Electricity Price Modeling Using Support Vector Machines by Considering Oil and Natural Gas Price Impacts

Ali Shiri[‡], Mohammad Afshar[§], Ashkan Rahimi-Kian[‡] and Behrouz Maham[‡]
[‡]SNL/CIPCE, School of Electrical and Computer Engineering, College of Engineering,
University of Tehran, Tehran, Iran.
Email: {ali.shiri, arkian, bmaham@ut.ac.ir}
[§] Mapna Groups, Tehran, Iran
Email: {afshar_mo@mapnagroup.com}

***Abstract*—Accurate electricity price prediction is one of the most important parts of decision making for electricity market participants to make reasonable competing strategies. Support Vector Machine (SVM) is a novel algorithm based on a predictive modeling method and a powerful classification method in machine learning and data mining. Most of SVM-based and non-SVM-based models ignore other important factors in the electricity price dynamics and electricity price models are built regard to just historical electricity prices; However, electricity price has a strong correlation with other variables like oil and natural gas price. In this paper, single SVM model is used to combine diverse influential variables as 1-Historical Electricity Price of Germany 2-GASPOOL price as first natural gas reference price 3-Net-Connect-Germany (NCG) price as second natural gas reference price 4- West Texas Intermediate (WTI) daily price as US oil benchmark. The simulation results show that using oil and natural gas prices can improve SVM model prediction ability compared to the SVM models built on mere historical electricity price.**

Keywords*—*Electricity Price Market, Electricity Price Forecasting, Electricity Price modeling, Support Vector Machines(SVM).

I. Introduction

After emancipation of electricity market in most of countries, electricity price inconstancy has an important role in production planning. Also, with the development of electricity market, electricity price prediction became a crucial parameter in such competitive markets [1]. Electricity price could be modeled by complicated time series. There are different essential factors that can affect the electricity price like high instability in supply and demand equilibrium, fuel sources price and seasonal patterns.

Under this deregulated environment, there are diverse methods to forecast the electricity price. These methods use conventional time series with historical data and statistical characteristics like ARIMA and GARCH approach, regardless of other effective factors [2]–[4]. These models are mostly used for short-term forecasting. One shortcoming of these models is that they ignore other factors that might affect the electricity price. For example electricity price and Natural Gas price have positive correlation but the price dynamics are not necessarily the same. So electricity price may show some new behavior because of some fundamental changes in natural gas dynamics. These changes cant be modeled by simple time series which dont incorporate other variables. The advantage of customary approaches such as linear regression and exponential smoothing is their minimum computations but the most significant disadvantage is their difficulty to deal with non-linear pattern in power systems [5].

Another method which is used for long-term forecasting by forward curves is delta-hedging. One of the advantages of this method is the value of generation plans to forward prices [6].

Artificial Neural Network (ANN) is a frequent forecasting technique of electricity price [7], [8]. However, artificial neural network has intrinsic restitution, for instance when the data is out of training sample, the error is extremely large; thus, it has limited generalization capability and uncontrolled convergence [9]. Another method for Next-Day electricity price prediction using the stochastic characteristic of the electricity price time series is based on Hidden Markov Model (HMM) which, its efficiency is higher than ANN method considerably [10].

Due to lots of electricity price dynamics, there are diverse models of forecasting. Temperature is one of these factors that can affect the market widely. The weather affects on spot trade volume that is a derivative of demand. Temperature effects change from season to season and it has the most effects in fall and spring when the heating system status is highly sensitive to temperature [11].

In deregulated markets, classification and data mining method like Support Vector Machine (SVM) based on time series is more robust and reliable compared to traditional approach and neural networks. SVM requires less training time and by using optimized threshold functions represents better forecasting results in comparison with ANN [12].

In this paper, we propose a novel approach in using SVM by including other significant variables such as oil and natural gas price to the model according to the past prices. The remainder of this paper is organized as follows: Section II provides a brief overview on Support Vector Machine Model and its parameters. Then, we illustrate the details of proposed methodology in section III. In section IV, we describe the results and effectiveness of the proposed Algorithm by numerical simulations. Finally, section V concludes the paper.

