Jurnal Kejuruteraan 37(5) 2025: 2431-2439
https://doi.org/10.17576/jkukm-2025-37(5)-31

Predicting Electricity Demand in Low-Voltage Distribution Networks Using an Optimized Support Vector Regression

Abdul Halim Ikram Mohamed*, Ruzlaini Ghoni & Mohd Tarmizi Ibrahim

Department of Electrical and Automation,
Faculty of Engineering Technology, University College TATI, Kemaman, Terengganu.

**Corresponding author: 24D01001@siswa.uctati.edu.my*

Received 11 December 2024, Received in revised form 30 April 2025
Accepted 15 May 2025, Available online 30 August 2025

ABSTRACT

Accurate electricity demand forecasting is crucial for maintaining grid stability and optimizing energy resources. Traditional methods often fail to capture power load demand's complex and variable nature. Hence, artificial intelligence techniques, such as Support Vector Regression, have emerged as promising tools for improving forecasting accuracy. Even though SVR has been used for electricity demand forecasting, most of the research has concentrated on input variables such as temperature and weather. This study aims to explore the potential of SVR in predicting electricity demand based on other characteristics such as land size, floor area ratio, build-up area, load density, diversity factor, and group diversity factor. An SVR model was built with data collected from industrial consumers in Malaysia Vision Valley. Hyperparameter tuning, including the selection of the kernel function and regularization parameters, was employed to enhance the model's accuracy. The SVR model accurately predicted electricity demand, achieving high R^2 values, low MAE and MAPE across different training and testing scenarios. The best performance was recorded at a 70/30 training/testing split, yielding a mean absolute error (MAE) of 0.0059, a mean absolute percentage error (MAPE) of 0.82%, and an R-squared value of 99.97%. These findings highlight the effectiveness of SVR in capturing complex relationships between input variables and electricity demand, which can aid utilities in effective planning and resource allocation, ultimately enhancing grid reliability and efficiency, reducing operational costs, and making informed decisions regarding energy resources.

Keywords: Support vector regression; low-voltage distribution network; electricity demand; hyperparameter tuning.

INTRODUCTION

Forecasting electricity demand is a critical aspect of our modern power system, serving as the backbone for effective energy management and grid stability. Accurate prediction of electricity consumption enables grid operators to maintain system stability and balance the supply and demand effectively. Inaccurate load forecasts can lead to severe consequences, such as power outages and disruptions to critical infrastructure due to unexpected peak demand (Wang et al. 2023). Such disruptions not only compromise the reliability of the power supply but can also result in significant financial losses, damage to equipment, and a reduction in the assets lifespan. Besides that, demand forecasting errors can also cause inefficient energy resource allocation, resulting in increased operational costs for utilities. This inefficiency can manifest in various ways, such as over-procuring energy during low-demand periods or under-procuring during peak times, both of which can strain financial resources and operational capabilities. Therefore, developing a practical solution that can capture the complexity and dynamics of power load demand in low-voltage distribution networks is imperative. Such advancements would enable utilities to plan more effectively for peak demand, thereby reducing the risk of power outages and enhancing overall grid reliability. Moreover, improved forecasting can assist utilities in identifying opportunities to reduce energy losses and greenhouse gas emissions, ultimately contributing to greater grid efficiency and sustainability.

However, forecasting electricity demand is inherently complex due to various factors influencing consumption patterns. These factors include climate change, economic growth, social behavior and technological advancements (Gökçe & Duman 2024). Traditional forecasting methods, which often rely on historical data and simplistic models, have frequently proven inadequate, leading to significant overestimations or underestimations of demand (Miraki, Parviainen & Arghandeh 2024). Moreover, some of the input factors are not easily measurable, complicating the forecasting process further.

Artificial intelligence (AI) techniques have emerged as promising tools for addressing these challenges in recent years. Support Vector Machine (SVM) is a widely used technique for solving complex problems, including image recognition and classification (Nasir et al. 2020). Furthermore, other studies used SVM to enhance the security of cloud-based Internet of Things (IoT) systems through comprehensive security management (Mohamed & Alosman 2024). Although support vector machines were initially designed to solve classification problems, their principles were later expanded to solve other problems, such as regression (Li et al. 2021).

