Short-Term Price Forecasting Considering Distributed Generation in the Price-Sensitive Environment of Smart Grids

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Abstract— **In smart grids environment, all participants, including different load types, are able to utilize the network. Advances in measurement tools in these networks make it easy to move towards dynamic pricing and non-fixed electricity tariffs. In this environment, the forecasted electricity price is declared to wholesale and retail consumers via Advanced Measurement Instruments (AMI). Therefore, motivated by different factors such as optimizing the economic/environmental issues or increasing the reliability, the customers are able to react to prices and manage their consumption. This pattern of reaction brings about extensive changes in the load and price curves of the network. On the other hand, environmental concerns resulting from the use of fossil fuels have increased the exploitation of renewable energies. But, as the penetration of renewable energy sources increases, serious improvements and modifications for the existing electric grid are needed to accommodate and integrate these intermittent sources. In this paper, a hybrid model is presented for simultaneous short term forecasting of electricity prices considering Distributed Generation (DG) in the price-sensitive environment of smart grids. The proposed model combines the Support Vector Regression (SVR) network with an Adaptive Neuro Fuzzy Inference System (ANFIS) network, and it is capable of tracking customers' reaction to declared prices. This model is applied on the data of power markets of Nordpool regrion, Denmark, where the smart grids are very active. The results of short term price forecasting for a target day (1/1/2016) shows the accuracy of the model.**

Keywords- adaptive neuro fuzzy inference system; distributed generation; price-sensitive; short-term price forecasting; smart grids.

I. INTRODUCTION

Due to the uncertain nature of electricity price in the competitive market, the participants in the market forecast the price for their utilization and scheduling activities. Examples of these activities include short term scheduling, setting short-term and long-term strategies and contracts, scheduled maintenance and development planning [1]. In the existing power markets, the demand side is mostly inelastic with the minimum participation of customers. It is expected that in presence of smart grids, this elasticity will be changed [2,3]. Customers' awareness of the existing load and price in smart grids causes them to change their consumption pattern according to the prices. In addition, it is expected that the utilization of advanced tools such as storage devices in smart grids will be increased. Using storage devices sometimes might change the role of the end load from energy consumer to energy producer [4-6].

In papers published about electricity price forecasting so far, it has been assumed that the consumption patterns of demand side do not have significant changes according to the forecasted prices, and therefore, the forecasted prices remain safe against customers' reactions [7,8]. In the price-sensitive environment of smart grids, however, it is expected that the customers on the demand side change their consumption pattern according to the forecasted prices.

Various methods have been presented for short-term price and load forecasting in power markets. The existing literature about price forecasting is mostly based on a unidirectional relationship between the load and the price. In other words, in a forecasting system, it is assumed that the future load forecast at the target hour is fairly correct. Then, these forecasts are used as the inputs of the forecasting models [9].

To respond to electrical load requirements of customers, excessive utilization of fossil fuels for energy production has led to the reduction of non-renewable energy resources and has increased environmental pollution. In these circumstances, renewable energy, especially solar PV and wind, is a promising option for electricity generation as they are clean energy sources and are now mature technologies. Today, the integration of renewable energy sources into smart grid system is increasingly gaining importance and widely studied by many researchers [10,11]. Integrating renewable energy sources into the smart grid system enables the cost reduction of sources required for building extra generators, improves power quality and reliability and achieves the customer satisfaction [12]. However, distributed generation resources have widely penetrated these networks and the real time balancing of the demand and generation of power systems has become extremely complicated due to the variable nature of DGs.

In this paper, a bidirectional relationship is used to discover the dynamics of the load and price. This paper is different from

[13] and [14] because the bidirectional dependence of the price and demand has been considered in it.

The electricity price data of the power markets of Nordpool region, Denmark, in year 2015-2016 is used in this research [15]. DGs have penetrated into this market and the demand side costumers are informed of the forecasted future load and price on an hourly basis and are able to manage their consumption.

The remainder of this paper is organized as follows: in section 2, problem description is discussed. In section 3, the proposed model is explained in details. Simulation results are presented in section 4. Finally, section 5 concludes the paper.

