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Development of an Optimized Support Vector Regression Model Using Hyper-Parameters Optimization for Electrical Load Prediction

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Abstract Electrical load prediction is important to the effective operation, management and control of electric power systems. Several machine learning forecasting models have been developed for electrical load prediction. However, inappropriate selection of model hyperparameters, could result in low prediction accuracy of machine learning models. Hence, the development of an optimized Support Vector Regression model for electrical load prediction was presented in this study. Historical daily data of temperature, rainfall, relative humidity and windspeed for Osogbo, Nigeria was obtained from the National Aeronautics and Space Administration; while electrical load data for the same location was collected from the Transmission Company of Nigeria. The data captured a period of five years (2017 to 2021). The SVR models were developed with MATLAB, and two hyper-parameters, epsilon and box constraint, were optimized. The models were evaluated using mean absolute error (MAE) and root mean square error (RMSE). The MAE and RMSE for the non-optimized SVR model were 6.1977 and 8.0926 respectively, meanwhile, for the optimized SVR model, the MAE and RMSE were 5.8031; 7.0571 respectively. The obtained results show that the optimized SVR performed better than the non-optimized SVR models. Electrical power utility providers could adopt the method developed in this research.

Keywords: Support vector regression, epsilon, box constraint, machine learning, optimization

I. Introduction

Efficient electrical energy plays major role in the growth and development of the society. Therefore, there is need for stable and affordable electrical energy. The increase in human population coupled with the improvement in technology had made human race to be in dire in need of reliable electrical energy which could be achieved through effective electrical power grid control and maintenance. Consequently, to achieve this, electrical load prediction is required. Electrical load prediction is the process of forecasting the energy needed using the historical energy data and meteorological parameters. A lot of load prediction strategies have been implemented viz-a-viz the time horizons.

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Electrical load prediction is generally divided into four different time horizons. Very Short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF) and long-term load forecasting (LTLF). VSTLF ranges from seconds to sixty minutes, it is useful for power system control, load fluctuation management, frequency regulation and real time grid operations. STLF is from sixty minutes to seven days. STLF plays significant role in daily operational planning, economic load dispatch, unit commitment, energy resource and maintenance scheduling. MTLF spans from seven days to twelve months. MTLF is implemented in fuel procurement, power system security analysis, maintenance and tariff planning. LTLF is employed for predcition for more than a year. Investment decision, power system expansion, infrastructure development, policy and regulatory decisions are all achieved through LTLF.

Artificial intelligence (AI) is the ability of a computer or machine to mimic or imitate intelligent human behavior [1]. Task that necessarily need human ingenuity are done and perfected by employing machine learning (ML) through the use of large amount of dataset. ML is a subset of AI. Deep learning is subset of ML. ML could be task specific and non-task specific. ML has been deployed in various aspects of human life from engineering to finance, from healthcare to agriculture, from communication to transportation.

ML requires large amount of dataset, which are trained using an algorithm that has the ability of recognizing hidden trends. This formed a model that is subsequently employed for prediction with respect to the hidden pattern identified in the datasets [2]. Some machine learning models are based on special rules that must be obeyed. Models like fuzzy logic, Artificial Neuro-Fuzzy Inference System (ANFIS) and Experts System are rule-based. The rules are employed during the training, which allow them to make informed decision and prediction. AI and ML have changed several areas of human endeavour in the society. Autonomous cars [3], smart grids, human identification [4] , environmental security, disease diagnosis and treatment [5] are some of the areas where ML has been applied. Although, the implementation of ML has eroded individual data privacy.

ML has the capabilities to change several spheres of human live and essentially has effect on the way we work and live. AI has been able to efficiently and precisely evaluate massive amounts of data, which proves essential for duties that would be onerous or vulnerable to inaccuracies if done by humans. This may lead to increased productivity and production across different sectors. By developing a machine learning algorithm that uses hardware and software to monitor changes in soil quality and related metrics, [6] demonstrated how AI can maximize output. The researchers also explored the creation of a cloud-linked mobile application that utilizes sensor data and weather forecasts to identify the optimal ploughing technique and project crop yield for a specific timeframe.

