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Enhancing Load Prediction Accuracy using Optimized Support Vector Regression Models

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Abstract: This paper investigates the effect of Support Vector Regression hyperparameters optimization on electrical load prediction. Accurate and robust load prediction helps policy makers in the energy sector to make inform decision and reduce losses. To achieve this, Bayesian optimization technique was employed for the hyperparameters optimization which are then used for the load prediction. The hyperparameters are the regularization parameters and the epsilon. In addition, the effects of sliding window during the load prediction were also evaluated. The sliding window values were varied from 1 to 5. The results showed that the sliding window of 1 had the optimized hyperparameters with the best performing evaluation metrics of 0.01912 and 0.09493 for MSE and MAE respectively.

Keywords: *Support vector regression, hyperparameters, Bayesian optimization, load prediction, sliding window*

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1. Introduction

Increase in population and industrialization have necessitate high consumption of electrical power [1], [2]. Consequently, attention has been devoted to the management and control of power system across the globe [3], [4]. Electrical load prediction plays crucial role in power system operation and planning [5]. Accurate and robust load forecasting is, therefore, needed [6]. Human and financial resources have been devoted to control and manage electric power efficiently [7]. There is, therefore, need to employed all necessary tools available to achieve stable, effective and affordable power system that is devoid of losses The forecasting of power generated from the generation and the power needed form the consumers end is at the heart of an Energy Panning Model [8]. Load forecasting is the way of anticipating future electric power based on previous data and the weather conditions [9]. There are several load forecasting horizons employed by the power system companies for different applications in the industries [10]. These applications include planning [11], control [12], future load scheduling [13], staff hiring [14] and equipment expansion [15]. Short term load prediction is the forecasting of future from minutes to a week [16]. STLF is useful in power system control [17]. Medium term load prediction is from a week to a year [18].. Long term load prediction has the longest time horizon which is usual more than a year [19]. Medium term prediction is employed in the area of setting up of fuel supply and sustainment operation and Long term prediction improves system operations delivery and planning [20]. Long term prediction is also employed for power system expansion [5].Therefore, accurate load prediction is absolutely essential on the efficient administration of power system planning, control and management. An inaccurate load forecast could lead to waste of scarce resources. Grid collapse is inevitable in absence of robust load prediction.

Several approaches have been employed for load predictions. Statistical methods and machine learning methods have been employed by researchers for the implementation of load forecasting. Statistical methods employed in load prediction include Time series analysis; like Moving average (MA), Autoregressive model (AR), Autoregressive integrated moving average (ARIMA), Autoregressive moving average model (ARMA), Exponential smoothing is also part of the method. [21] presented a study that aims to develop and evaluate an ARIMA for forecasting radiation of the sun in South Korea's capital, Seoul. The dataset used was more than 37 year and was collected from the Korean Meteorological Administration. To test the accuracy of the model, it was compared with Monte Carlo simulations using RMSEs, Coefficient of Determination (R^2), Phillip-Perron Test and Jarque-Bera Test as evaluation metrics. However, the study does not consider other factors such as cloud cover, humidity and temperature which could affect the correctness of solar predictions. Additionally, more data points from different locations would be needed to further validate the results obtained in the study for a wider range of applications.

[22] employed ARIMA-based modelling to study factors that affect traffic congestion and provides a guide on how to build an effective model for predicting abnormal status. However, the study does not address the underlying causes of traffic congestion such as population growth or inadequate infrastructure. [23] presented an analysis and forecasted results for short-term electrical load forecasting, employing three predictive models: ARMA, ARIMA and Autoregressive Integrated Moving Average Model with Exogenous variable. The performance of the models was evaluated using MAPE. Although, the paper did not discuss the limitations of using time series approach for short term load prediction.