II. PROBLEM DESCRIPTION

The reaction of customers to the forecasted price has been considered only in a small number of papers published so far [4]. The reaction of customers to the forecasted price brings about significant changes in the demand pattern of the target day, which consequently, causes the price of electricity to change. The main reason that a unidirectional relationship has been used in conventional load and price forecasting techniques is the low elasticity of the load with respect to the electricity price. With the development of smart grids, the electric load tends to change its conventional inelastic behavior to a price-sensitive one. In such an environment, using a bidirectional relationship for load and price forecasting will be possible and it seems necessary to consider the mutual impact of these two factors [4].

Generally, the load is considered as the key of electricity price and has been reported as the input of many price-forecasting models. The effect of this input on improving the accuracy of price and load is more obvious in the interactive environment. On the other hand, distributed generation resources, which are considered as key elements in the future of smart grids, are expected to be widely present in these networks. As a clean energy resource, DGs can be used for solving environmental problems by decreasing greenhouse gases. Along with the many benefits of utilization of renewable energy, the most important challenge in using DGs is their variable nature. In power markets with high penetration of DGs, it is necessary to consider the effect of these generations on the spot price.

DG producers usually bid close to price floor of electricity markets and act as price-takers [16]. Thus, DG Owners bid their products among the bids from low cost units which form the bottom of the supply curve. Therefore, adding wind power to the system results in shifting the supply curve to the right [17]. Hence, large-scale integration of wind power into electricity grids affects the electricity market prices [18]. The impact of wind power on electricity prices is shown in Fig. 1. As depicted in this figure, for the demand curve, i.e., Q, increasing wind power causes the shift of supply curve from S_1 to S_2 and thus decreasing the electricity price from P_1 to P_2. Electricity demand is considered to be sensitive to electricity prices in Fig. 1, and hence, shifting supply curve changes demand level from D_1 to D_2. Nevertheless, shifting supply curve because of wind power penetration leads in reducing electricity prices even with inelastic demand. Same results have been found in simulation-based approach [16, 19] and historical data approach [20].

Fig. 2 shows the hourly electricity price and wind generated power of Nordpool spot market zone, Denmark, where 28% of electricity demand is supplied through wind turbines, for the three consecutive days (31/12/2015, 1/1/2016 and 2/1/2016).

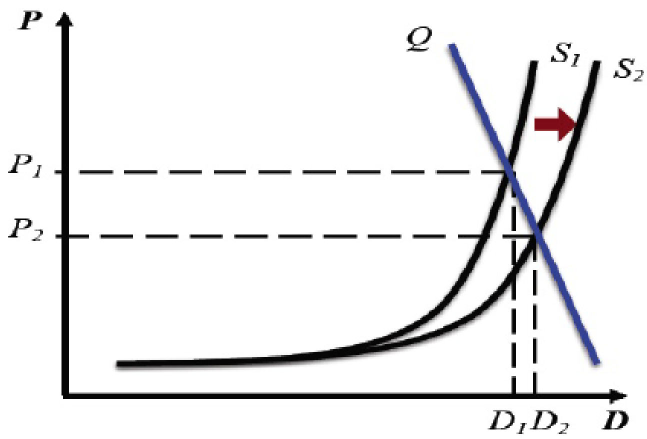

Figure 1. The impact of wind power on electricity prices [20]

