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Support Vector Machines (SVM) Based Short Term Electricity Load-Price Forecasting

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***Abstract*-- This paper presents a support vector machine based combined load – price short term forecasting algorithm. The algorithm is implemented as a classifier and predictor for both load and price values. The implicit relationship between price and load is modeled employing time series. A pre-classification technique is applied to reject the unwanted data before starting the process of the data using the proposed model. In the implemented model, support vector machine plays the role of a classifier and then acts as a forecasting model. Principle component analysis (PCA) and K nearest neighbor (Knn) points techniques are applied to reduce the number of entered data entry to the model. The model has been trained, tested and validated using data from, Pennsylvania-New Jersey-Maryland. The results obtained are presented and discussed.**

***Index Terms*—Deregulation, Electricity prices, load forecasting, Price forecasting, Support Vector Machines (SVM).**

I. Introduction

Forecarsting is a very crucial issue in the new construction of energy market, deregulated energy market. In the deregulated market, forecasting is divided into two parts; load and price forecasting. All types of forecasting are important for Planning (long term and short term) and operations. Long, middle, or short term forecasting are the different forecasting models based on time period. The scope of the daily market is the short term forecasting results. More than one element is committed to load and price forecasting such as: independent system operator, ISO, market engineers, and market dealers. Both load and price time series are hourly clarified and announced for the market. Other factors such as temperature and weather conditions are not easy to be determined or need some forecasting analysis. Therefore, it was encouraging finding another way to link time series, load and price series.

Price forecasting is a newly issued topic. Accordingly, it has been discussed using many techniques. An artificial neural network technique has been gathered 3 time series which are reflecting the market performance: system marginal price, system potential reserve, and system potential which are building a price forecasting model [1]. Dealing with time series, many theories tred to explain the link between the points in the same time series, one of these theories is defining the embedded dimension of the series. The embedded dimension concept has conducted based on Chaos theory [2]. With the implementation of this concept a price forecasting model has been achieved [2]. Still with Chaos implementation but from another prospective and with the help of wavelet analysis, a new forecasting model has been utilized [3].

Time series firstly was decomposed into different levels using wavelet analysis then secondly, according to lyapunov exponent each level had been forecasted then wavelet decomposed these levels to have the whole forecasted time series [3]. Decomposition levels of a time series is a tempting issue to be forecasted separately, with the help of ARIMA model. A forecasting model has been achieved using both wavelet and ARIMA model [4]. A new model has predicted the price error as a way to enhance the short term price forecasting model [5]. The target is to predict the market clearing price, MCP. The methodology is implementing not only the price model but also the confidence interval of such value using ARIMA model [5]. With the help of load data, wavelet technique has been applied to decompose the price time series into three levels; high, medium, and low levels according to their demands to facilitate the prediction for each level [6].

Both load and price data have been combined together in spike classification [7-9] and determination of the spike value with the help of classification technique. Many statistical classification techniques have been implemented such as naïve Bayesian classifier to find the probability of spike occurrence [7]. The aim of the research is to estimate the occurrence and the magnitude of price spikes [7]. Combining both price spike analysis with the normal price analysis, the complete model, was achieved. The prediction of spike occurrence part of the spike prices analysis has reached 100% efficiency in the proposed algorithm [7]. With the same SVM model and with same target as in [7], a model had been implemented to enhance the model performance in [7] by applying extreme learning machine, ELM [8]. With the assist of Data mining in price spikes classification, a new model has combined naïve Bayesian with data mining to relate the given data points to certain

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classes: abnormal high price, abnormal jump, and negative spike based on certain threshold [9].

In this paper, with the help of Pennsylvania-New Jersey-Maryland PJM data, an analysis of one day ahead price and load forecasting has been performed. A dynamic closed loop load-price model has been proposed to build a load price classifying and forecasting model with the help of SVM.

II. THE PROPOSED ALGORITHM

The proposed algorithm in this paper has been implemented to link both load and price forecasting models. For time series studies, the load or price at time, *t,* is related to a set of previous data points from the same time series with certain attitude. In this study, the number of previous points, which is related to the forecasted point, is selected from the set of data with the same spike indices.