Artificial intelligence techniques have employed by researchers for load predictions. Examples of AI techniques used are expert systems [24], artificial neural network [25], Fuzzy logic systems [26], evolutionary algorithms [27] and deep learning [28], [29]. [30] presented a extensive study of very-short term (hour-ahead) and short-term (day ahead)

JDFEWS 4 (2): 23-36, 2023
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load prediction in an urban building by applying neural networks (NN). The performance of the NN was evaluated in view of two backpropagation learning principle, the Levenberg-Marquardt and Bayesian technique. It also investigates how network model parameters, such as number of neurons, hidden layers, and input layers, affect the model's ability to precisely predict loads. To exhibit its efficiency, it was tested on exact dataset from a campus in downtown Montreal that constitutes many types of buildings with diverse functionalities. However, the effects of different work design parameters on load forecasting accuracy could be further explored. Also, it would be beneficial to investigate alternative machine learning models such as Support Vector Regression (SVRs) or ensembles in order to compare their performance against ANNs for short-term load prediction tasks. [31] proposed a model employing fuzzy logic to forecast short-term energy demand with respect to weather parameters. They employed triangular membership functions with support upon collected data along with production rules formed through basic language understanding in order to make forecasts about future load demand. Finally, they suggest further studies could focus on tuning their proposed model more accurately while reducing time and computational effort required for such tasks. [32] presented a machine learning with evolutionary models based short term load prediction model for power systems, which uses Wavelet Transform and Artificial Fish Swarm Optimization to improve the predictive process. However, the authors suggested that future studies could focus on improving predictive outcomes of this method by using deep learning and hyper-parameter optimization techniques. [33] investigated the potential of using deep learning approaches for residential load forecasting under high volatility and uncertainty. A new Pooling-based Deep Recurrent Neural Network (PDRNN) was proposed to solve overfitting challenges caused by naïve deep networks, accepting more layers before occurrence of overfitting while still capturing geographical information common between interconnected customers. Although further research could be done to explore how data privacy and security can be addressed when using deep learning techniques for residential load forecasting. Additionally, investigating if the findings of the study are applicable to other types of households.

The aim of this study is to optimize the hyperparameters of the Support Vector (SVR) for improved load prediction. The specific objectives of the studies are to develop the SVR models with Python using Google Collab platform and to also evaluate and compare the SVR models using sliding window techniques.

2. Review of Literature

Ref [34] proposes a hybrid model called SVR-LSTM for short-term load forecasting in a microgrid (MG) in Africa. The model combines Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) algorithms. The SVR-LSTM model is compared with conventional SVR and LSTM models, and it shows better results with a correlation coefficient of 0.9901, compared to 0.9770 and 0.9809 for SVR and LSTM respectively. [35] developed a machine learning algorithm for electric load forecasting that incorporates an asymmetric loss function to account for the different costs associated with over-prediction and under-prediction errors. The framework is tested using electric load data from New South Wales in Australia and is shown to result in a significant reduction in daily economic costs compared to basic support vector regression. The cost reduction ranges from 42.19% to 57.39% depending on the actual cost ratio of the two types of errors. [36] propose a hybrid support vector regression (HSVR) for medium and long-term load forecasting in the smart grid. It focuses on the coupling and interdependent relationship between hyperparameters and model parameters in the optimization process.

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

3. Materials and Methods

3.1 Description of the dataset

Monthly dataset for the six-business hub in Ogun State were used in this study. The six hubs were used in order to captured the entire load consumption of Ogun State. The initial dataset was in Mega-Watt-hour (MWh), its summation was divided by twenty-four to convert it to MW. The duration of the entire dataset is 5 years, from 2018 to 2022. The actual total consumption in MW, which is the target during the prediction, was evaluated. The sample of the 2018 dataset was presented in Table 1. The data was obtained from Ibadan Electricity Distribution Company (IBEDC). Ogun State is a state in the southwestern zone in Nigeria, it is the second largest economy in the region. The state was created on 3rd February 1976. Ogun State borders Osun and Oyo states in the northern zone, to the north is Lagos state, Ondo state and Republic of Benin in the eastern and western zone respectively. Ogun state capital is Abeokuta, the most densely populated area in the state. Other notable areas in the state are Sagamu, Ota, Ijebu-Ode and Sango.

Table 1: Energy consumption distribution

Months	Ijebu	Ijeun	Olumo	Ota	Sagamu	Sango	Actual Total Consumption in MW
January	7,187	7,383	7,961	15,072	17,814	11,222	2,777
February	5,374	7,142	8,572	14,130	18,565	11,106	2,704
March	6,882	7,530	8,300	16,321	21,947	11,206	3,008
April	7,258	7,383	8,383	15,296	21,312	10,931	2,940
May	6,763	5,696	6,554	14,466	21,410	10,301	2,716
June	4,105	4,960	5,618	14,360	19,401	10,158	2,442
July	6,046	4,301	5,449	15,674	22,679	11,266	2,726
August	6,621	4,756	6,455	16,494	23,729	12,403	2,936
September	5,322	4,606	6,133	15,071	16,615	9,965	2,405
October	4,930	4,870	6,305	16,559	18,383	11,145	2,591
November	3,915	6,058	6,900	15,376	19,097	12,837	2,674
December	5,412	6,245	7,533	16,447	21,538	11,373	2,856