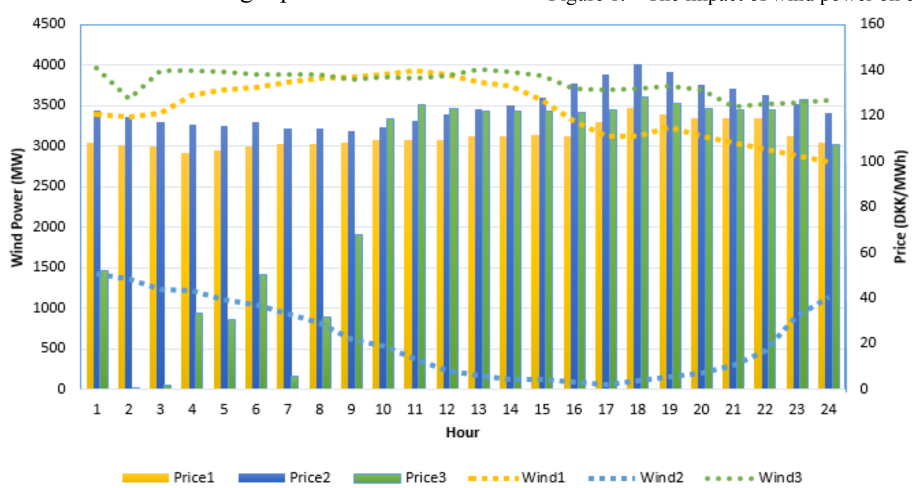

Figure 2. Hourly electricity price and wind generated power of Nordpool spot market zone for the three consecutive days (31/12/2015, 1/1/2016 and 2/1/2016).

Despite the obvious high non-linearity of price in the market, a general downwards trend in price can be concluded when wind generated power increases. The correlation coefficient between price and wind power for these days are -0.56, -0.65 and -0.38, respectively. As it can be seen, the instantaneous wind power output has an inverse effect on prices, i.e. whenever the wind generation is high, the prices decrease. In other words, the significant effect of wind generation on the price of Nord Pool market in DK region is because of the high penetration of wind generation in the power system of the aforementioned region.

Therefore, in these markets, distributed generations can be considered as a negative load, which is subtracted from the total load of the network, and the result can be defined as the net or residual demand. The residual demand is the individual firm's demand, which is that portion of the market demand that is not supplied by other firms in the market. Therefore, the residual demand is defined by the following equation [20]:

$$RD_t = D_t - DG_t \tag{1}$$

where, D_t is the electrical demand and DG_t is the distributed generation at the t^{th} hour.

III. The Proposed Model

In this section, a hybrid model is presented for forecasting the electricity price. This model combines a machine learning system with an ANFIS network.

So far, factors such as electrical load, hour indices, shadow prices, transmission constraints, load level of adjacent system, generation capacity, variable reserve systems, existing hydro generation, and the output of generation have been considered as the inputs of price forecasting models. Also, the past load data, the past and forecasted environmental changes (even humidity, temperature and so on) are generally used as the inputs of load forecasting models. Some papers use the different system data (received from Supervisory Control and Data Acquisition (SCADA) system), and instead of forecasting the sum of system loads, focus on load buses [21]. However, including the aforementioned inputs does not necessarily guarantee the higher accuracy of the results.

The proposed model is shown in Fig. 3. The model consists of three blocks, which are explained in details as follows.

A. *The Fuzzy C-Means (FCM) clustring algorithm*

Clustering is one of the unsupervised techniques and is an automatic process through which a certain data set is divided into a set of classes or clusters. The aim of data classification by using this kind of process is to separate the data in such a way that two data objects in a cluster are as similar as possible and two data objects in two different clusters are as distinct as possible. In this paper, one of the most successful clustering models, called FCM [22], is used.

In this model, each data is assigned to a cluster to a certain degree that is determined by a membership function. By creating membership functions, the FCM output helps in constructing fuzzy inference system for stating the fuzzy quality of each cluster. Through clustering, the input data is classified according to the load type (peak or off-peak), day type (weekday or weekend), DG penetration (high or low) and so on. In this paper, the historical price and residual demand data are classified by FCM and proper data is obtained for training the SVR network.

B. *The Support Vector Machin (SVM)*

The Support Vector Machine (SVM) is one of the supervised learning techniques which are used for classification and regression in recent years. Its strong mathematical foundation has caused it to exhibit excellent performance in time series forecasting and in classification [23, 24].

