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Probabilistic day-ahead system marginal price forecasting with ANN for the Turkish electricity market

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Abstract: This study presents a system day-ahead hourly market clearing price forecasting tool for the day-ahead (DA) market and a system DA hourly marginal price forecasting tool for the real-time market of the Turkish electric market (TEM). These forecasting tools are developed based on artificial neural networks (ANNs). A series of historical price data of the TEM are utilized to model and optimize the ANN structure and to develop the ANN-based price forecasting tool. The methodology used to select the optimum ANN architecture provides the minimum daily mean absolute percentage error for both day-ahead market prices in the TEM. Performances of the proposed ANN model and the multiple linear regression model in forecasting the day-ahead hourly market clearing price are compared. The proposed ANN model is modified using volatility analysis and the Bienayme–Chebyshev inequality in order to forecast system marginal prices probabilistically within a lower and an upper boundary.

Key words: Artificial neural networks, electricity market, price forecasting, system marginal price

1. Introduction

In recent years, electricity price forecasting has become a very challenging area in electrical markets, and a considerable research effort has focused on this issue in order to find methods that estimate prices most accurately. Due to the nonlinear nature of the price mechanism, artificial neural networks (ANNs) have been frequently used rather than linear forecasting methods [1]. The high probability of volatility in wholesale electricity prices and trends that are generally nonuniform are a challenge when forecasting future prices using simple backpropagation feedforward ANNs [2]. The approach in this study is a simple but also very effective tool for forecasting problems since it has the ability to approximate any nonlinear function. Due to its data-driven properties, it is also able to solve problems where the input–output relationship is neither well defined nor easily computable [3–8]. According to the literature, the single hidden layer feed-forward network [9] is the most popular model for time series modeling and forecasting. This type of network has been frequently used to address the demand forecasting problem in electric networks [10,11]. Recently, ANN methodology has been utilized in dealing with the short-term price-forecasting problem as well as the demand forecast problem [12]. In [13], the authors propose an ANN model-based methodology in order to forecast weekly electricity prices in the PJM market. The superiority of the proposed model is demonstrated via extensive analysis conducted using data from the PJM interconnection. Szkuta et al. [14] present system marginal price (SMP) short-term

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forecasting implementation using the ANN computing technique. Historical SMP real-world data, acquired from the deregulated Victorian power system, were employed for training and testing the ANN.

The authors in [15] propose an ANN architecture with the premise that the electricity price profile for a given year can be assigned a structure that can then be related to the structure of the reference year, in such a way that a transformation can be found from the reference year's structure to the forecasting year's structure. The authors in [16] propose a technique to forecast day-ahead electricity prices based on the mean reverting process using a properly fitted model. Contreras et al. [17] implemented price forecasting using time series procedures, dynamic regression, and transfer function methodologies. Making use of neural networks, the main concern of the methodology presented in [18] was to find the maximum and minimum SMPs for a specific period with a certain confidence level.

Our study presents the development of a system day-ahead hourly market clearing price (SDAP) forecasting tool for the day-ahead market and a SMP price forecasting tool for the Turkish electric market (TEM). Both price forecasting tools are developed based on ANNs. A series of historical price data of TEM are utilized to model and optimize the ANN structure and to develop the ANN-based price forecasting tools. The methodology to select the optimum ANN architecture that provides the minimum daily mean absolute percentage error (DMAPE) for both day-ahead market prices in TEM is discussed. The performances of the proposed ANN model and the multiple linear regression (MLR) model are compared in terms of SDAP forecasting. The proposed ANN model is modified using volatility analysis and Bienayme–Chebyshev inequality in order to forecast SMP probabilistically within a lower and upper boundaries. This approach is the main contribution of the study.

2. Day-ahead market clearing price (MCP)

The methodology used to select the optimum ANN architecture for the SDAP forecasting problem in the TEM is presented in this section. In the study, hourly data of the TEM between 01/01/11 and 31/12/11 are utilized. Variations of the load and the price are shown in Figure 1. Typical low and high demand days are selected as the target forecasting days for assessing the performance of the proposed ANN architecture.

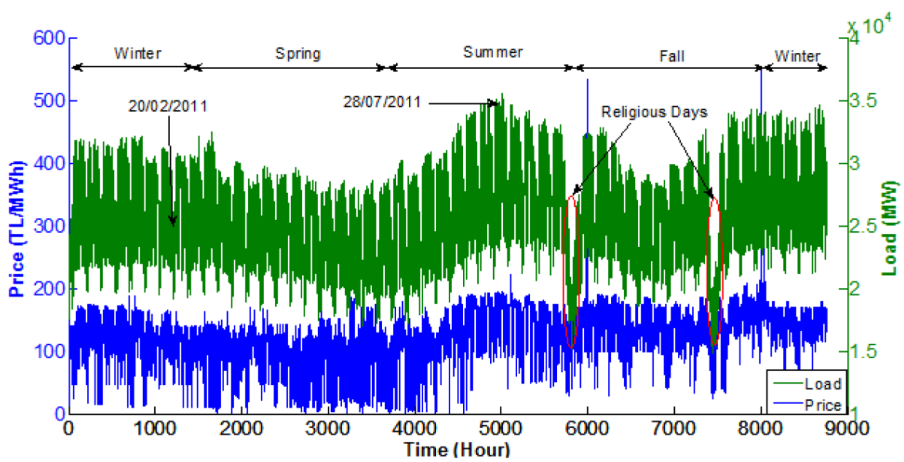

Figure 1. Load and price curves of the TEM from 01/01/11 to 31/12/11.