A. Step1: Spike indices

Spike indices are to be calculated for both load and price time series. Previously in [7, 8], spike index was calculated to price time series only. In [7, 8], two methods have been employed to determine whether the point is over spike, under spike or normal trend. Both ways based on the mean and the standard deviation of the time series. As long as, the data could be refined, the forecasting model response can be enhanced. In this work, the indices are splitting the date into 6 categories as follow: 1 if the value is higher than $\mu + \sigma$, 2 if the value is between $\mu + \sigma$ and $\mu + 0.5\sigma$, 3 if the value is between $\mu + 0.5\sigma$ and μ, 4 if the value is between μ and $\mu - 0.5\sigma$, 5 if the value is between $\mu - 0.5\sigma$ and $\mu - \sigma$, or 6 if the value is less than $\mu - \sigma$.

B. Step2: Refined time series

The points to each category are selected based on the spike index. This process will be applied to both load and price time series. Then after selecting the related points, a feature selection and reduction techniques must be implemented. In this model, two classifying and filtering techniques are implemented; principle component analysis, PCA and K nearest neighbor points, Knn. PCA is analyzing the signal into its principle components. Then, certain threshold will be determined to select the effective components to reduce the selected data entry. The problem is that PCA works like low pass filter. Knn will relate the output of the model to the average of the K points of the previously selected points using PCA. The selection of K points is based on trial and error.

C. Step3: Normalization

Due to different types of observations, all observations will be normalized from 0 to 1. Therefore, these observations will have a mean of 0 and standard deviation of 1. In engineering term, it is like transferring the problem into per unit values, to neglect the effect of different units and types.

D. Step4: SVM *classifying model*

In order to select certain points having the same spike index to forecast a coming point having the same trend, SVM will be employed as a classifier to determine the value of the spike index for both load and price of the forecasted point. The classifying model is based on finding the hyper-plane which separates the data into two indices 1, or -1, if classification is binary or hyper-planes if classification is multiclass.

E. Step5: SVM *forecasting model*

SVM forecasting model is completing the model after finding the hyper plane by entering a new parameter *ε,* where ε represents adding certain error around the hyper plane, to split the plane into three areas, inside, above, and under the intensive tube to locate the feature space point in one of these three areas. The three areas are illustrated as shown in Figure 1.

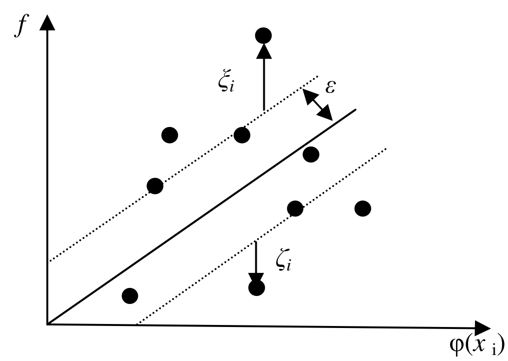

Figure 1 The topology of the feature space

One of the main factors affecting the SVM model is the determination of the kernel and its parameters. Kernel is responsible of remapping the input data to transfer it into feature space points. As consequences, distance between points is a property of the data set. Thus, one of the best kernels to be functionalized is the radial basis function with its parameter *σ* would be better to be very small to enhance the output performance. The mathematical model of the SVM model is based on optimization problem to find the Lagrange multipliers which are called support vectors. The mathematical model is presented in the Eqs(1-5).

$$f = \langle \omega x \rangle + b \tag{1}$$

Optimization Formulation

Minimize

$$\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i^2 + \zeta_i^2) \tag{2}$$

Subject to

$$(\langle \omega . x_i \rangle + b) - y_i \le \varepsilon + \xi_i, i = 1,\dots\dots, l \tag{3}$$

$$y_i - (\langle \omega . x_i \rangle + b) \le \varepsilon + \zeta_i, i = 1,\dots\dots, l \tag{4}$$

$$\xi_i, \zeta_i \geq 0, i = 1, \ldots, l \quad (5)$$

Where

f is the hyper-plane function

x the input data set to the model.

ω is vector perpendicular to the plane.

b is a variable scanning the space.

y_i is the output of SVM, load or price.