Machine learning algorithms, such as Support Vector Regression (SVR) and Random Forest, have demonstrated their ability to handle high dimensional data and manage nonlinear relationships, making them suitable for diverse applications, especially predicting electricity demand (Selvam et al. 2024). These models excel at processing large datasets and provide precise forecasts, making them valuable tools for energy management and planning (Gomez, Wang & Lo 2024). While SVR is a powerful tool for predicting electricity demand, many studies focus on climate, humidity, period and temperature as their input parameter (Jie, Baba & Kumada 2023). Fortunately, other factors can still be considered in predicting electricity demand that are unexplored yet and need to be addressed, such as building area and diversity factors (Peplinski 2024).

Therefore, this study aims to explore factors that can influence electricity demand by focusing on specific input variables: land size area, floor area ratio, build-up area, load density, diversity factor and group diversity factor. Specifically, this study will explore the potential of SVR in predicting electricity demand based on the input variables for industrial consumers within low-voltage distribution networks, therefore improving the accuracy of prediction.

The rest of the paper is organized as follows: Section II explains the research methodology and study area in detail. Next, a discussion of the results is presented in Section III. Finally, the conclusions of this paper are summarized in Section IV, together with suggestions for future work.

METHODOLOGY

SUPPORT VECTOR REGRESSION

The SVR model is visualized in Figure 1 with the x-axis corresponding to the input variables and the y-axis corresponding to the target variables or predicted output.

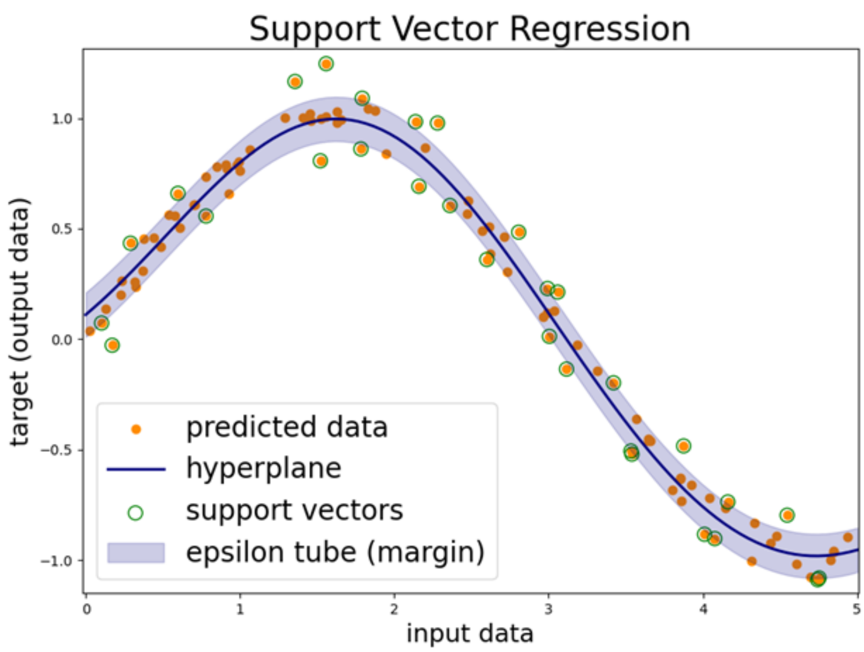

FIGURE 1. Support vector regression model.

The blue line represents the hyperplane line that the model has learned from the training dataset. The green circles represent the support vectors that show the decision boundary. The shaded region represents the epsilon tube. This area defines a margin where errors are accepted and does not affect the model's loss function. A larger epsilon means a wider margin, allowing more points to fall. Hence, any error in the dataset within this margin can be ignored.

Suppose given a dataset for SVR composed of G samples in Eq. (1)

$$G = (x_a, y_a) \quad a = 1, 2, 3, \ldots\ldots, (x_n, y_n) \tag{1}$$

Each sample contains input variables x_a, and the corresponding output variables y_a. In this research, x_a and y_a are defined in Table 1.

TABLE 1. Input and output variables.