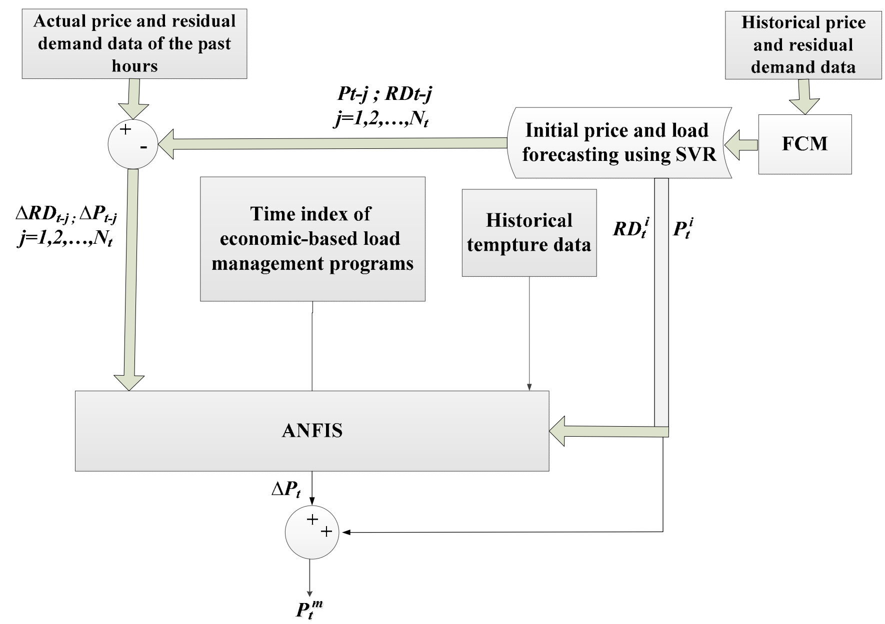

Figure 3. The proposed model

Compared to older methods, such as perceptron Neural Network (NN), this technique has shown great efficiency in short-term forecasting [21]. Its function is based on the statistical learning theory, which solves the problem of over-fitting, local optimal solution and low convergence rate existed in NN. When the subject of SVM is raised in regression problems, the idea of using Support Vector Regression (SVR) is raised too. In fact, the SVR is a generalization of the idea of SVM. This approach is used for curve fitting, time series forecasting and similar applications.

In this block, initial residual demand and price forecasting is carried out. Simultaneous use of net demand and price in this block causes the mutual impact of load and price to be tracked in this model. Therefore, the effect of elasticity and sensitivity of load and price are studied in order to extract the dynamics of the problem of forecasting the price in the price-sensitive environment of smart grids. In this block, SVR network is used for initial forecast of residual demand and price.

The classified RD_t and P_t data, which are obtained from FCM block, are simultaneously used as the inputs of this block. The output of this model is two sets of data. The first set is the initial forecast of price and residual demand for t^{th} target hour. The second set is the set of forecasted residual demand and price for the past N_t hours. The difference between the forecasted and actual prices and the difference between the forecasted and actual residual demands are calculated as follows:

$$\Delta P_t = P_t^a - P_t^f \tag{2}$$

$$\Delta RD_t = RD_t^a - RD_t^f \tag{3}$$

where, $P_t{}^f$ and $RD_t{}^f$ (for $t= 1, 2, ..., N_t$) are the forecasted price and residual demand for the past N_t hours, respectively. Also, $P_t{}^a$ and $RD_t{}^a$ (for $t= 1, 2, ..., N_t$) are actual price and residual demand for the past N_t hours.

C. Adaptive Neuro-Fuzzy Network (ANFIS)

This block contains the adaptive neuro-fuzzy system. An adaptive neuro-fuzzy network has advantages such as capability of learning, optimization and balancing. Whereas the fuzzy logic is a method based on if-then rules. In fact, ANFIS combines the advantages of using adaptive neural networks and fuzzy logic. In ANFIS, the inputs are estimated by means of input membership functions and then they enter the if-then rules where the value of output is determined [25]. Once all outputs are determined, they are multiplied in appropriate weights and are summed up to form a single output. Two types of membership functions that are widely used in ANFIS for load and price forecasting, are the Gaussian and Bell-shaped membership functions.

To extract the if-then rules, many inputs can track the reaction of costumers to the forecasted load. In this model, the past data of temperature, which is one of the effective factors on the demand of the system, is used. Furthermore, the demand response programs of the under-study power market are also used as the inputs of the ANFIS network. The demand response programs usually include two types of programs:

- Economic-based load management programs:

These programs, which are carried out based on the time-of-use (TOU) pricing, are common in most smart grids. The program is declared to the customers who are equipped with smart grid measurement tools. In this pricing system, weekdays are divided into three load levels; shoulder-peak, peak, and off-peak. Also, weekend and holidays are divided into two load levels; shoulder-peak and off-peak. So, in smart grids, customers who are equipped with smart grid measurement tools can change their consumed load range every half an hour, and by shifting their consumption from high price periods to low price periods, they can have a better economic operation .