3.2 Models Implementation

Python code was employed for the development of the Support Vector Regression model. Python libraries like Pandas, Numpy, Matplotlib, Scikit-learn and skopt were imported. To optimize the hyperparameters of the SVR, Bayesian optimization techniques was employed. Sliding window techniques was used to develop the SVR models. The sliding window values were varied from 1 to 5 in order to observe the effects of the variation on the performances of the models. The dataset was divided into 70% for training and 30% for testing.

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

3.3 Support Vector Regression

Support vector regression (SVR) is a supervised machine learning model to handle regression problems [37]. SVR is a machine learning regression algorithm. Regression model is suitable to analyze the link between input and output variables. SVR develops an optimization question to learn a regression function that maps input and output variables [38].

The mathematical development of a linear support vector regression can be put as follows. Suppose Using the training data $\{(x_1, y_1),...,(x_n, y_n)\}$, where x_n and y_n are input and target output respectively. The linear function f can be put as [38]:

$$y = f(x) = w \cdot x + b = w^T x + b \tag{1}$$

where $w \cdot x$ stands for the dot the product of input data x with the weight vector w. Equation (1) can also be re-written as:

$$\min \frac{1}{2}\|w\|^2$$

$$subject\ \ to \begin{cases} y_n - w^T x_n - b \le \varepsilon \\ w^T x_n + b - y_n \le \varepsilon \end{cases} \tag{2}$$

The original optimization problem in Equation (2) is now be represented as a multiobjective optimization problem with supplementary parameters ξ and ξ^*

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\left(\xi_n + \xi_n^*\right),$$

$$subject\ to \begin{cases} y_i - w^T x_n - b \le \varepsilon + \xi_n \\ w^T x_n + b - y_n \le \varepsilon + \xi_n^* \\ \xi_n, \xi_n^* \quad \ge \quad 0 \end{cases} \tag{3}$$

where $C > 0$ is a regularization parameter that determines the trade-off between the flatness of function f and the prediction errors. A large C value gives more weight to minimizing the prediction errors, while a small C value gives more weight to minimizing the flatness.

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

Two SVR hyperparameters, the regularization parameters (C) and epsilon (ε), were optimized. The mean test score and the rank test score of the optimize hyperparameters were obtained. The best ranked hyperparameter was subsequently used for the training and testing.

3.4 Model Performance Evaluation

To evaluate the Support Vector Regression models, mean square error (MSE) and mean absolute error (MAE) were employed. Equation 4 and 5 represent the MSE and MAE respectively. The more the evaluation results are closer to zero, the better the performance of the model. The metrics were used to interpret and determine the accuracy of the model.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y - \hat{y}\right| \qquad (4)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y - \hat{y}\right)^2 \qquad (5)$$

4. Results and Discussion

4.1 Hyperparameters Optimization

Table 2 shows the results of the hyperparameters optimization when the sliding window, w is one (w=1). The hyperparameters were graded according to their rank test score with respect to the mean test score. The lower the mean test score, the higher the rank test score. The best ranked hyperparameters' values for regularization parameter, C and epsilon, ε are 333.131121 and 0.01 respectively with a mean test score of -0.039581. Table 2 represents when the sliding window is two (w=2). The best hyperparameters for C and ε are 380.189396 and 0.01 respectively, with a mean test score of -0.044034. The optimization results when the sliding window is three (w=3) is shown in Table 3. The value of the hyperparameters C and ε is 1.513561 and 0.01 respectively. Iteration indices 2 and 10 have the same rank test score of 1.