Variables		Description	Unit
Input variables (x_a)	Land size	Dedicated area of each sellable land for development industry	ft^2
	Floor area ratio	Percentage of building area or usable area on a land.	0.7
	Build up area	Actual building or usable area on a land. It is the product of land size area and floor area ratio.	ft^2
	Load density	The average load required per square foot	$16W / ft^2$
	Coincident factor	A measure of the variation in load among different consumers.	
		Diversity factor	0.8
		Group diversity factor	0.75
Output variables (y_a)	Total maximum demand	Predicted electricity demand	MW

The SVR model is mathematically represented by the Eq. (2)

$$f(x)=\omega\phi(x)+b \tag{2}$$

where $f(x)$ is the predicted output of electricity demand (MW), ω is the weight vector which is crucial as it determines the influence of each input variable on the prediction, $\phi(x)$ is the input variables mapped into high dimensional feature space, allowing the model to capture complex relationships between the input features and the target output, and b is the bias term which helps adjust the output independently of the input variables, ensuring that the model can fit the data more flexibly.

To solve the $f(x)$, the optimal values ω and b can be determined by minimizing the quadratic optimization problem as in Eq. (3)

$$\mathrm{R(C)} = \min {}^{1}/_{2} \|\omega\|^2 + {}^{C}/_{n} \sum_{a=1}^{n} L_\varepsilon[y_a, f(x_a)]$$
$$L_\varepsilon[y_a, f(x_a)] = \begin{cases} |y_a - f(x_a)| - \varepsilon, & \text{if } y_a - f(x_a) \geq \varepsilon \\ 0 & \text{if } y_a - f(x_a) < \varepsilon \end{cases} \tag{3}$$

where $\frac{1}{2}\|\omega\|^2$ is a regularized term and ${}^{C}/_{n} \sum_{a=1}^{n} L_\varepsilon[y_a, f(x_a)]$ is the empirical risk. From the Eq. (3), regularized term controls the model from overfitting by adding a penalty term to the loss function. This loss function introduces an (ε)- insensitive zone around the predicted values, meaning that small errors within this zone do not contribute to the loss. This characteristic allows the model to ignore minor deviations, focusing instead on larger errors that exceed the threshold defined by (ε).

To solve the quadratic optimization problem effectively, Lagrange multipliers are implemented by introducing slack variables ζ_a and ζ_a^* as in Eq. (4)

$$\begin{aligned} & R(C) = min \tfrac{1}{2}\|\omega\|^2 + C\textstyle\sum_{a=1}^{n}(\zeta_a + \zeta_a^*) \\ & s.t.\ f(x_a) - \ y_a \leq \varepsilon + \zeta_a \\ & y_a - f(x_a) \leq \varepsilon + \zeta_a^* \\ & \zeta_a\zeta_a^* \geq 0, a = 1,2,3,\ldots.,n \end{aligned} \tag{4}$$

The slack variable ζ_a is introduced when the predicted output $f(x)$ violates the upper margin constraint, i.e., $f(x_a) \leq y_a + \varepsilon + \zeta_a$. It quantifies the extent to which the prediction exceeds the upper boundary of the margin. Meanwhile, the slack variable ζ_a^* is introduced when the predicted output $f(x)$ violates the lower margin constraint, i.e., $f(x_a) \leq y_a - \varepsilon - \zeta_a^*$. It quantifies the extent to which the prediction falls below the lower boundary of the margin.

These multipliers are incorporated with the constraints in the quadratic optimization problem equation. The optimal solution can be resolved by taking partial derivatives of the equation concerning the primal variables (Gupta, Acharjee, & Richhariy 2020).

By solving Eq. (4), the kernel function maps the input data to a higher-dimensional feature space, allowing the SVR model to capture complex relationships in the data as expressed in Eq. (5)

$$f(x) = \sum_{a=1}^{n}(\zeta_a - \zeta_a^*) \cdot K(x_a, x) + b \quad (5)$$

Kernel function can be categorized into four types: Linear, Polynomial, Sigmoid and Radial Basis Function (RBF). RBF is strongly recommended and widely used for its performance and complexity (Abderrahim, B., & Zohra, G. F. 2021). RBF kernel function is given by Eq. (6)

$$K(x_a, x) = e^{\frac{-\|x_a - x\|^2}{2\sigma^2}} \quad (6)$$

where x_a is the input vectors from the dataset, x is input vectors for training samples, $\|x_a - x\|^2$ is the Euclidean distance between two vectors, and σ is the width parameter of the Gaussian function. A smaller value of σ will result in a narrower curve of the decision boundary, while a larger value of σ will result in the curve being wider.

Malaysia Vision Valley (MVV) is a new growth area development consisting of Hamilton City, New Labu, Labu and Kirby located in Negeri Sembilan, Malaysia. In line with the state government's priorities, a high-tech industrial zone, commercial, residential and institutional areas were developed respectively, as shown in Figure 2, the overall MVV development master plan.