II. Support Vector Machine

Support vector machine is a new and promising technique for data classification and regression [13]. In fact by using Support Vector machine, we can achieve an excellent classification of data which we can use it later for prediction. The SVM problem can easily finds a line in two dimensions that has the most distance from points which we call Support Vectors. The basic idea is to do an optimization in which we can maximize the distance between support vectors. This is shown in figure 1. In this figure, the distance between the dotted lines is [13]:

$$\frac{|\alpha-\beta|}{||\omega||^2} \tag{1}$$

So by putting $\alpha = b - \varepsilon$ and $\beta = b + \varepsilon$, then the optimization problem will be:

$$\text{minimize}\frac{1}{2}||\omega||^2 \tag{2}$$

$$\text{subject to}:\begin{cases} y_i - \omega'\chi_i - b \leq \varepsilon \\ \omega'\chi_i + b - y_i \leq \varepsilon \end{cases} \tag{3}$$

This is for feasible convex programming. As it is not always the case, we can introduce slack variables ξ_i and ${\xi_i}^*$ and then we can reach to the optimization problem as below [14]:

$$\text{minimize}\frac{1}{2}||\omega||^2 + C\sum\begin{matrix} l \\ i=1\end{matrix}\ (\xi_i + {\xi_i}^*) \tag{4}$$

$$\text{subject to}:\begin{cases} y_i - \omega'\chi_i - b \leq \varepsilon + \xi \\ \omega'\chi_i + b - y_i \leq \varepsilon + \xi_i \\ \xi_i \text{ and } {\xi_i}^* \geq 0 \end{cases} \tag{5}$$

Where C is the regularized constant determining the trade-off between the empirical error and the regularization term [15] and ξ is the upper training error and ${\xi_i}^*$ is the lower [12]. Furthermore, in most of the cases, the linear dividing line or hyper plane cant be found in training data as points with different mixed characteristics. So in some cases we need a transforming function to change the shape of data so that we can separate them linearly. In this case, we will have the optimization problem on transformed data [16].

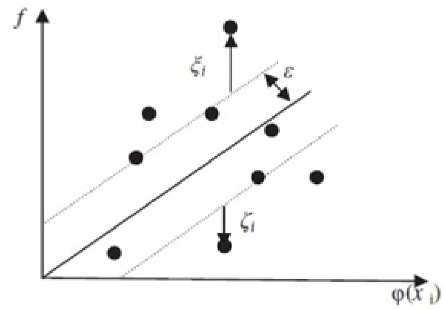

Fig. 1. The topology of the feature space [14]

III. Methodology

Our method is to incorporate advantages of SVM as well as taking various influential variables on electricity price in a single model according to our case study based on Germany electricity price. For this reason, we have a pool of variables which are supposed to have the most influence on electricity price of Germany. These variables are: 1-German Base-Load Electricity Price 2-GASPOOL daily price as first gas reference price 3-Net-Connect-Germany (NCG) daily price as second gas reference price 4-West Texas Intermediate (WTI) daily price as US oil benchmark. We will use daily prices and we didnt make any special adjustment to data for each time series.

Without any assumption about the influence of each variable, we ran the SVM model on different combination of these variables as well as electricity price. A part of sample time is selected as estimation period. After that each of them is ranked according to their out-of-sample prediction performance that is measured by Mean Square Error (MSE). The model with the lowest MSE has the best prediction capability. In this way, we have 16 different combinations of variables including a model in which we just have electricity price.

The studied time is from first of 2010 till end of 2012; Furthermore, at the last two weeks of 2012, the electricity price went negative deeply for three days that is a rare event. Actually negative price in electricity market is due to the high cost of shut down in some power plants like atomic power plants, thus the owner prefers to sell the electricity with negative price rather than paying the cost of a restart. Though this event is really rare, Germany experienced it at the end of 2012.In this way we encounter two different cases for negative and positive prices. So we will have two models. The training period of first model starts from first of Jan. 2010 till 3th of Dec. 2012 and the prediction period is for two weeks and it starts from 4th of Dec. 2012 till 17th of Dec. 2012. This model doesnt contain those negative prices and shows the power and efficiency of model in normal situation and it is called 2012a. Figure 2 shows model 1 graphically.

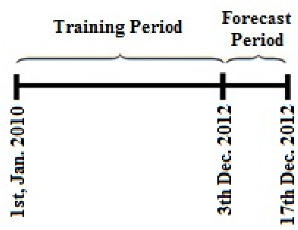

Fig. 2. Model 1 time period

In the second model, the training period is from first of Jan. 2010 till 17th of Dec. 2012 and the prediction period is for two weeks after that, which is from 18th of Dec. 2012 till 31th of Dec. 2012 and it is called 2012b. In this period, the last two weeks of Dec. 2012 experienced negative electricity price rate and it is a particular case study of prediction. Figure 4 shows model 2 graphically.