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

Table 2: Optimization results when sliding window, w, is one (w=1)

Iteration index	Hyperparameters		Mean Test Score	Rank Test Score
	C	Epsilon		
10	333.131121	0.01	-0.039581	1
13	125.892541	0.01	-0.039581	2
11	380.189396	0.01	-0.039616	3
2	1.513561	0.01	-0.040062	4
0	1.513561	0.07	-0.045347	5
7	1.148154	0.05	-0.046432	6
6	660.693448	0.08	-0.047407	7
5	109.647819	0.1	-0.053295	8
12	6.918310	0.1	-0.053298	9
9	0.165959	0.04	-0.057868	10

Table 2: Optimization results when sliding window, w, is two (w=2)

Iteration index	Hyperparameters		Mean Test Score	Rank Test Score
	C	Epsilon		
11	380.189396	0.01	-0.044034	1
12	660.693448	0.01	-0.044117	2
10	331.131121	0.01	-0.044328	3
14	109.647820	0.01	-0.045258	4
2	1.513561	0.01	-0.045411	5
13	1.148154	0.01	-0.045602	6
7	1.148154	0.05	-0.050325	7
6	660.693448	0.08	-0.051769	8
0	1.513561	0.07	-0.053758	9
5	109.647820	0.1	-0.060272	10

Journal of Digital Food, Energy & Water Systems [JD-FEWS]

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

Table 3: Optimization results when sliding window, w, is three (w=3)

Iteration index	Hyperparameters		Mean Test Score	Rank Test Score
	C	Epsilon		
2	1.513561	0.01	-0.045954	1
10	1.513561	0.01	-0.045954	1
12	1.513561	0.03	-0.052053	3
7	1.148154	0.05	-0.058582	4
11	1.513561	0.05	-0.059019	5
13	1.513561	0.06	-0.060360	6
0	1.513561	0.07	-0.062599	7
6	660.693448	0.08	-0.065770	8
9	0.165959	0.04	-0.067642	9
5	109.647820	0.1	-0.074636	10

Table 4 shows the optimization results when sliding window is 4. The regularization parameter, C and Epsilon, ε are 1.513561 and 0.01 respectively. The minimum mean test score is -0.057324 with iteration index of 2. Table 5 represents the result when the sliding window is 5. Iteration index of 5 has the most optimized hyperparameters of 109.657820 and 0.01 for C and ε respectively.

Table 4: Optimization results when sliding window, w, is four (w=4)

Iteration index	Hyperparameters		Mean Test Score	Rank Test Score
	C	Epsilon		
2	1.513561	0.01	-0.057324	1
11	1.513561	0.01	-0.057324	2
10	331.131121	0.01	-0.065398	3
7	1.148154	0.05	-0.070806	4
9	0.165959	0.04	-0.076877	5
5	109.647820	0.1	-0.078764	6
0	1.513561	0.07	-0.081203	7
4	0.023988	0.02	-0.083706	8
1	0.036308	0.1	-0.084794	9
14	0.006918	0.01	-0.085940	10

Journal of Digital Food, Energy & Water Systems [JD-FEWS]

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

Table 5: Optimization results when sliding window, w, is five (w=5)

Iteration index	Hyperparameters		Mean Test Score	Rank Test Score
	C	Epsilon		
5	109.647820	0.1	-0.051088	1
6	660.693448	0.08	-0.061645	2
10	109.647820	0.06	-0.066291	3
12	6.918310	0.1	-0.068731	4
2	1.513561	0.01	-0.076404	5
7	1.148154	0.05	-0.078657	6
0	1.513561	0.07	-0.084140	7
9	0.165959	0.04	-0.085037	8
4	0.023988	0.02	-0.086637	9
1	0.036308	0.1	-0.090386	10

4.2 Performance evaluation of the Optimized Hyperparameters

The most optimized hyperparameters were subsequently selected and were employed for the prediction. Figures 1-5 show the actual versus predicted values of the load. The data points are 16, 15, 14, 13, and 12 are for sliding window 1, 2, 3, 4 and 5 respectively. Figure 1 shows the actual data with the predicted when the sliding window is one. The maximum predicted value 2549.80 MW in the sixth month while the actual value is 2625.56 MW in the fifth month. The minimum actual and predicted was at twelfth and eleventh month respectively. The predicted and actual value was 1911.39 MW and 1725.18 MW respectively. Figure 2 shows the actual and predicted for the sliding window of two, the maximum value of predicted and actual was 2552.51 MW at fifth month and 2625.56 MW at fourth month respectively. On the other hand, the minimum predicted, and actual value was at 1857.00 MW at eleventh month and 1725.18 MW at tenth month respectively. Figure 3 shows the actual and predicted when the sliding window is three. The maximum and minimum value of predicted energy consumed was 2551.29 MW for fourth month and 1884.14 MW for tenth month respectively. Figure 4 depicts the actual and predicted when the sliding window is four. The maximum and minimum value of predicted energy consumed was 2550.09 MW for third month and 1943.88 MW for sixth month respectively. Figure 5 shows the actual and predicted when the sliding window is five. The maximum and minimum value of predicted energy consumed was 2545.60 MW for first month and 1931.80 MW for fifth month respectively.