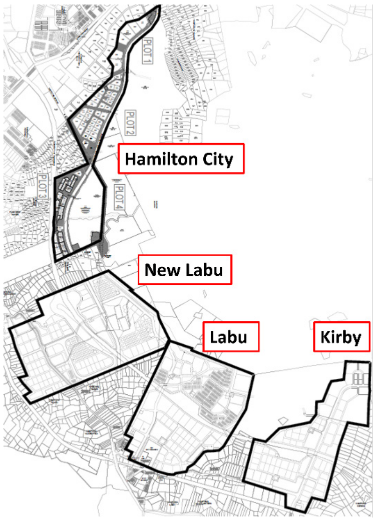

FIGURE 2. Malaysia Vision Valley development

Hamilton City was divided into four plots based on different development phases with a total area of 285 acres. Plots 1 and 2 were allocated for high-tech zones. Meanwhile, Plots 3 and 4 were for commercial, detached, and semi-detached factories. This research only focuses on predicting electricity demand in plots 1 and 2 as they involve high-tech zones and will be the primary electricity consumers in low-voltage distribution networks. From the information provided such as sellable land area (ft^2) and number of individual buildings, the data was filtered by considering the sellable land development area (ft^2) only. The number of individual buildings is excluded because the electricity demand is small. Hence, this research focuses on 42 out of 52 sellable lands for predicting electricity demand. Meanwhile, load density and coincidence factors were collected from the utility's power supply handbook for other input variables.

RESULTS AND DISCUSSION

Three distinct training and testing sets were implemented for optimizing SVR model performance as tabulated in Table 2.

TABLE 2. Amount of training and testing dataset implemented in this study.

No	Training dataset	Testing dataset	Total
1.	30%	70%	100%
	13	29	13+29 = 42
2.	50%	50%	100%
	21	21	21+21 = 42
3.	70%	30%	100%
	29	13	29+13 = 42

Figure 3 to Figure 5 illustrate the input and output variables for every training and testing dataset. The x-axis represents the build-up area in thousand ft^2 while the y-axis represents the total maximum demand (MW) for the corresponding area. Meanwhile, the floor area ratio, load density and coincidence factors are constant values.

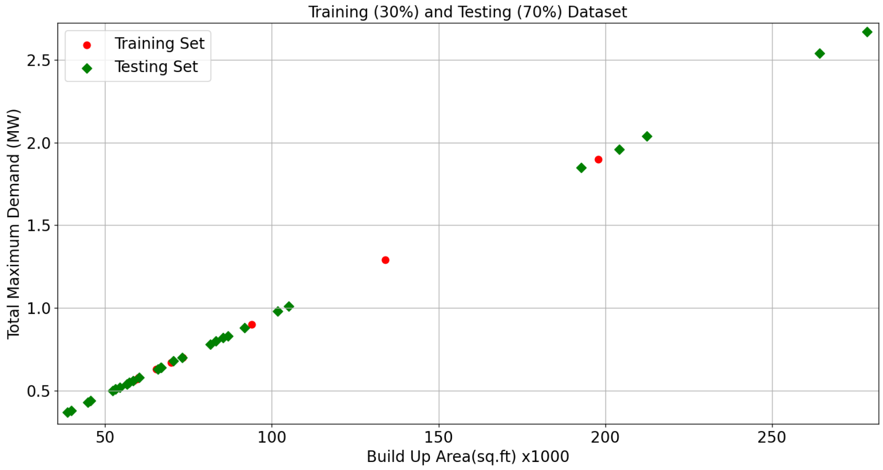

FIGURE 3. Input and output variables for training (30%) and testing (70%) dataset.