Data analysis could provide a platform that thoughtful suggestion could be achieved through machine learning implementation to make informed decision. Also, hidden market pattern could be studied though machine learning. This may help policy makers and potential investor in their respective market choices. The use of neural network together with ensemble approaches of information technology and marketing has been presented by [7] in making unique decision making. The research work also examines the intermediary function of marketing approaches on technological strategy, evaluation and functional policy decision as well as mitigating the effects of ecological changes and organizational architecture.

Statistical techniques include regression, iterative reweighted least square and exponential smoothing [8]. Furthermore, [9] added Box and Jenkins method, Kalman filter, minimum mean square estimation, and state estimations as part of classical method. called the statistical approaches, the traditional forecasting techniques. Also, adaptive demand prediction, SVM and time series were classified as modified traditional techniques (Patel *et al*., 2019). The major weakness of this method is its potential to cause variation due to environmental factors. Nevertheless, this drawback is solved by using AI based techniques due to its capability of performing comprehensive search [10]. However, Several studies [11], [12], [13] have implemented statistical approach such as Autoregressive Moving Average Model (ARMA), Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Model (AR).

The most applied load prediction approaches by researchers presently is the AI and ML. [14] employed Experts system, Support Vector Regression (SVR) was utilized by [15]. [16] implemented neural network for their study. [17], [18] and [19], [20] presented fuzzy logic systems, Evolutionary algorithms and deep learning respectively.

SVR is a ML model that is used for regression problems [21]. Support vector models can also handle complex classification problem. Regression problems outcomes are in continuous form while the classification problems are mostly in discrete in the form of binary. One major merit of implementing SVR is the computational duration of the model because it converged faster than the NN. SVR can also take care of non-availability of large volume data unlike an NN [22]. In the implementation of SVR, the most essential parameters that determines the overall performance of the SVR model are the kernel function, regularization parameters, epsilon and loss function [23]. [24] presented a novel SVR model for the prediction of electrical load consumption using data integrity attack. The authors carried out the study with the available public data for the Global Energy Prediction 2012 and International Standard Organization (ISO) England. The data were intentionally altered in order to investigate attacks on data security and integrity. The findings from the research indicate that the model had better results compared to other literatures available on load predictions. Although, future studies should explore the efficiency and performance of the proposed model if validated using real world data from power utility company. [15] developed an optimal SVR model for the forecasting of electrical load. The optimized model was realized using Bayesian optimization with sliding window approach. Sliding values for 1 to 5 were evaluated and the study revealed that a sliding window of 1 had the best results with MAE and MSE as 0.09493 and 0.01912 respectively. [25] focused on short-term load prediction in power systems, which is important for power system dispatch and demand response. The authors discussed the daily load characteristics of a city in China, Jinan in the summer of 2016 and established a cooling maximum load. The authors presented support vector short term forecast model that is useful for demand and dispatch response. The Least Square SVM model developed in their research was used to analyze the daily electricity load features of Jihan in 2016 summer season. The authors investigate the effects of weather parameters on the model. Estimated maximum cooling load was calculated with the regression model. The LS-SVM method changed the regression model to an optimization problem in the primal weight space. The cooling maximum load forecast with LS-SVM model based on accumulated temperature effect and meteorological factors. [23] developed a prediction model for accurate electrical energy prediction with SVR in Smart Grid (SG). Classification and feature engineering were the two-stage model included in the model. To minimize redundancy, extraction techniques and feature selection were employed. A load prediction of 98% was achieved when market data was employed for the evaluation when the proposed model was implemented. An Asymmetric support vector regression (AsySVR) is an SVR that integrates an insensitivity parameter and linear-to-linear objective function for adequate fitting. [26] performed electrical load prediction in their study using AsySVR. Dataset from the New South Wales in Australia was employed to determine the performance of the developed model. The suggested framework reveal that a daily economic cost was reduced to 42.19% from 57.39%, based on real cost ratio of under-prediction and over-prediction errors. However, the difficulties and approaches of choosing the actual and appropriate regularization parameter needs to be explore with respect to the findings in the study.