ξ_i is a positive slack variable. This means that the point is above the hyper-plane

ζ_i is a negative slack variable. This means that the point is below the hyper-plane.

The proposed algorithm consists of four steps as described and illustrated in Figure 2:

1. Classifying each time series, load, price according to their spike index.
2. To train the model, select the points of the training set with the same index to forecast the target point.
3. Initially, forecasting load and price series given the load and price values of the selected points.
4. Having the output of step three to be the input for the forecasted model in step four.

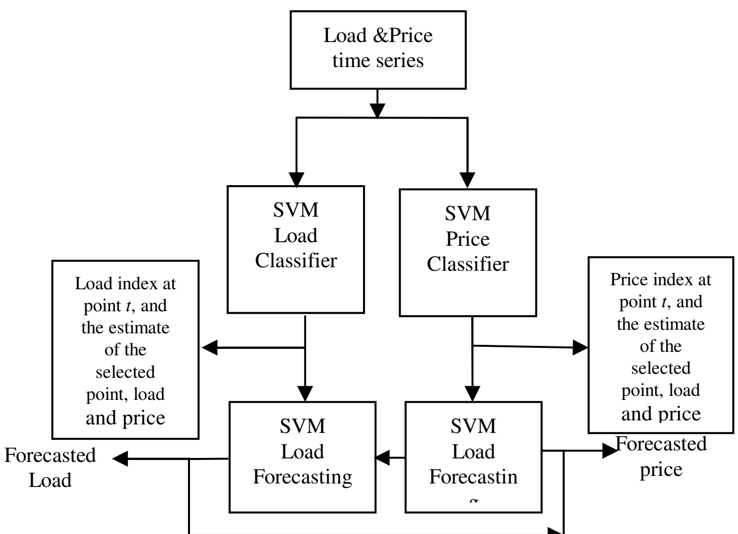

Fig 2 The proposed model

SVM model has three free parameters which are controlling its performance, ε, σ, and C where C is the regularization parameter [10]. The values of these parameters differ from a case study to another. A new SVM, ν-SVM, model has been proposed in [11] conducted another variable ν which is optimizing the number of support vectors points. ν is controlling over ε. Cross validation is utilized to determine the best parameters used to minimize the error between the actual and the forecasted values. To facilitate cross validation job, C, ν, and σ will be previously defined and leaving cross validation to determine the best ε. All machines learning algorithms have been applied using SPIDER software which is operated using MATLAB.

III. Results and simulation

Pennsylvania-New Jersey-Maryland, PJM, is a very well known electricity market in United State. The Hourly historical data contains load demand in MWH and price data, Regional Reference Price, RRP $/MWH. The available full detailed data which are used in this work is obtained from March 1997 to April 1998 [12].

In the proposed algorithm, some parameters must be determined previously such as SVM free parameters, K for Knn, and the number of previous points in the load and price time series. SVM free parameters are set to: C = 10000, σ = 0.0001, ν = 1 and ε will be determined using cross validation. Trial and error is to be utilized to determine K and the appropriate number of the previous points.

In the proposed model, time series are considered to be the load or price values in hour, *t,* throughout the whole year. The evaluation of the proposed model is based on MAPE which is described in Eq. (6).

$$MAPE = \frac{1}{n} \sum_{l=0}^{n} \frac{|forecasted_l - actual_l|}{actual_l} * 100\ \% \quad (6).$$

Where

$MAPE$ is the mean absolute percentage error.

$actual_l$ is the actual load or price value at point l.

$forcasted_l$ is the forecasted load or price value at point l.

n is the number of the forecasted point in the set.

Tables 1,2 show the load and price, actual and forecasted, and their MAPE%, for PJM 1998. The forecasted 24 forecasted hour, is shown in Table 1 for Monday 26 of January, 1998, working day. Table 2 shows the 12 forecasted hours for Sunday 29 of March, as a day off.

From the shown results, the model proved its efficiency in load forecasting for working day or off day with error equals to 1.3847 %, 3.7345% for off day, and with price forecasting error equals to 2.3805% given load and price time series only. The coming results are conducted form the same proposed model which is applied for the whole data set without differentiation between working days or off days and for all types of seasons.