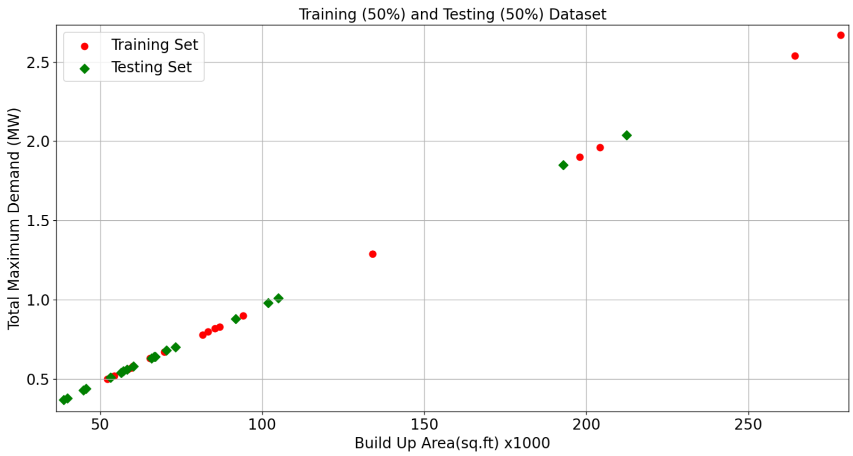

FIGURE 4. Input and output variables for training (50%) and testing (50%) dataset.

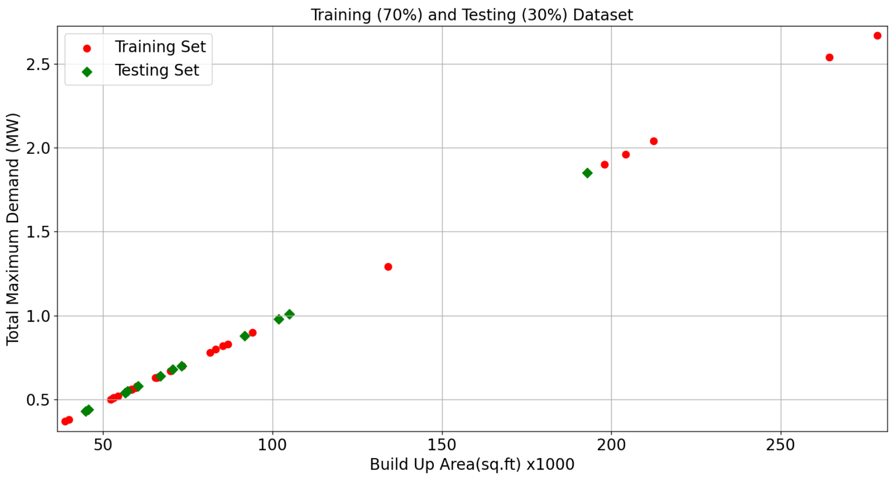

FIGURE 5. Input and output variables for training (70%) and testing (30%) dataset.

Table 3 to Table 5 summarize the output of the SVR model's performance with 5 different gammas, (y) value.

TABLE 3. A dataset of 30% training and 70% testing.

y	MAE	MAPE (%)	R^2 (%)
0.01	0.0150	1.19	99.62
0.02	0.0253	1.81	98.80
0.03	0.0282	1.90	98.34
0.04	0.0296	1.95	98.11
0.05	0.0315	2.02	97.77

TABLE 4. A dataset of 50% training and 50% testing.

y	MAE	MAPE (%)	R^2 (%)
0.01	0.0092	1.64	99.93
0.02	0.0069	1.15	99.96
0.03	0.0070	1.17	99.96
0.04	0.0069	1.17	99.96
0.05	0.0071	1.20	99.96

TABLE 5. A dataset of 70% training and 30% testing.

y	MAE	MAPE (%)	R^2 (%)
0.01	0.0074	0.96	99.94
0.02	0.0062	0.80	99.96
0.03	0.0062	0.81	99.96
0.04	0.0063	0.84	99.96
0.05	0.0059	0.82	99.97

The error cost, C, and ε- insensitive loss function width, ε were determined through K-fold cross-validation and grid search hyperparameter tuning to fine-tune the SVR model's parameters (Liu, L. et al. 2022). C balances the training data and minimizing the margin, while ε allows for a degree of error tolerance. The optimal parameter combination $C=40$ and, $\varepsilon=0.01$ were finalized. Five kernel coefficient (y) values were manually tuned to optimize the shape of the decision boundary. The appropriate y value balances model complexity and generalization ability. The training algorithm was executed using the training dataset for each C, ε, and y combination. The SVR model was then established with the input variables to predict the electricity demand. Three widely used statistical performance metrics, mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient determination (R^2), were implemented to evaluate the SVR model's performance in predicting electricity demand.