II. Materials and Methods

A. Data Acquisition

The electrical load dataset of Osogbo, Osun State employed in this study was obtained from the Transmission Company of Nigeria (TCN). Osogbo, an ancient city in Osun State, is the capital city. The city is situated on $7^{o}46^{'}N$ longitude and $4^{o}34^{'}E$ latitude. The population of the state is 4,705,589 (National Population Commission, 2006) and land mass area of 9,026 sq. km. The weather parameters were collected from National Aeronautics and Space Administration (NASA) database. The electrical load dataset is daily dataset from 2017 to 2021. Data from 2017 to 2020 were used for developing the model while the 2021 dataset were employed for validation of the model.

B. Support Vector Regression

The support vector regression function in MATLAB R2022a was used to train the Support Vector Regression (SVR) model using input data and corresponding target values. The trained model was used to make predictions on new data. SVR found the best line that maximizes the margin between the data points and the line. This line is the support vector.

The SVR hyper-parameters optimized in this study are regularization parameter (C) and epsilon (ε). A regularization parameter controls the trade-off between maximizing the margin and minimizing the error. A smaller value of C results in a larger margin but a higher training error, while a larger value of C results in a smaller margin but a lower training error. Epsilon (ε) on the other hand controls the width of the margin around the target value. A smaller value of epsilon results in a wider margin but a higher training error, while a larger value of epsilon results in a narrower margin but a lower training error.

C. Support vector regression kernels

There are three major SVR kernel functions. Linear kernel, polynomial kernel and radial basis kernel. The radial basis kernel was employed in this study because it has wider domain of convergence [27]. Equation (1) represents the radial basis function.

$$K_{rbf}(x, x_i) = \exp\left(\frac{-\|x - x_i\|^2}{\sigma^2}\right) \quad (1)$$

x and x_i represent the input features and support vectors respectively, K_{rbf} is the radial basis function while σ is the standard deviation of the radial basis kernel function. Radial basis kernel function is the most stable kernel function [27].

D. Support vector regression model implementation

Given the training data and test data, Support Vector Regression Model could be expressed using Equation 2

$$f_{\phi}(x) = \sum_{i=1}^{N_{sv}} \alpha_i K(x, x_i) + b \qquad (2)$$

ϕ represents the hyper-parameters of the Support Vector Regression model. In this study, the hyper-parameters are the Box Constraint, C and the Epsilon, ε.

α_i are the coefficients associated with the Support Vectors.

K is the kernel function and the bias is the b.

N_{sv} is the number of support vectors and x_i are the support vectors.

For non-optimized SVR model, the initial value of the hyper-parameters was set to 1 and 0.1 for the box constraint and epsilon respectively.

E. Optimized support vector regression model

In order to find the optimal hyper-parameters of the SVR model that minimizes the prediction error on the model while satisfying the constraints. A constraint optimization was formulated using Equation 3.

$$\left.\begin{array}{l} Min_{\phi} MAE(\phi) \\ Min_{\phi} RMSE(\phi) \\ \textit{subject to} \\ \quad 0.001 \leq C \leq 1000 \\ \quad 0.001 \leq \varepsilon \leq 1 \\ \textit{where} \\ \quad C, \varepsilon > 0 \end{array}\right\} \qquad (3)$$

ϕ is the hyper-parameters of the SVR model, Box Constraint and Epsilon. The objective is to minimize the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as a function of the SVR hyperparameters. Box Constraint was set from 0.001 to 1000 and Epsilon was set from 0.001 to unity. The two SVR hyper-parameters should be greater than zero. The task is to find the hyperparameters, ϕ, that minimize the MAE and RMSE on the dataset while satisfying constraints C and ε

The performance metrics minimized were defined with Equations 5 and 6.

$$MAE(\phi) = \frac{1}{N_{test}} \left| y_i - f_{\phi}(x_i) \right| \qquad (5)$$

$$RMSE(\phi) = \sqrt{\frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left(y_i - f_{\phi}(x_i) \right)^2} \qquad (6)$$

N_{test} is the number of samples in the test dataset.

