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Multi-Kernel Learning based Sugar Industry Load Forecasting

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***Abstract**: Sugar industry which plans for power usage from Bagasse also needs the load forecasting carried out using the energy audit data. The stochastic nature of the load demand of the sugar industry needs to be forecasted in advance for the assuring uninterrupted power delivery to the industry. The manual energy audit data obtained from the sugar industry for a period of time is obtained and trained on a regression based on MultiKernel Learning (MKL). The Support Vector Regression (SVR) formulation is applied with the MultiKernel topology and the performance parameters including the Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) is observed in the implementation. The algorithm is the Multi Kernel Support Vector Regression algorithm using the Python based toolbox.*

Keywords: MultiKernel Learning, Support Vector Regression, Load Forecasting, Sugar Industry Energy Audit

I. INTRODUCTION

The Energy consumption during the period when the sugar cane availability is there and while sugar cane shortage is discussed in [1]. Energy consumption characteristics are found to be different at different stages of the production season. Juice extraction season and other seasons have a big difference in the energy utilization. Thus prediction using regression algorithms are to be adopted for forecasting the load power usage. Load Forecasting is predicted using the data obtained from the energy audit data along with the temperature and humidity data of the sugar plant area. Load Forecasting the load power usage of the plant is dependent on variety of input parameters such as humidity, temperature, and also historical data pattern trends of similar month's or day's power usage and average load. Regression algorithms perform better with a greater number of parameters. Hence, having more number of variables supports the estimation of values that are closer to optimal operation load power requirement. Furthermore, the forecast estimates which change daily are different from long term variation hence forecasting has to done on day to day basis. With the value of load forecasting we can extrapolate the demand response of the plant. This data is helpful at various decision-making level in the higher operation processes within the organization. Some of the problems that are apparent due to lack of load forecasting is increased wastage of power in the plant, and unplanned system maintenance which ultimately lead to increased downtime and loss to the company. A standard operating procedure can be developed for load forecasting. These standard help in the mitigation of serious load fluctuation that are caused during peaks demands of the day potentially saving corers to the power suppliers in equipment and upgrades. By developing a demand response profile, it becomes informative to set an optimal baseline of the load requirement. This demand response profile can utilize by numerous stake holders such as the power system operators, municipal planners, etc. Distributed energy resources (DER) which basically constitute renewable energy generators such as solar farms or wind farms. DER's are seen as potential options for alternate source of power supply to reduce of the increased reliance on grid. Centralized grid system is expensive and generation of power through coal is environmentally hazardous. Hence the use of DER's, electric vehicles, and batteries the emissions can be bought to an acceptable level [2]. The use of PV solar and its increased adoption is discussed in [3-4]. These DER's rely on the load forecasting for efficient generation and transmission. They store energy in batteries and supply to the grid at the time of peak load requirement. The power generated at DER is also utilized locally to power the residents or electric vehicle charging stations. Load forecasting used at user level does not guarantee optimal power utilization while load forecasting used at DER show improved performance as discussed in [6]. The definition of load demand as explicated in [7] is the prediction of load demand in a particular area also called the load horizon. According to the time period load forecasting can be defined as short-, medium-, or long-term forecasting. Current research on load forecasting are finding increased adoption of machine learning algorithm such as support vector regression (SVR), principal component analysis (PCA) [8-20]. The constrain on these machine learning algorithms are mean absolute error (MAE) and mean absolute percentage error (MAPE). This paper discusses about the implementation of multi-kernel SVR for load forecasting. A model is developed and the performance is evaluated.

II. SUPPORT VECTOR REGRESSION FORMULATION

The input for load forecasting is taken as 'x_i'. with N dimensions where $i = 1,2..N$.
The learning methodology is chosen is statistical learning as implemented by Vapnik chervonenkis (VC) in [27] to develop the Support Vector Regression (SVR). The combination of generalized Support vector machine along with statistical learning helps in the creation of sparse matrix.

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The classifier can be optimized using the objective function below:

$$min\frac{1}{2}||w||^2 + C\sum_{i=1}^{N}\zeta_i$$

Where, ||w|| is the amplitude of normal vector coefficients, C is the positive defined trade-off parameter between model simplicity and classification error. ζ_i is the vector of the slack variable.

The constraints subject to,

$$y_i - w^T\varphi(x_i) \leq \varepsilon + \xi_i^* \quad i = 1 \ldots..N$$
$$w^T\varphi(x_i) - y_i \leq \varepsilon + \xi_i \quad i = 1 \ldots..N$$
$$\xi_i \quad , \xi_i^* \geq 0 \quad i = 1 \ldots \ldots N$$

Where is the slack variable to guard against outliers. The Lagrange multipliers, or dual variables, are, and are nonnegative real numbers. is the threshold value that defines the margin between the hyperplane with the support vector. The normal vector is defined by the equation:

$$w = \sum_{i=1}^{N_{SV}}(a_i - a_i^*)k(x_i, x)$$

Where the kernel function is defined as:

$$k(x_i, x) = \varphi(x_i).\varphi(x)k(x_i, x) = \varphi(x_i).\varphi(x)$$

Using multi-kernel to finding the transformation is carried out by adding multiple kernels or mixing multiple kernels using the equation below.

$$\sum_{i=1}^{\infty}\phi(x_i).\phi(x)\sum_{i=1}^{\infty}\phi(x_i)\phi(x)$$

The constants like $\xi_i \quad , \xi_i^*\xi_i \quad , \xi_i^*$ and $\alpha, \alpha^*\alpha, \alpha^*$ are optimized to map the objective function on the input output curve fitting.