MAE measures the average difference between the predicted and actual electricity demand (MW) values. The equation is given by Eq. (7)

$$MAE = \frac{1}{n}\sum_{a=1}^{n}|f(x) - y_a| \tag{7}$$

The lower the values of MAE, the better the model performance in predicting electricity demand, as they reflect smaller average errors between predicted and actual values. MAPE measures the average percentage difference between the predicted and actual values. The equation is given by Eq. (8)

$$MAPE = \frac{1}{n}\sum_{a=1}^{n}\frac{|f(x) - y_a|}{f(x)} \times 100\% \tag{8}$$

The lower the values of MAPE, the better the model performance is in predicting electricity demand, as it signifies that the predicted values are closer to the actual value of electricity demand. In the comparative analysis of machine learning algorithms for electricity demand forecasting, MAPE is one of the evaluation criteria used to assess the accuracy of the models.

The R^2 is a key metric in linear regression models that quantifies how well the SVR model explains the variation in electricity demand. It measures the proportion of variance in the dependent variable that is predictable from the independent variables (Milad, A., et al. 2023). The equation is given by Eq. (9)

$$\left[1 - \frac{\sum_{a=1}^{n}(y_a - f(x))^2}{\sum_{a=1}^{n}(y_a - \overline{y_a})^2}\right] \times 100\% \tag{9}$$

where $\sum_{a=1}^{n}(y_a - f(x))^2$ is the summation square of the difference between actual and predicted output, while $\sum_{a=1}^{n}(y_a - \overline{y_a})^2$ is the summation square of the difference between actual and average output.

A high R^2 value signifies an excellent fit and suggests that the model effectively captures the underlying patterns in the data. The 70/30 training testing split better predicts electricity demand, achieving the lowest MAE of 0.0059, MAPE of 0.82%, and the highest R^2 of 99.97%. In contrast, a 30/70 split exhibits the highest MAE (0.0150) and MAPE (1.19%) and the lowest R^2 (99.62%). Although the 70/30 split offers the most accurate predictions, all three splits can still be considered adequate for forecasting future electricity demand. The SVR model's performance depends on the gamma (y) parameter. A smaller y value may result in underfitting. In comparison, a larger value can lead to overfitting; thus, to achieve optimal model performance, careful tuning of the error cost (C), ε- insensitive loss function, and y is necessary to mitigate underfitting and overfitting.

The best fit SVR model for the three training and testing sets of 30/70, 50/50 and 70/30 are illustrated in Figure 6 to Figure 8, respectively. Each graph illustrates the correlation between actual versus predicted electricity demand (MW) with Figure 6 at the combination parameters of C=40, ε=0.01 and gamma, y=0.01. Figure 7 shows the dataset training for 50% and 50% testing at the combination parameters of C=40, ε=0.01 and gamma,y=0.02. Figure 8 shows the dataset training for 70% and 30% testing at the combination parameters of C=40, ε=0.01 and gamma, y=0.05.

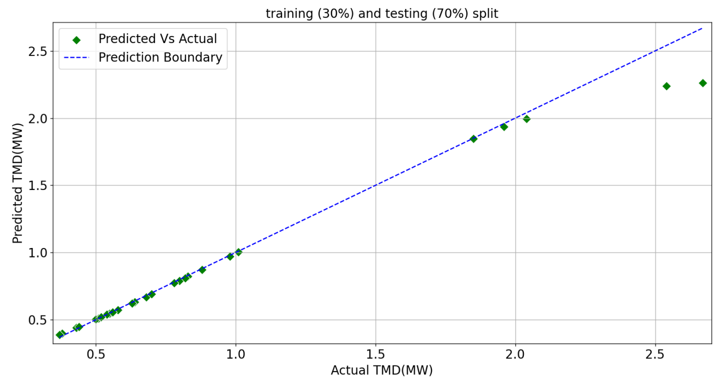

FIGURE 6. The actual versus predicted total maximum demand (MW) value for dataset 30% training and 70% testing.

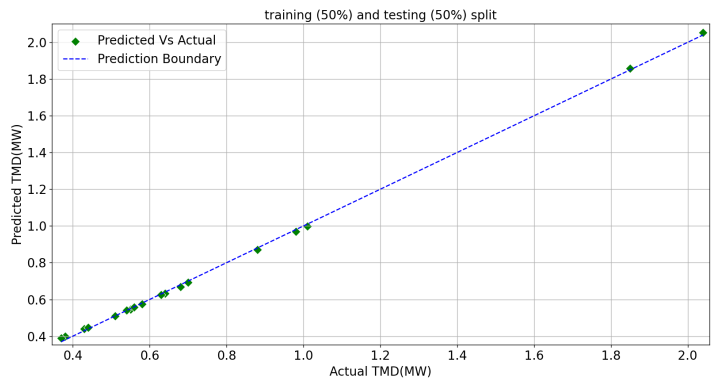

FIGURE 7. The actual versus predicted total maximum demand (MW) value for dataset 50% training and 50% testing.