Totally in these two models, we will have 16 different modes, 8 modes in each group. The first 8 modes are used to find the best model in normal situation and the second 8 modes are used to find the best model at the time of strong negative shocks to the electricity price and also assessing the ability of SVM model to predict such shocks. Figure 3 indicates the simple structure of model.

Our model has two parts. One part is training in which model parameters and kernel function are determined, and in next part which is the prediction part, the model uses the output of training process to forecast the future price. In this paper, radial basis function (RBF) is chosen as the kernel function that would be encountered with less numerical difficulties than polynomials kernel and sigmoid kernel. Its formula is as follows:

$$k(x_i, x) = \exp\left(-\frac{|x_i - x_j|}{2a^2}\right) \tag{6}$$

All the original data have been normalized using the following formula:

$$X_{ij} = \frac{m_{ij} - \min(m_j)}{\max(m_j) - \min(m_j)} \tag{7}$$

The normalized data have been used in model to predict new data, and in the end of process, the predicted data will be denormalized to main data.

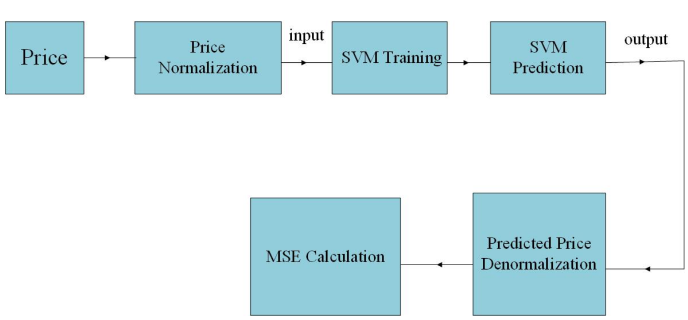

Fig. 3. The structure of proposed model

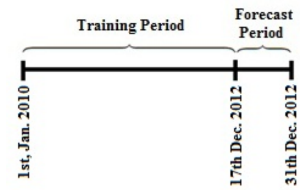

Fig. 4. Model 2 time period

Through the training SVM model, suitable parameters are selected properly to get a good model, so we can determine the proper normalized values for 2012a as following:$C = 1$, $\sigma^2 = 0.03125$ and $\varepsilon = 0.05$. Also these normalized values for 2012b are $C = 0.5495$, $\sigma^2 = 1$ and $\varepsilon = 0.01$

IV. Simulation Results

In this study by considering German electricity price, daily reference price of natural gas (NCG), daily reference price of Natural GASPOOL and WTI spot price as input data for modeling and calculation, following results have been achieved.

In our modeling, we used both Cross-Correlation and Auto-Correlation for time series in order to find the best time lags for prediction. We tested these two correlations for both positive and negative electricity price and discovered that using the information of one day lag cannot estimate well in SVM model and needs more than one lag. Simulation shows that in the time of positive electricity price we should consider the correlations of electricity price for 6 intervals of seven days. It means that we should use the information of first day, 7th day, 14th day, 21th day, 28th day, 35th day and 42th day lag before prediction day. This condition is indefeasible for negative electricity price but it needs 4 intervals of seven days and it will be continued till 28th day lag before prediction day. Also, we used pool of inputs in training period frequently and found best results of other lags for NCG, GASPOOL and WTI.

The simulation results are based on both modes of positive and negative electricity price and it is called 2012a for positive and 2012b for negative.

Mean Square Error (MSE) is the basis of our collation. Mean square error has been calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y_i})^2 \tag{8}$$

Table 1 shows the combination of explained variables as well as electricity price. Simulation results show that taking advantage of WTI data is more beneficial than the other parameters. In the case which electricity spot price and WTI information is used to predict the electricity price, Mean Square Error (MSE) has the lowest value. Therefore by using these parameters simultaneously, we will have the best electricity price prediction. It should be noted that negative electricity price is a rare event in the world and due to this, there is a lack of information about that event; so, SVM

