SHORT TERM LOAD FORECASTING IN POWER SYSTEM USING MULTI-KERNEL SUPPORT VECTOR REGRESSION

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Abstract
Load Forecasting in power system is a power system planning application. The stochastic nature of the power system and load usage at different weather conditions needs advanced Load Forecasting methods. Modern learning algorithms and its performance improvement in regression supports robust forecasting. This paper is an attempt to exploit Multi-Kernel learning method in power system short term load forecasting. Humidity, temperature, day of the week, current power usage, previous day's average load, hour of the day, load at same time previous day, load from the same hour and same day from the previous week are the input data that is considered for forecasting the load. Data acquired from substation in Tumakuru a city in India is used for the proposed implementation. Data during the years 2014 till 2019 is used to check the Load Forecasting using Multi-Kernel Support Vector Regression (MKSVR) algorithm. Performance evaluation of the MKSVR algorithm on the basis of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) is observed in the implementation.
Keywords- Multi-kernel Learning, Support Vector Regression, Load Forecasting, Machine Learning, Power System Planning

I. INTRODUCTION

Load Forecasting is an integral part of power system planning. Power system expansion needs details about the additional load that is added to the power system in any level. Power plants respond to the demand thus reducing the peak load risk. Load Forecasting aids in regulating the demand response of the power plants. Load Forecasting is dependent on input parameters including humidity, temperature, day of the week, current power usage, previous day's average load, hour of the day, load at same time previous day, load from the same hour and same day from the previous week. If more input conditions are used better Load Forecasting can be attributed. Eventually a better demand response can be carried out. Having implications both technically and commercially Load Forecasting if not done properly leads to operation of the power system which is inefficient and unplanned in nature. Beneficial to both the consumers who need to know about their power availability and to utility companies which needs to maintain accuracy, this Load Forecasting is an important factor. The factors that involve the Load Forecasting are weather conditions, the pattern how people use their power. The adjustment for the forecasting has to be done every day by the operator.

An accurate practice has to be developed for the Load Forecasting. Safety in power supply that gets rid of the issues including the reduction in grid risk caused by higher peak load is controlled by the demand response. A baseline of the load is developed in the demand response application. Demand response baseline is created that acts as a resource for all the planners and the power system operators to respond to the demand variation in the load side. An accurate practice has to be developed for the Load Forecasting. Distributed Energy Resources (DERs) are energy sources that tend to generate, store and consume power since it has a bidirectional power flow from the source to the load and from load to the source. Photovoltaic (PV) power, battery storage and electric vehicles are few examples. Australia uses PV technology exclusively for the residential usage, with 1.8 million and above PV systems it accounts to a larger PV user in the residential areas [1]. With the use of the DER, electric vehicles and battery technologies the carbon emissions can be brought to an acceptable range by 2100 [2]. Discussion on PV penetration in future is discussed in detail in the publication [3-4]. DER coordination with the grid is developed and checked in Bruny Island, Tasmania using the optimal distributed resource penetration in the grid [5]. The peak shifting is implemented that shifts the peak of the grid by utilizing the distributed generator instead of the diesel generator. Although the Load Forecasting used in user level does not guarantee accurate forecast, while implementing in the grid with DER introduction, higher accuracy is an important desirable property [6].

For a particular planning horizon, the prediction of the load demand in a particular area is called the Load Forecasting [7]. An hourly prediction of load demand for the next 24 hours can be predicted by the Load Forecasting implemented for a 24-hour planning horizon. According to the period of the planning horizon the Load Forecasting is defined as short term, long term and medium-term load forecasting. Different machine learning techniques are utilized in [8-20] which has concentrated on objectives like the Mean Absolute Percentage Error (MAPE) to train the models. Support Vector Regression (SVR) is the extension of the Support Vector Machine (SVM) model. The SVM model is meant for the classification purpose while the SVR is for the regression purpose. SVR by Drucker et al. [21] is widely applied by different researchers [22-26] with MAPE as the objective function of regression. Support Vector Regression based Load Forecasting is developed in [27]. This paper implements Multi-Kernel SVR (MKSVR) as the tool to develop the model that is used to Load Forecasting and performance is evaluated.