Table 1 A PJM sample of 24 forecasted hours in a working day

Hour	$LOAD_F*10^4$	$LOAD_A*10^4$	$MAEP_L$	$PRICE_F$	$PRICE_A$	$MAEP_P$
1	2.4452	2.4446	0.0941	11.2000	11.1000	0.9010
2	2.3657	2.3975	1.3263	11.4000	11.4000	0
3	2.4612	2.4613	0.0041	12.7000	12.6000	0.7937
4	2.3657	2.3975	1.3263	11.4000	11.4000	0
5	2.4775	2.4718	0.2306	12.8000	12.7000	0.7874
6	2.5804	2.7088	4.7393	13.1001	13.1000	0.0006
7	2.9251	3.0982	5.5884	21.6000	19.8000	9.0909
8	3.4172	3.3542	1.8782	50.1000	50.1000	0
9	3.4146	3.4046	0.2938	16.8000	16.7000	0.5988
10	3.3267	3.3110	0.4742	19.4000	19.2000	1.0417
11	3.4132	3.3729	1.1948	18.5000	18.5000	0
12	3.1854	3.1756	0.3086	15.2000	15.5000	1.9355
13	3.1876	3.1896	0.0627	15.2000	15.8000	3.7975
14	3.1854	3.1756	0.3086	15.2000	15.5000	1.9355
15	3.2986	3.2598	1.1903	18.2000	18.9000	3.7037
16	3.4140	3.1049	1.9550	13.3000	13.6000	2.2059
17	3.2482	3.1796	2.5175	15.8000	14.0000	12.8571
18	3.4460	3.4195	0.1608	21.6000	23.6000	8.4746
19	3.5527	3.5195	0.6716	20.8000	21.8000	4.5872
20	3.4974	3.4834	1.7196	20.2000	20.5000	1.4634
21	3.3025	3.4328	1.8819	21.9000	23.2000	5.1948
22	3.1147	3.2680	1.0557	16.6000	16.7000	0.5988
23	3.4460	3.0029	3.7231	13.5000	13.5000	0
24	2.7437	2.7293	0.5276	12.7	12.9000	1.5504

$MAEP_P$ over 24hours= 2.3805%
$MAEP_L$ over 24hours= 1.3847%

Table 2 A PJM sample of 12 forecasted hour in a off day

Hour	$LOAD_F*10^4$	$LOAD_A*10^4$	$MAEP_L$
1	2.0456	2.0487	0.1495
2	1.8426	1.8790	1.9754
3	1.9136	1.8925	1.1032
4	1.8426	1.8790	1.9754
5	1.8467	1.8924	2.4744
6	1.8741	1.9502	4.0632
7	1.8903	2.0213	6.9311
8	1.9954	2.1775	9.1266
9	2.2200	2.3359	5.2207
10	2.3741	2.4746	4.2333
11	3.0674	3.1734	3.4547
12	2.4438	2.4969	2.1740

$MAEP_L$ over 12hours= 3.7345%

Where

$MAPE_P$ is the mean absolute percentage error for a price data point.
$MAPE_L$ is the mean absolute percentage error for a load data point.
$PRICE_A$ is the actual price value $/MWH.
$PRICE_F$ is the forecasted price value $/MWH.
$LOAD_A$ is the actual load value MWH.
$LOAD_F$ is the forecasted load value MWH.
$MAPE_P$ over 12hours is the mean absolute percentage price error over the 12 forecasted points.
$MAPE_L$ over 12hours is the mean absolute percentage load error over the 12 forecasted points.
$MAEP_P$ over 24hours is the mean absolute percentage price error over the 24 forecasted points.
$MAEP_L$ over 24hours is the mean absolute percentage load error over the 24 forecasted points.

IV. CONCLUSION

In this paper, an algorithm based on pre-classification and combined with SVM is presented to predict the load and price values based on their time series only. The algorithm is dynamic closed loop which changes its parameters based on the new data entry. Very important indices, load and price spike index, have affected the selection of the trained data. With the same parameters, many samples have been validated and tested under different conditions. The model outputs show good results. For future work, there will be different model with different pre-classifying techniques for each predicted hour.

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