TABLE I. COMBINATION RESULTS OF VARIOUS PARAMETERS FOR PREDICTION

	Spot price	NCG	GASPOOL	WTI	MSE
Input Lags			*2012a*		
	1,7,14,21,28,35,42	-	-	-	44.5005
	1,7,14,21,28,35,42	1,2		-	40.8446
	1,7,14,21,28,35,42	-	1,2	-	38.809
	1,7,14,21,28,35,42	1,2,7	1,2,7	-	39.7895
	1,7,14,21,28,35,42	**-**	**1,2**	**1,2**	**38.0211**
	1,7,14,21,28,35,42	-	1,2	1,2	39.5046
	1,7,14,21,28,35,42	1,2	-	1,2	39.5317
	1,7,14,21,28,35,42	1	1	1	39.6464
			2012b		
	1,7,14,21,28	-	-	-	969.009
	1,7,14,21,28	1,2	-	-	990.9719
	1,7,14,21,28	-	1,2	-	999.7683
	1,7,14,21,28	1,2	1,2,3	-	996.4356
	1,7,14,21,28	**-**	**-**	**1,2,3**	**737.514**
	1,7,14,21,28	-	1,2,3	1,2,3	759.5717
	1,7,14,21,28	1,2,3	-	1,2,3	762.6222
	1,7,14,21,28	1	1	1,2,3	762.9656

model cannot predict electricity price as well as common situation of electricity network and the value of MSE is somehow higher than normal situation. Figure 5 and 6 show deviations between predicted electricity price value and real price. According to MSE values, best results are for electricity spot price and WTI combination. In order to show the power of proposed model, the comparison results between SVM and Artificial Neural Network (ANN) are shown in Table 2. From the results of comparison, it is obvious that SVM algorithm has better prediction accuracy than ANN, the prediction ability of SVM model is remarkably stronger than ANN and it has lower error in its prediction. Thus it is proved that SVM model has superiority in electricity price prediction and its estimated values are closer and more accurate to real data than ANN. As mentioned in methodology section, negative price is a rare event and prediction in this mode has some difficulties due to lack of information for training period. According to MSE formula, square of real(negative) and estimated value(positive)differences is high in this mode; So, MSE criterion for 2012b is high.

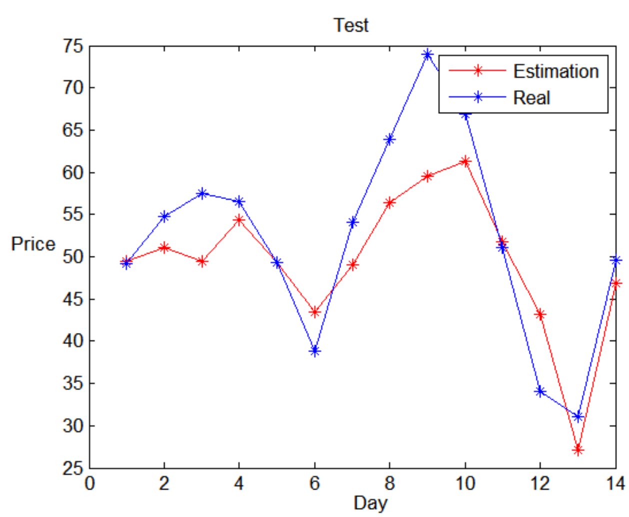

Fig. 5. 2012a - Germany electricity spot price prediction considering historical data and WTI

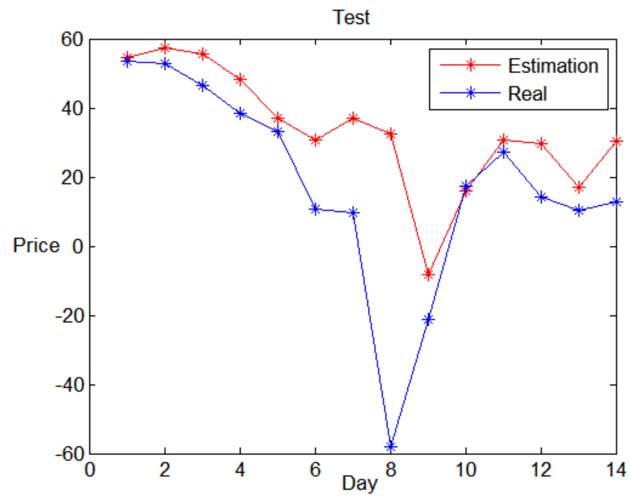

Fig. 6. 2012b - Germany electricity spot price prediction considering historical data and WTI