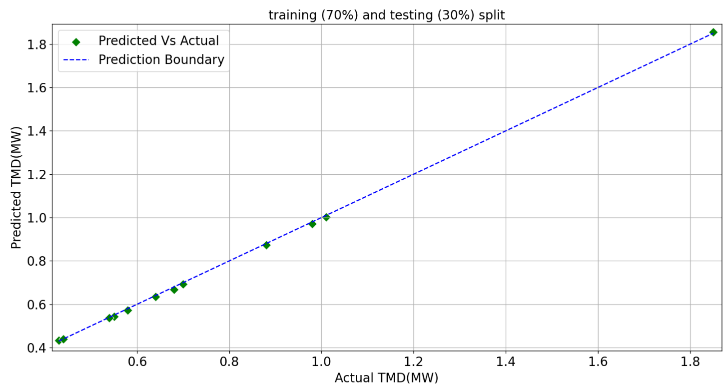

FIGURE 8. The actual versus predicted total maximum demand (MW) value for dataset 70% training and 30% testing.

From the result, the outlier is more significant in the 30% training and 70% testing dataset than in other training and testing sets. It can arise due to variability in the measurement, errors in data collection, or they might indicate a rare sample worth investigating (Solís-Villarreal 2024). Outliers can significantly impact SVR model's performance and generalization ability to forecast electricity demand (Songhua, H. 2024). These anomalies can lead to inaccurate predictions, skewing the model's understanding of typical electricity demand patterns. Addressing outliers is crucial for improving model accuracy and reliability. Various strategies have been proposed to mitigate the effects of outliers in electricity demand forecasting (Chen, C. et al. 2022).

Table 6 compares the prediction and actual performance of the SVR model in predicting electricity demand. The training dataset used was 29 samples, while the testing dataset is 13 samples. The parameter chosen is C=40, ε=0.01 and gamma, y=0.05.

TABLE 6. SVR model performance

No.	Actual value (MW)	Predict value (MW)	Relative error (%)
1.	0.58	0.572	1.34
2.	0.43	0.433	0.766
3.	0.68	0.668	1.73
4.	0.54	0.537	0.46
5.	1.85	1.856	0.30
6.	0.55	0.544	1.18
7.	0.70	0.694	0.92
8.	0.64	0.634	0.90
9.	0.98	0.971	0.96
10.	0.88	0.873	0.82
11.	0.54	0.537	0.46
12.	1.01	1.002	0.82
13.	0.44	0.440	0.03

CONCLUSION

SVR model with hyperparameter tuning was developed to predict the electricity demand for Hamilton City in low-voltage distribution networks. By considering six input variables that are land size area (ft^2), floor area ratio, build-up area (ft^2), load density (W/ft^2), diversity factor and group diversity factor, the model demonstrated a robust capability to capture the complex relationships inherent in electricity consumption patterns.

The evaluation metrics employed, including MAE, MAPE, and R-squared values indicate that the SVR model accurately predicts the electricity demand based on the training and testing set given. Notably, the model recorded a remarkable MAE of 0.0059, a MAPE of 0.82%, and an R^2 value of 99.97% when utilizing a 70/30 training and testing split. These results underscore the effectiveness of the SVR approach in addressing the challenges associated with electricity demand forecasting, particularly in the context of low-voltage distribution networks.

The findings of this research have significant implications for utility companies and grid operators. By leveraging the predictive capabilities of the SVR model, utilities can enhance their planning and resource allocation strategies, ultimately leading to improved grid reliability and efficiency. Accurate demand forecasts can help mitigate the risks of power outages, optimize energy procurement, and reduce operational costs, thereby contributing to a more sustainable energy source.

In the future, there is ample opportunity for further research to refine and expand upon the findings of this study. Future models could benefit from the inclusion of additional factors that influence electricity demand, such as climate change, population growth, and the geographical characteristics of the development area. Moreover, exploring the integration of real-time data and advanced machine learning techniques could enhance the model's adaptability and accuracy in dynamic environments. Investigating the impact of emerging technologies, such as smart grids and IoT devices, on electricity consumption patterns may also provide valuable insights for future demand forecasting efforts.