I. FORMATTING YOUR PAPER

2.1. SVR Formulation

The input vector for the training the Load Forecasting is defined as x with N dimensions i=1…N. Vapnik-Chervonenkis (VC) or statistical learning theory as discussed in [27] is adopted in the SVR concept. Generalized form of the Support Vector Machine (SVM) with the kernel learning concept that develops the sparse matrix of kernel using the statistical learning algorithm is involved in Support Vector Regression. Load Forecasting being the non-linear mapping between the input vectors and the output targets the kernel learning is adopted. The input is mapped on the kernel space which is a higher dimensional space to the input variables. The primal formulation which is the kernel matrix is defined as k(xi , xj). The input features are transformed to the kernel space for orthogonality using the transformation defined as $\varphi(.)$. SVR is the generalization of the SVM algorithm. The formulation of SVR starts with the SVM algorithm where the features are adopted for the objective functions and constraints in the VC formulation. SVR uses the Kernel instead of the features and generalized to get the mapping. The formulation of SVR starts with the formulation of SVM algorithm as defined on Equation (1); this is a minimization objective function.

$$min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i + \xi_i^* \dots\dots\dots (1)$$

Where, $\|w\|$ is the amplitude of the normal vector to the surface that gets approximated after the optimization. C is the constant that is meant to reduce the error.

The constraints subject to,

$$y_i - w^T\varphi(x_i) \le \varepsilon + \xi_i^* \quad i = 1 \dots\dots N$$
$$w^T\varphi(x_i) - y_i \le \varepsilon + \xi_i \quad i = 1 \dots\dots N$$
$$\xi_i \quad , \xi_i^* \ge 0 \quad i = 1 \dots\dots N$$

Where ξ_i is the slack variable to guard against outliers. The Lagrange multipliers, or dual variables, are λ, λ^* and α, α^* are nonnegative real numbers. ε is the threshold value that defines the margin between the hyperplane with the support vector. The normal vector is defined as in equation (2).

$$w = \sum_{i=1}^{N_{SV}} (\alpha_i - \alpha_i^*) k(x_i, x) \dots\dots\dots (2)$$

Where the kernel function is defined as $k(x_i, x) = \varphi(x_i).\varphi(x)$. Using multi-kernel to finding the transformation is carried out by adding multiple kernels or mixing multiple kernels using the equation (3)

$\Sigma_{i=1}^{\infty}\varphi(x_i).\varphi(x)$…... (3)

The constants like ξ_i , ξ_i^* and α, α^* are optimized to map the objective function on the input output curve fitting.

2.2. Training Phase

Demand Response (DR) aims at improving the operation efficiency of power plants and grids, and it constitutes an effective means of reducing grid risk during peak periods to ensure the safety of power supplies. One key challenge related to DR is the calculation of load baselines. A fair and accurate baseline serves as useful information for resource planners and system operators who wish to implement DR programs. Baseline calculation for the Load Forecasting needs simple calculations to attain the forecasted load from the input data which includes weather and previous load characteristics.

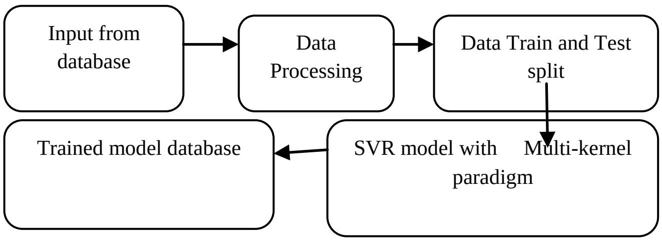

Figure 1. MKSVR Training Phase

This nonlinear mapping of the input data on the target is developed using machine learning algorithms. MKSVR algorithm applied in this paper is defined as training and testing phase. Humidity, temperature, day of the week, current power usage, previous day's average load, hour of the day, load at same time previous day, load from the same hour and same day from the previous week are the input data that is considered for forecasting the load. Figure 1 depicts the training phase of the MKSVR algorithm.

2.3. Testing Phase

Figure 2 depicts the testing the modeled MKSVR algorithm. The modeled MKSVR is the trained model that contains the trained hyperparameters.