TABLE II. COMPARISON OF THE FORECASTING RESULTS BETWEEN SVM AND ANN MODELS

SVM	ANN
2012a	
38.0211	45.3853
2012b	
737.514	2435.07

V. CONCLUSION

There are many effective parameters in electricity market that can change the strategies of producers. In this study, support vector machine is used to forecast electricity price based on the combination of these various deterministic parameters in electricity market like oil and gas prices. Simulations show that one of the effective parameters in electricity market is West Texas Intermediate (WTI) daily price as US oil benchmark. We found that forecasting the daily electricity price is relevant to the correlation of last electricity and WTI daily prices and by considering these two parameters in prediction modeling, we will have more accurate prediction. Precise prediction of electricity price can help private electricity markets in decision making and future strategies of production.

REFERENCES

[1] F. J. Nogales, J. Contreras, A. J. Conejo, and R. Espínola, "Forecasting next-day electricity prices by time series models," *Power Systems, IEEE Transactions on*, vol. 17, no. 2, pp. 342–348, 2002.

[2] J. Contreras, R. Espinola, F. J. Nogales, and A. J. Conejo, "Arima models to predict next-day electricity prices," *Power Systems, IEEE Transactions on*, vol. 18, no. 3, pp. 1014–1020, 2003.

[3] R. C. Garcia, J. Contreras, M. Van Akkeren, and J. B. C. Garcia, "A garch forecasting model to predict day-ahead electricity prices," *Power Systems, IEEE Transactions on*, vol. 20, no. 2, pp. 867–874, 2005.

[4] M. ZENG, Y.-l. ZHAO, and J. ZHANG, "Electricity price forecasting methods combining arima and garch with confidence intervals," *East China Electric Power*, vol. 36, no. 12, pp. 1–5, 2008.

[5] W. Sun, J.-c. Lu, Y.-J. He, and J.-q. Li, "Application of neural network model combining information entropy and ant colony clustering theory for short-term load forecasting," in *Machine Learning and Cybernetics, 2005. Proceedings of 2005 International Conference on*, vol. 8. IEEE, 2005, pp. 4645–4650.

[6] M. Povh and S.-E. Fleten, "Modeling long-term electricity forward prices," *Power Systems, IEEE Transactions on*, vol. 24, no. 4, pp. 1649–1656, 2009.

[7] R. Gareta, L. M. Romeo, and A. Gil, "Forecasting of electricity prices with neural networks," *Energy Conversion and Management*, vol. 47, no. 13, pp. 1770–1778, 2006.

[8] H. Yamin, S. Shahidehpour, and Z. Li, "Adaptive short-term electricity price forecasting using artificial neural networks in the restructured power markets," *International journal of electrical power & energy systems*, vol. 26, no. 8, pp. 571–581, 2004.

[9] L. Tian and A. Noore, "A novel approach for short-term load forecasting using support vector machines," *International Journal of Neural Systems*, vol. 14, no. 05, pp. 329–335, 2004.

[10] J. Zhang, J. Wang, R. Wang, and G. Hou, "Forecasting next-day electricity prices with hidden markov models," in *2010 5th IEEE Conference on Industrial Electronics and Applications*, 2010, pp. 1736–1740.

[11] G. Caro, M. Hildmann, and D. Daly, "A quantitative analysis of weather effects on traded volume in the swiss energy spot market," in *European Energy Market (EEM), 2012 9th International Conference on the*. IEEE, 2012, pp. 1–6.

[12] W. Sun, J.-C. Lu, and M. Meng, "Application of time series based svm model on next-day electricity price forecasting under deregulated power market," in *Machine Learning and Cybernetics, 2006 International Conference on*. IEEE, 2006, pp. 2373–2378.

[13] V. N. Vapnik and V. Vapnik, *Statistical learning theory*. Wiley New York, 1998, vol. 1.

[14] R. Swief, Y. Hegazy, T. Abdel-Salam, and M. Bader, "Support vector machines (svm) based short term electricity load-price forecasting," in *PowerTech, 2009 IEEE Bucharest*. IEEE, 2009, pp. 1–5.

[15] L. Jinying and L. Jinchao, "Next-day electricity price forecasting based on support vector machines and data mining technology," in *Control Conference, 2008. CCC 2008. 27th Chinese*. IEEE, 2008, pp. 630–633.

[16] N. Cristianini and J. Shawe-Taylor, *An introduction to support vector machines and other kernel-based learning methods*. Cambridge university press, 2000.