Table 6 depicts the performance evaluation of the support vector regression models. Mean Square Error (MSE) and Mean Absolute Error (MAE) were employed for evaluation. The Model with sliding window of 1 had the best performance of MSE and MAE of 0.01912 and 0.09493 respectively. The model at sliding window of 3 had the least performance with 0.02209 and 0.10404 for MSE and MAE respectively. The sliding window technique is a viable approach that had proved to increase the performance of load prediction.

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

Table 6: Performance evaluation with the Sliding window

Sliding Window (w)	MSE	MAE
1	0.01912	0.09493
2	0.02116	0.10366
3	0.02209	0.10404
4	0.02048	0.10206
5	0.01999	0.09974

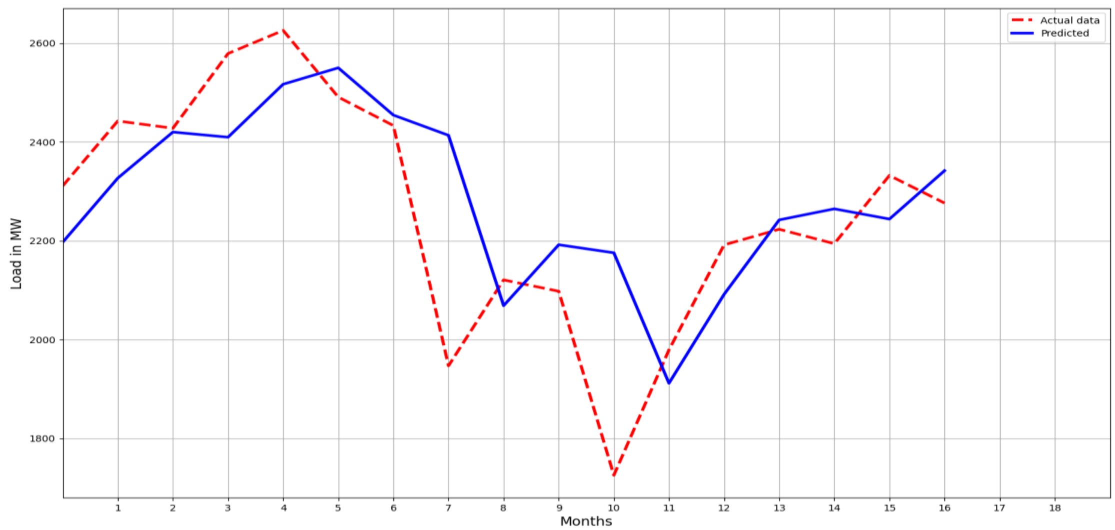

Figure 1: Actual and predicted values for w=1

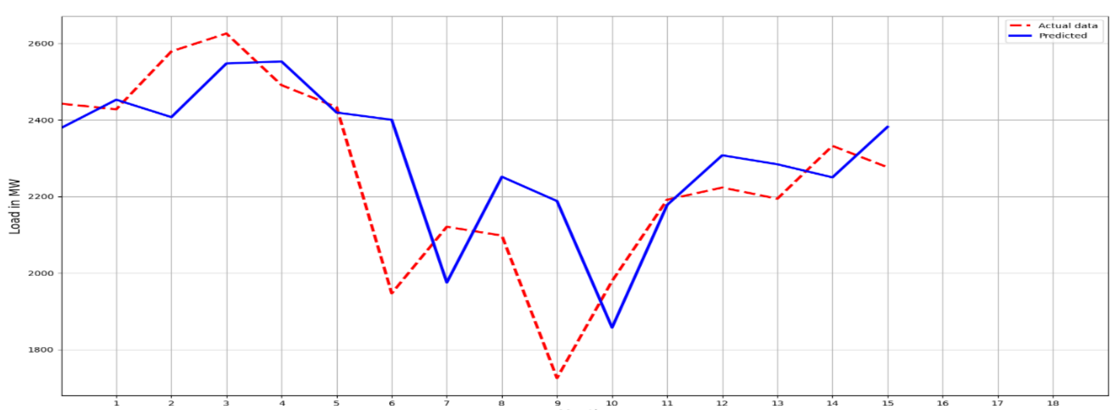

Figure 2: Actual and predicted values for w=2

Journal of Digital Food, Energy & Water Systems [JD-FEWS]