(x_i, y_i) are the input-output pairs in the test dataset.

$f_{\phi}(x_i)$ is the prediction of the SVR model with hyper-parameters ϕ for input x_i

The SVR optimization model was developed using MATLAB R2022a. The optimization of SVR model flowchart is shown in Figure 3.1. The figure shows SVR model optimization procedure. After loading the dataset, the objective function was defined as well as the hyper-parameters space. For the optimization of the two SVR hyper-parameters employed in this research, Bayesian optimization was employed. The iteration of the optimization was set to 100. Then the ten best hyper-parameters were recorded and evaluated using the MAE and RMSE.

One of the important stages in machine learning is the preprocessing of data, as it ensures that the data is formatted in a way that is suitable for optimal analysis and modeling. This study utilizes data cleansing, data formatting, and data exploration techniques. Data formatting involves altering the structure of data to ensure its compatibility with analysis or modeling purposes. The data formatting method utilized in this research is normalization. The data in this study was normalized using the min-max scaling technique.

III. Results and Discussion

A. Non-optimized Support Vector Regression

Figure 1 shows the results of an electrical load prediction using a non-optimized Support Vector Regression (SVR) model across 110 sample points. The model aims to predict the electrical load and evaluates its performance by contrasting the predicted load with the actual load. The close proximity between the anticipated load and the actual load suggests that the model accurately represents the overall pattern of the electrical demand. The error values have a relatively small and random distribution, indicating that the model predictions are unbiased and reasonably reliable. The error plot demonstrates that errors fluctuate over time but consistently fall within a specific range, primarily between -10 MW and +10 MW. This indicates that the model is generally precise, although there are occasional discrepancies that could be attributed to abrupt variations in the electrical demand that the model may not have fully accounted for. The non-optimized SVR model has the epsilon and Box Constraint (C) set to be 0.1 and 1 respectively. Its MAE and RMSE value of 6.1977 and 8.0926 respectively.

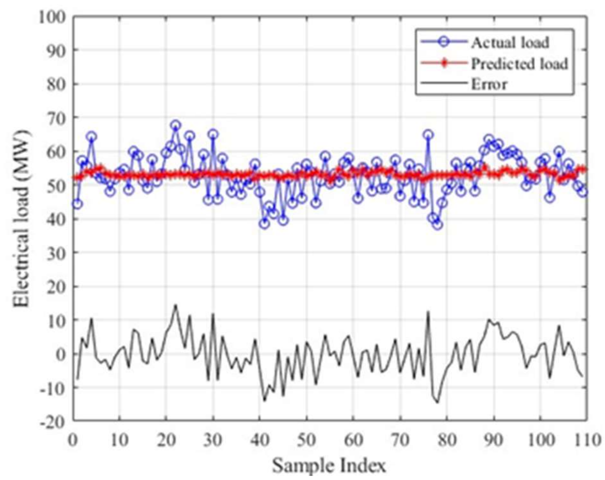

Figure 1: Prediction using Non-Optimized SVR Model

B. Optimized Support Vector Regression Model

Figure 2 represents the results of an optimized SVR model employed for forecasting electrical load. The figure comprises three essential components: the real electrical load, the forecasted load, and the error between the forecasted and actual values. The electrical load is expressed in megawatts (MW) and plotted in relation to a sample index. The y-axis shows the electrical load in MW, ranging from 30 to 70 MW, while the x-axis indicates the sample index, ranging from 0 to 110. Upon inspection, it is clear that the predicted load closely aligns with the actual values, demonstrating that the optimized SVR model effectively captures the patterns and variations in the electrical load. The close proximity of the prediction and actual load indicates that the model's predictions are generally precise, with very few variations. The error plot provides additional evidence of the model's correctness, as the error values consistently fluctuate near zero, suggesting that the variations between the observed and projected values are generally low. The error's magnitude often falls between the range of -10 and 10 MW, which is considered a tolerable margin of error considering the overall amount of electrical demand.