Training Phase:

The primary purpose of the Demand response is to improve the grid risk that is posed during peak period. The approach to ensure safety is compute the load baseline. This is one of the challenges in the implementation of the DR program i.e. the computation of the load baseline. The non-linear mapping of the input data on the load forecasting using multi kernel is the approach of training the model. The variables that are input to the model include humidity, temperature, day of the week, current power usage, and historical data of the similar parameter at similar days of the year.

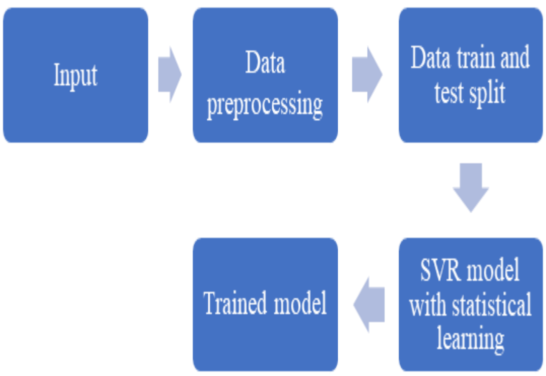

Figure II.1Training flow

The incoming data is first preprocessed to remove outliers and also to remove transients. The data is then split into parts, one part is taken as the training data points and the other is taken as the test data point. The model is first trained in the training data points and later the accuracy and fit is check using the test data point. The measure of the correctness of the model is difference in error between the model and the test data points. The parameter that is used is mean square error (MSE) or mean absolute percentage error (MAPE).

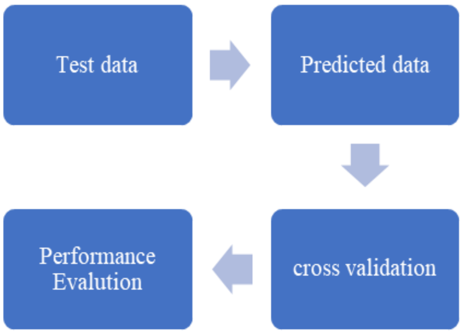

Figure II.2 Testing flow

The training of the model that was done using MKSVR is then feed with the future data to compute the load base line on hourly basis to get real time informatics.

III. RESULTS AND DISCUSSIONS

To verify the working of the model a short-term load forecasting was carried out. The inputs to the forecasting model along with the load output parameter is tabulated in the table given below,

Table.1 Input and Output Variables

SI	Input	Output
1	Previous day same hour load	
2	Previous week same hour load	Load of the specific day of testing
3	Average of last 24 hour load	
4	Working or non-working day considering the holidays	
5	Hour of the data	
6	Day of the week	

The histogram of the input data is given in the below figure and these data are trained with different hyperparameter values models. The code was developed in Python language to apply Load Forecasting for the input output pair that is mentioned in the Table 1. The training models are developed using the “MKLpy” toolbox where the multi-kernel is developed while “sklearn” toolbox is used to adopt the SVR model. In order to visualize the input data, a histogram is created using the input variables as mentioned in Table 1. The given below shows the histogram.

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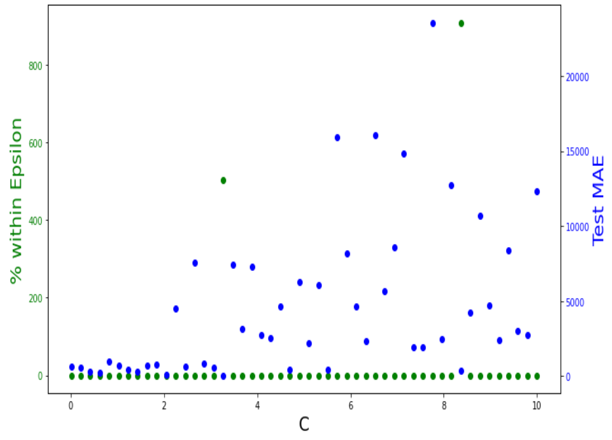

Figure 4. C, ε vs ε vs MAE

Constant C and ζ_i is optimized for the best MAE and MAPE. Formula of MAE is as defined is shown below:

$$\frac{\sum_{i=1}^{n}|y_i - x_i|}{n}$$

Where y_i is the prediction, x_i is the true value.
The formula for MAPE is shown below:

$$\frac{100}{n}\sum_{i=1}^{n}\frac{y_i - x_i}{y_i}$$

The values of C, ε ε and MAE is tabulated in the Table 2.

C	MAE	MAPE
0.5	2.2650714194016865	0.25176062321357795
1	2.48212565032939	0.2816567895339256
2	4.6868443372757245	0.40589642170913653
3	6.275930395532303	0.6803164465633526
4	5.68427413121331	0.5311408280293644
5	7.686513974483534	0.6477176555458856
6	9.056905365751218	0.8206941281890189

Table 2.C, MAE and MAPE

The Table 2 defines the MAPE that is obtained from the variable hyper-parameters (C) that is involved in the implementation The Table 2 infers that the MAE and MAPE is best for the C value with 0.5 value. Although the power shutdown that is there in the dataset is not considered as the shutdown there is a good regression performance for lower C values.

IV. CONCLUSION

In conclusion multi-kernel machine learning algorithm is implemented in load forecasting for estimate the demand response and computing the load power baseline for sugar industry. The tools used for implementing the machine learning algorithm were acquired from sklearn and MKL py. The model is developed on top of the multi-kernel form MKLpy libraries and SVR from sklearn library. The objective function of MAPE is observed for variable hyper-parameter. We have demonstrated that MKSVR performs satisfactorily and minimal error between observed data point and predicted data point. This is established through minimizing the error of MAPE objective function

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