JDFEWS 4 (2): 23-36, 2023
ISSN 2709-4529

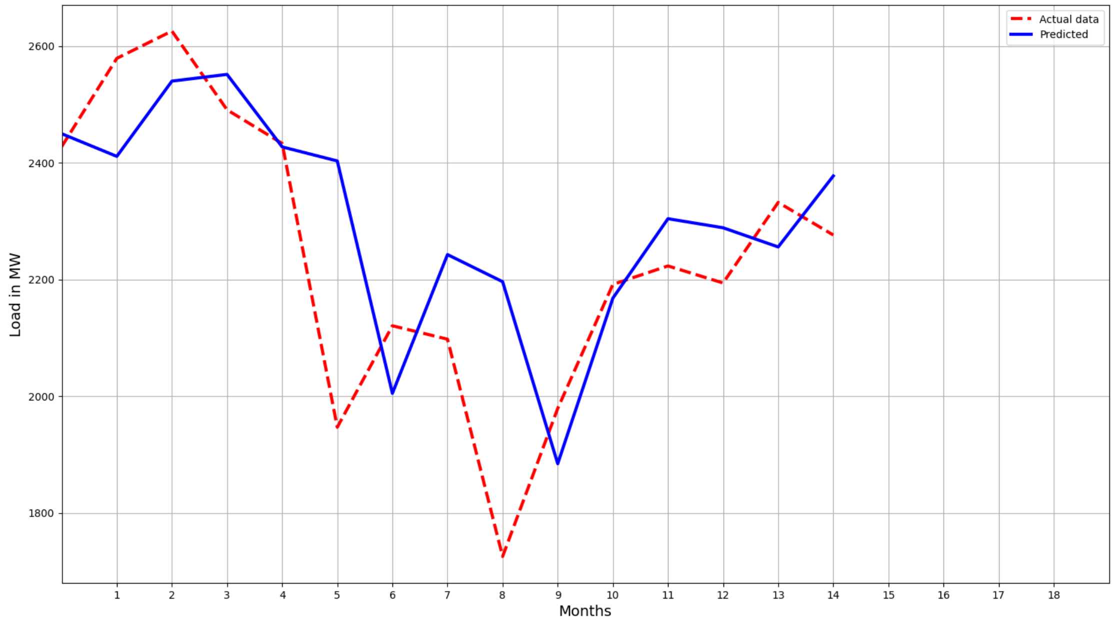

Figure 3: Actual and predicted values for w=3

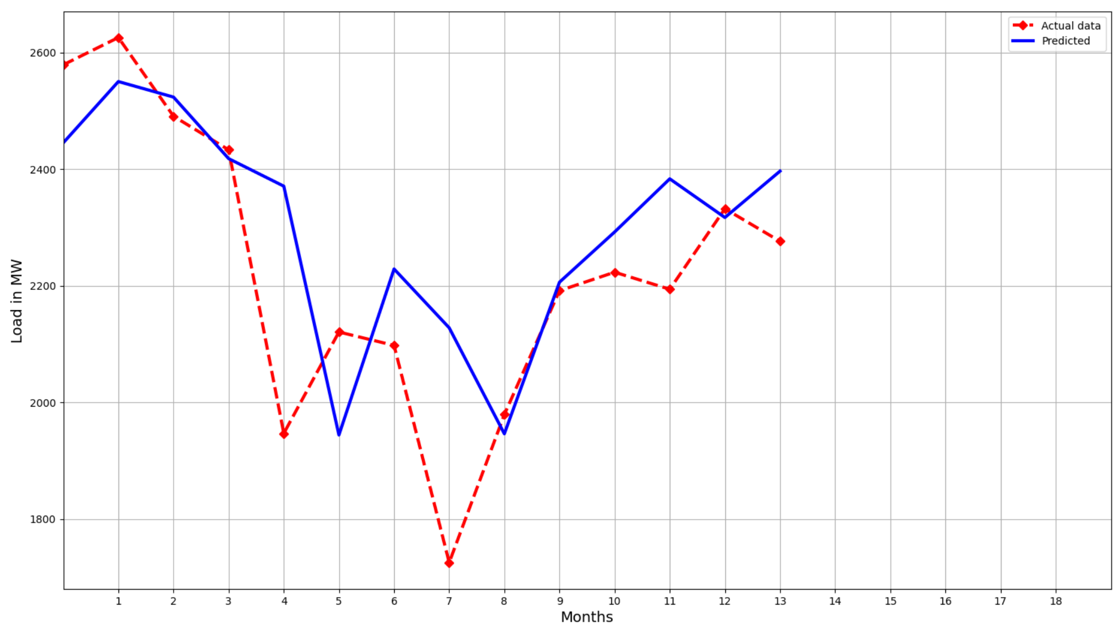

Figure 4: Actual and predicted values for w=4

Journal of Digital Food, Energy & Water Systems [JD-FEWS]

JDFEWS 4 (2): 23-36, 2023
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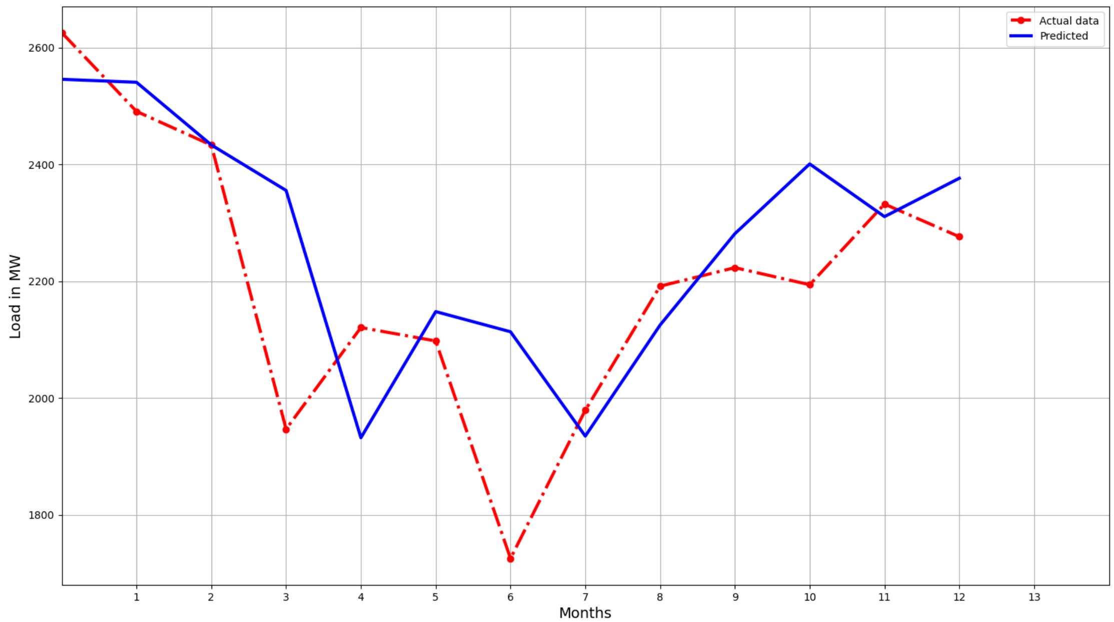

Figure 5: Actual and predicted values for w=5

5.0 Conclusion

The study investigated the performance of Support Vector Regression (SVR) models using sliding window (w) technique. The electrical load dataset of six business hubs in Ogun State, Nigeria was employed for the development of the models. The results showed that, the values of the sliding window have effect on the load prediction. For efficient and effective load forecasting, the hyperparameters of the SVR were also optimized using Bayesian technique. The best performing model was obtained when the sliding window was one, that is, w=1. Summarily, this work discovered that, a sliding window technique could be employed to enhance load prediction. This could be used to reduces electrical load losses and revenue generation increment. Since this research study developed a linear SVR, in future, Radial basis function of SVR could also be investigated. In addition, optimization of the neural network hyperparameters could also be investigated in future studies.

Future studies could employ other machine learning algorithm like optimized neural network and ensemble methods. The sliding window techniques can also be used with different dataset. Furthermore, weather parameters could also be added in future research.

JDFEWS 4 (2): 23-36, 2023
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