The use of optimized SVR in predicting electrical load is supported by recent literatures. A hierarchical optimization technique was proposed by [26] to optimize the parameters of SVR, resulting in improved accuracy in predicting industrial power loads. Using a nested strategy and the State Transition Algorithm (STA), the hierarchical optimization method found the best parameters for SVR models, which led to more accurate predictions. When compared to standard models, the implementation of the hierarchical optimization method to forecast industrial power loads.

Table 1 shows the top ten performance metrics and hyper-parameters of a tuned Support Vector Regression (SVR) model, measured using the Mean Absolute Error (MAE). The hyper-parameters considered were regularization parameter, C, and the Epsilon, ε. The total number of iterations was 100. The best combination of the hyper-parameters that will minimize the objective function.

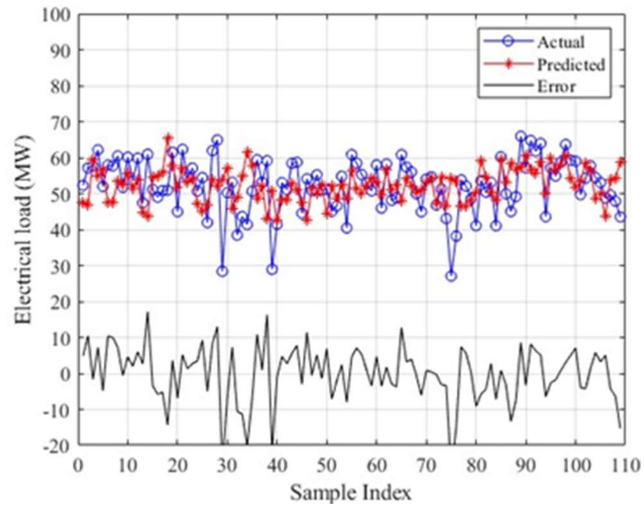

Figure 2: Prediction using Optimized SVR Model

Table 1: Top 10 Performance Metrics and Hyper-Parameters of Optimized Support Vector Regression Using MAE

BoxConstraint (C)	Epsilon (ε)	MAE
1.0823	0.0010401	5.8031
1.0563	0.0040462	5.8043
1.0147	0.0010883	5.8050
1.0399	0.0010121	5.8071
1.0406	0.0046554	5.8074
1.1596	0.017097	5.8074
1.0481	0.0011096	5.8078
1.1566	0.013988	5.8091
1.2396	0.98874	5.8103
1.0280	0.0010952	5.8104

The best 10 combination of hyper-parameters of an optimized SVR using RMSE is shown in Table 2. The objective function is minimized at 7.0571 when the BoxConstraint is 1.2861 and Epsilon is 0.11821. The RMSE value of 7.0571 shows that the optimized SVR model has a good prediction accuracy.

Table 2: Top 10 Performance Metrics and Hyper-Parameters of Optimized SVR Model using RMSE

BoxConstraint (C)	Epsilon (ε)	RMSE
1.2861	0.11821	7.0571
1.2439	0.09714	7.0585
1.1871	0.093762	7.0669
1.1671	0.0011256	7.0672
1.6035	0.96191	7.0687
1.2576	0.021924	7.0691
1.1947	0.0010176	7.0692
1.1624	0.0010165	7.071
1.0229	0.020351	7.0718
0.9050	0.0010383	7.0726

IV. Conclusion

This study emphasizes the importance of hyperparameters optimization. The performance of any machine learning models can be fully capture without investigating its various hyperparameters. Other SVR hyperparameters like kernel function and gamma could be investigated in further studies. Future studies can also consider the effects hyperparameters of other machine learning models like neural network and decision tree

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