- Reliability-based load management programs:

These programs are regulated based on the reliability of the system. They are declared to customers who are ready to reduce their consumption whenever the reliability of the system is threatened. For example, the reserved system data could be used in the proposed model as an 'if' rule in determining the if-then rules in order to consider the reliability of the under-study smart grid.

IV. Numerical Studies And Simulations

Based on the discussion presented in previous section, in order to forecast the initial residual demand and price, the data of the past 1440 hours is used in this model for training the SVR network to forecast the t^{th} target hour. This is done recursively for the future 24 hours.

To extract the if-then rules, after a large number of experiments, the forecast is carried out for 4 weeks before the target hour. The length of this period is selected based on short-term and long-term tendencies. Therefore, $N_t = 672$.

Based on available data, the following inputs are used in the proposed model for extracting the if-then rules and for training the ANFIS model:

- Time index of economic-based load management programs,
- The temperature data for the past N_t hours,
- P_t^i and RD_t^i for the past N_t hours.

In this case, the ANFIS network extracts those rules that include the extensive changes in the price-sensitive behavior of the customers. These rules show how load and price will change in response to the reaction of customers to the forecasted prices.

The ANFIS network forecast is carried out by using the Guassian membership function. In addition, the number of membership functions selected for the 4 aforementioned inputs are 5, 3, 5, and 5 respectively. Under these conditions, the ANFIS network classifies the input data based on the determined membership functions. Therefore, the input data (the forecasted price and residual demand, the residual demand and price changes, temperature, etc.) are classified based on their value. It should be mentioned that, for each hour t, a time index is selected based on the economic-based load management programs of each market.

The price in the price-sensitive environment of the smart grids are finally calculated by using the following equation:

$$P_t^m = P_t^i + \Delta P_t \tag{4}$$

where P_t^m is the modified price.

There are various indices for evaluating the efficiency of forecasting models. The most common indices are the mean absolute percentage error (MAPE), mean absolute error (MAE), forecast mean square error (FMSE), and the error variance (σ^2) which are calculated by the following equations:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|Act.MCP(t) - For.MCP(t)|}{Act.MCP(t)} \times 100 \tag{5}$$

$$MAE = \sum_{t=1}^{N}\frac{|Act.MCP(t) - For.MCP(t)|}{N} \tag{6}$$

$$FMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Act.MCP(t) - For.MCP(t))^2} \tag{7}$$

$$\sigma^2 = \frac{1}{N}\sum_{t=1}^{N}\left(\frac{Act.MCP(t) - For.MCP(t)}{\overline{Act.MCP(t)}} - \frac{MAPE}{100}\right)^2 \tag{8}$$

where, N is the number of hours, *Act._MCP(t)* is the actual market-clearing price at the hour t, *For._MCP(t)* is the forecasted market-clearing price at the hour t, and $\overline{Act.MCP(t)}$ is the average value of actual market-clearing price.

Application of the proposed model on the data of the power market of Nordpool, DK region

The Nord Pool power market is the biggest and the oldest power market in Europe since the 1990s. This market is active in four countries of Norway, Sweden, Finland and Denmark.

Denmark is a long-time leader in wind energy, and in May 2011 Denmark derived 3.1% of its gross domestic product from renewable (clean) energy technology and energy efficiency, or around €6.5 billion ($9.4 billion). Denmark is connected by electric transmission lines to other European countries. On 6 September 2012, Denmark launched the biggest wind turbine in the world, and will add four more over the next four years [15]. Denmark's electricity sector has integrated energy sources such as wind power into the national grid. Denmark now aims to focus on intelligent battery systems (V2G) and plug-in vehicles in the transport sector. The country is a member nation of the International Renewable Energy Agency (IRENA).

In this region, where the penetration of DGs (especially wind power) are higher than any other region in the world, customers instantaneously become aware of prices and are able to react to this factor. Because of high penetration of DGs in this region and because of the ability of the customers to generate locally during the times when the price is high, the data of aforementioned market is used in this paper for studying the short-term price forecasting.