In conclusion, this study highlights the potential of SVR as a powerful tool for predicting electricity demand in low-voltage distribution networks. By continuing to explore and incorporate diverse input variables and advanced modeling techniques, researchers can further enhance the accuracy and reliability of electricity demand forecasts, ultimately supporting the transition to a more resilient and efficient energy system.

DECLARATION OF COMPETING INTEREST

None.

REFERENCES

Abderrahim, B., & Zohra, G. F. 2021. Medium term electricity load forecasting using machine learning techniques (pp. 50–60).

Chen, C., Ou, C., Liu, M., & Zhao, J. 2022. Electricity demand forecasting with a modified extreme-learning machine algorithm. *Frontiers in Energy Research* 10.

Gökçe, M. M., & Duman, E. 2024. A deep learning-based demand forecasting system for planning electricity generation. *Kahramanmaraş Sütçü Imam Üniversitesi Mühendislik Bilimleri Dergisi* 27(2): 511–522.

Gomez, W., Wang, F.-K., & Lo, S.-C. 2024. A hybrid approach-based machine learning models in electricity markets. *Energy* 289: 129988.

Gupta, D., Acharjee, K., & Richhariya, B. 2020. Lagrangian twin parametric insensitive support vector regression (LTPISVR). *Neural Computing and Applications* 32(10): 5989–6007.

Jie, B., Baba, J., & Kumada, A. 2023. Mathematical analysis of time-series & meteorological factors in electricity demand forecasting based on carbon neutrality. 2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia): 137–142.

Li, L., Cen, Z.-Y., Tseng, M.-L., Shen, Q., & Ali, M. H. 2021. Improving short-term wind power prediction using hybrid improved cuckoo search arithmetic - Support vector regression machine. *Journal of Cleaner Production* 279: 123739.

Liu, L., Yang, J., & Chen, W. 2022. Electricity consumption forecasting in Jiangsu province based on machine learning model. 2022 4th International Academic Exchange Conference on Science and Technology Innovation (IAECST): 613–616.

Milad, A., Mohamad Zaki, A. H., Ali Omar, H., Albrka Ali, S. I., Memon, N. A., & Md. Yusof, N. I. 2023. Predicting the rheological properties of bitumen-filler mastic using machine learning techniques. *Jurnal Kejuruteraan* 35(4): 889–899.

Miraki, A., Parviainen, P., & Arghandeh, R. 2024. Electricity demand forecasting at distribution and household levels using explainable causal graph neural network. *Energy and AI* 16: 100368.

Mohamed, M., & Alosman, K. 2024. A comprehensive machine learning framework for robust security management in cloud-based internet of things systems. *Jurnal Kejuruteraan* 36(3): 1055–1065.

Nasir, T., Asmael, Mohammed., Zeeshan, Q., & Solyali, D. 2020. Applications of machine learning to friction stir welding process optimization. *Jurnal Kejuruteraan* 32(2): 171–186.

Peplinski, M., Dilkina, B., Chen, M., Silva, S. J., Ban-Weiss, G. A., & Sanders, K. T. 2024. A machine learning framework to estimate residential electricity demand based on smart meter electricity, climate, building characteristics, and socioeconomic datasets. *Applied Energy* 357: 122413.

Selvam, N., Seenivasan, D., Naveen, G., Sudahar, R., Janagan, P., & Dhanushmathi, S. 2024. Monitoring of individual household electrical appliances and prediction of energy consumption using machine learning. 2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV): 925–931.

Songhua, H. 2024. A novel outlier calendrical heterogeneity reconstruction deep learning model for electricity demand forecasting. *Journal of Intelligent & Fuzzy Systems* 46(2): 3363–3394.

Solís-Villarreal, J.-A., Soto-Mendoza, V., Navarro-Acosta, J. A., & Ruiz-y-Ruiz, E. 2024. Energy consumption outlier detection with ai models in modern cities: a case study from north-eastern Mexico. *Algorithms* 17(8): 322.

Wang, J., Han, L., Zhang, X., Wang, Y., & Zhang, S. 2023. Electrical load forecasting is based on variable T-distribution and dual attention mechanism. *Energy* 283.