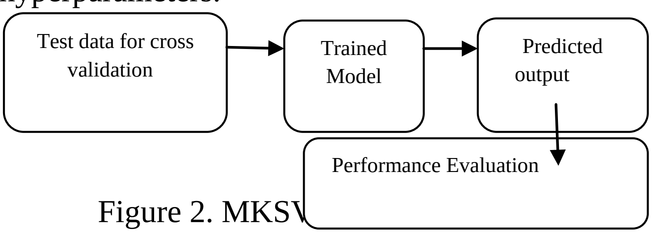

Figure 2. MKS

The modeled MKSVR model is mapped in such a way that the target which is the load in the next day in hourly basis. The prediction output thus developed is compared with the actual output for finding all the parameters that is needed for regression analysis.

III. RESULTS AND DISCUSSIONS

The short-term load forecasting implementation is carried out and the results obtained from the Multi-Kernel SVR and the performance is evaluated. The input that is generated to the training and testing of Load Forecasting implementation is as given in the following table.

Sl.	Inputs	Output
1	Previous Day Same hour Load	Load of the specified day of testing
2	Previous week same hour load	
3	Average of last 24 hours load	
4	Working or Non-Working Day considering the holidays)	
5	Hour of the data	
6	Day of the week	

Table 1. Input output pair used for load forecasting model.

The histogram of the input data is given in the below figure and these data are trained with different hyperparameter values models. Python based code is developed to apply the 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 the histogram of all the input variables mentioned in Table 1 is as shown in Figure 3.

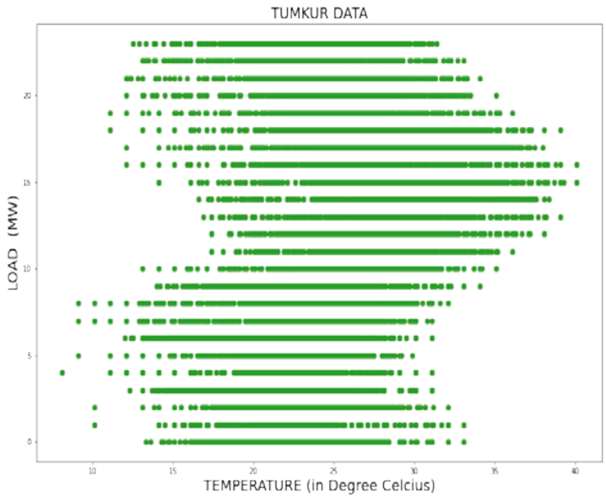

Figure 3. Temperature vs Load

Constant C and ε(Epsilon) that is optimized for the best MAE. Formula of MAE is as defined as given in figure 4.

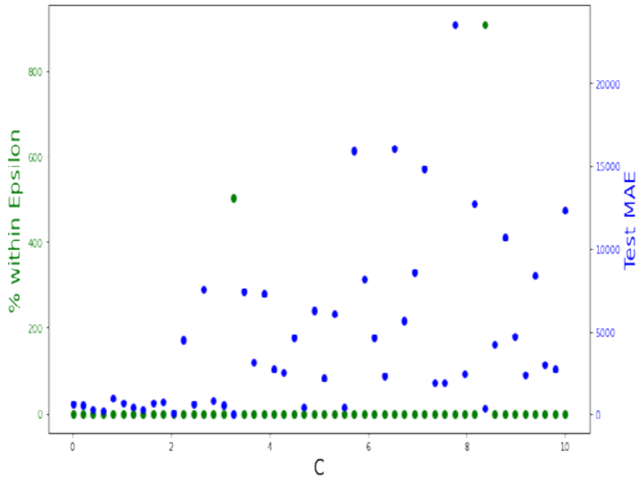

Figure 4. C, ε *vs* MAE

MAE and MAPE are defined as given. Actual and the predicted values are observed for different C and ε values. MAE is defined as the equation (4)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \ldots \ldots (4)$$

Where y_i is the actual target and $\hat{y}_i$ is the predicted target. MAPE is defined as in equation (5),

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{y_i} \ldots \ldots \ldots (5)$$

The values of C, 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	5.684274131213314	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. CONCLUSIONS

Multi-Kernel SVR is implemented on the Load Forecasting implementation with the substation in Tumakuru city. Python based implementation is carried out with the tool boxes including the sklearn and MKLpy. The multi-kernel is developed using the MKLpy toolbox while the SVR is implemented using the sklearn toolbox. The objective function of MAPE is observed for variable hyper-parameters and found that MKSVR performed satisfactorily in the implementation. Thus, the proposed MKSVR is found to be effective while checked for the MAPE performance is involved.

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