergence behaviour. A smaller population with fewer generations may result in insufficient exploration, whereas a larger population or too many generations may result in increased computation time. A larger population size frequently improves solution space exploration. A large population, on the other hand, may necessitate more computational time and resources. A large number of generations may result in overfitting, resulting in poor generalization to new data.

Furthermore, Fig. 5 depicts the GA plots corresponding to the three cases, which represent the progression and behaviour of the GA during the validation stages or period. The plot shows the value of the fitness function over successive generations to help visualize how the algorithm refines solutions over time.

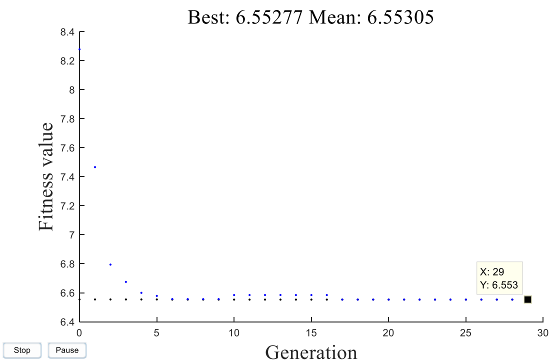
Table 4. Total efficacy of the LSSVM-GA framework for daily and weekly SMP forecasts

Forecasting horizon	Daily forecast		Weekly forecast
Optimization	Paramete r and input	Paramete r	Paramete r
Validation MAPE	6.85	6.55	9.22
Testing MAPE	9.18	7.09	8.55
MAE	0.023	0.018	0.02
Regression	0.456	0.614	0.818
Population size	10	10	20
Generation size	30	30	40

The optimization procedure ends when either the predetermined number of populations and generations has been attained or the MAPE threshold criteria are met. Notably, convergence was evident within 30-40 generations, resulting in the modelling process ending at this juncture.



(a)



(b)

(c)

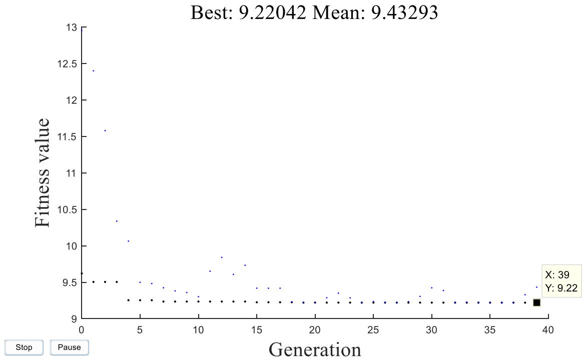


Fig. 5. GA plots for (a) daily SMP forecast with parameter optimization and input selection; (b) daily SMP forecast with parameter optimization, and (c) weekly SMP forecast with parameter optimization.

4. Conclusion

Short-term SMP forecasting accuracy is critical for efficient energy market operations and decision-making. This task necessitates selecting forecasting inputs and configuring network parameters. As a result, by optimizing LSSVM parameters, the proposed LSSVM-GA hybrid model provides significant advances in short-term SMP forecasting. In this model, the GA concurrently optimizes the inputs and LSSVM parameters by incorporating the most current inputs, specifically the SMP from the preceding day. The results show that the LSSVM-GA model predicts SMP values with greater accuracy and robustness for short-term SMP forecasting. The model is compared to a model generated by the SB and a baseline data set, which is the actual SMP.

The findings demonstrate that the proposed LSSVM-GA model surpasses the SB forecasts by 3.54% and 1.19%, respectively, for daily and weekly SMP forecasts. Its ability to capture underlying patterns and adapt to dynamic market conditions makes it a valuable tool for electricity market participants, allowing them to make well-informed decisions about power generation, trading, and demand response. Furthermore, by providing reliable SMP forecasts, the model aids in optimizing the electricity supply-demand balance, facilitating efficient resource allocation, and promoting the incorporation of renewable energy sources through the power grid system.

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Author contributions

Intan Azmira Wan Abdul Razak: Conceptualization, Methodology, Data curation, writing-original draft, Writing - Review & Editing, Visualization

Wan Syakirah Wan Abdullah: Writing - Review & Editing, Resources, Supervision

Mohamad Fani Sulaima: Writing - Review & Editing, Validation.

Conflicts of interest

The authors confirm that they have no competing financial interests or personal affiliations that could have appeared to influence the findings presented in this paper.

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