The hourly electricity price of the Denmark region in Nordpool power market are forecasted. Fig. 4 shows the forecasted price curve of this market by the proposed model for the target day (1st of January in 2016). It is a holiday and the historical data, obtained from FCM clustering, must be used for forecasting this case. As it can be seen, the outcome of the proposed model has high accuracy in short-term forecasting of electricity price.

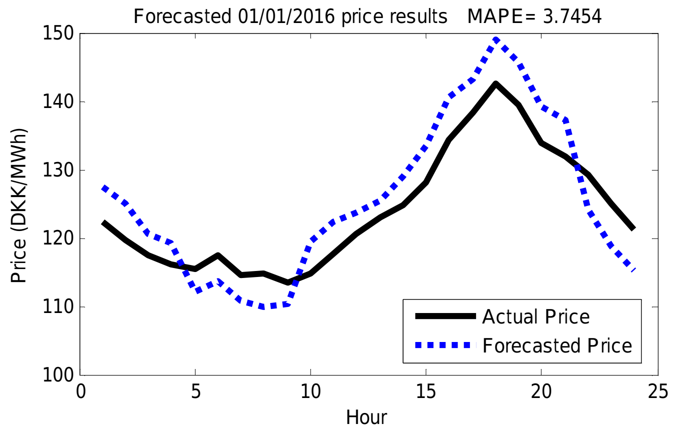

Figure 4. Price forecasting for the 1st of Jan. of 2016 in Nordpool electricity market region DK

In order to show the efficiency of this model, representative results of price forecasting for the year 2015 are provided in Table I. Monthly price forecasting results are reported to give a better insight of the overall forecasting results. MAPE, MAE, FMSE and σ^2 obtained for price's test data subset (i.e for year 2015) are also presented in Table I. The obtained results are surprisingly very good with minimum MAPE of 2.38% and Standard Deviation of 3.42%. The highest MAPE of 13.62% is obtained in September.

V. Conclusion

The main feature of a smart grid is the full-automatic delivery of electrical power, which could establish a bi-directional flow of electricity and information between different equipment of the network and all the points between them. Therefore, in these networks customers are able to react to the fluctuations of electricity price. Modified load curve causes the initial forecasted prices to be different from the actual prices. On the other hand, The increasing installation of distributed renewable energy resources, emerging utility scale energy storage, rapid growth of plug-in hybrid electric vehicles, and the maturing demand response in the distribution systems bring unprecedented opportunities and challenges to utilities, end users, manufacturers, and other participants in distribution system operations. Under these circumstances, the real time balancing of the demand and generation of power systems and price forecasting has become extremely complicated due to the variable nature of DGs.

In this paper, the reaction of customers to the forecasted price has been considered, and then, a hybrid model is used for simultaneous short term forecasting of electricity price in the price-sensitive environment of smart grids. The main idea is to use the effect of elasticity and sensitivity of residual demand and price in order to extract the dynamics of the problem of price forecasting in smart grids.

TABLE I. RESULTS OF MONTHLY PRICE FORECASTING FOR THE YEAR 2015.

Month	MAPE [%]	MAE [%]	FMSE [%]	σ^2[%]
Jan.	2.97	3.23	4.89	0.0053
Feb.	4.54	4.21	5.54	0.004
March	3.65	5.68	8.02	0.105
April	7.32	5.08	7.05	0.0041
May	2.38	5.85	7.87	0.0055
June	8.12	4.65	5.92	0.0522
July	4.42	3.75	5.17	0.0034
Aug.	9.70	4.56	5.83	0.004
Sept.	13.62	4.61	5.97	0.0011
Oct.	10.05	5.43	7.27	0.0084
Nov.	6.21	4.93	6.72	0.0029
Dec.	4.03	2.69	4.53	0.0052
Std. Dev	**3.42**	**0.96**	**1.15**	**0.031051**

The proposed model, which is combining the SVR network with an ANFIS network, is applied on the data of power markets of Nordpool region DK, where the smart grids are very active and most of energy is produced from DGs. The forecasting results for a target day (1/1/2016) is investigated. The results of short term forecasting of the price signal show the capability of extracting the reaction of customers to the initial forecasted price and achieving the modified price curve. The inclusion of influencing factors (e.g. data of reserve market) for customers' response can lead to an efficient demand side management, and can improve the accuracy of forecasting results.

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