2.1. Training and transfer function selection

In order to select the most suitable training and transfer functions of the ANN day-ahead price forecasting for the TEM and to achieve minimum daily MAPE for the test sets, combinations of the following training functions of the MATLAB 2012a Neural Network Toolbox are considered: gradient descent with adaptive learning rate backpropagation (Traingda), Levenberg–Marquardt backpropagation (Trainlm), gradient descent with momentum and adaptive learning rate backpropagation (Traingdx), resilient backpropagation (Trainrp), and conjugate gradient backpropagation with Powell–Beale restarts (Traincgb). Due to its easily differentiable property permitting the evaluation of weight increments via the chain rule for partial derivatives used for gradient-based error minimization in backpropagation procedures [12], 'logsig' and 'tansig', which are the most widely used transfer functions in the literature, are employed for the transfer functions of the ANN in this study. In order to decrease error randomness, training and testing procedures are repeated 10 times for each case. The results for a typical winter day are given in Figure 2.

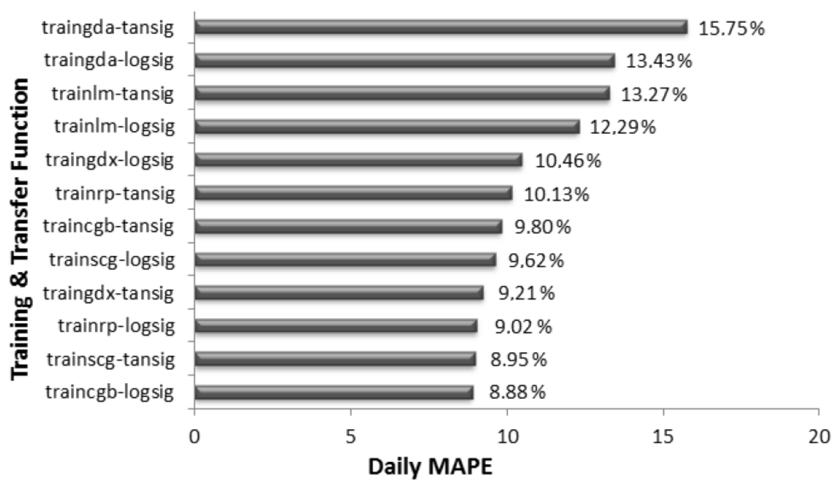

Figure 2. MAPE values of training and transfer function combinations for 20/02/11.

Figure 3 shows the load and price relationship for the forecasted, previous, and one-week period before days in February 2011, along with fitting curves and correlation coefficients. Although the regression results in Figure 3 correspond to a low degree of explainability (i.e. $R^2 = 0.57$), the main scope in this regression analysis is to observe the level of interrelation between demand and price values. The low R^2 value is indeed an indicator for the need to use heuristic approaches for price forecasting like the ANN proposed in this study.

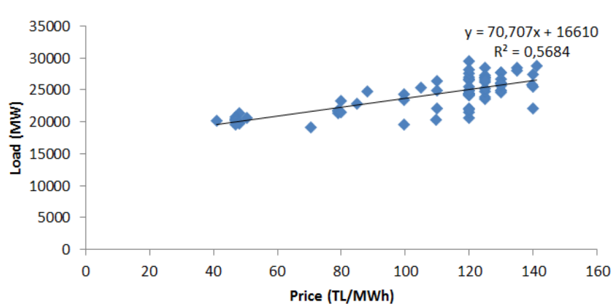

Figure 3. Load and price relationship for a typical three-day period in February of 2011.

2.2. Optimum ANN architecture

In general, increasing the number of hidden neurons improves the forecasting performance of ANNs. However, a further increase of hidden neurons deteriorates the forecasting performance due to the complicated interconnection structure and large number of synaptic weights that result in an overfitting of the ANN [1]. In this study, minimum DMAPE for a typical winter day is achieved when the ANN model has 15 hidden neurons, as illustrated in Figure 4. Accordingly, the architecture of the ANN, as presented in Figure 5, is considered to be a three-layered feed-forward with a 10-15-1 structure, meaning that the ANN consists of 10 input neurons, 15 neurons at the hidden layer, and 1 neuron at the output layer. This ANN architecture has been utilized successfully in short-term price forecasting studies [19]. Figures 6 and 7 present the price forecasting results.

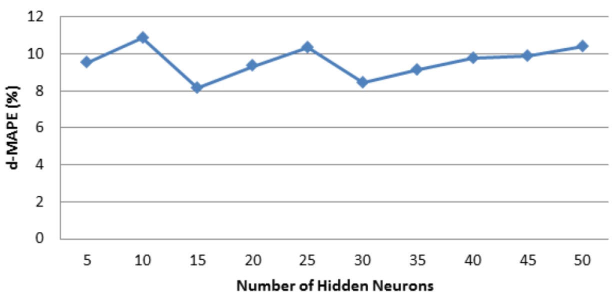

Figure 4. Impact of number of hidden neurons on DMAPE for a typical day in winter.

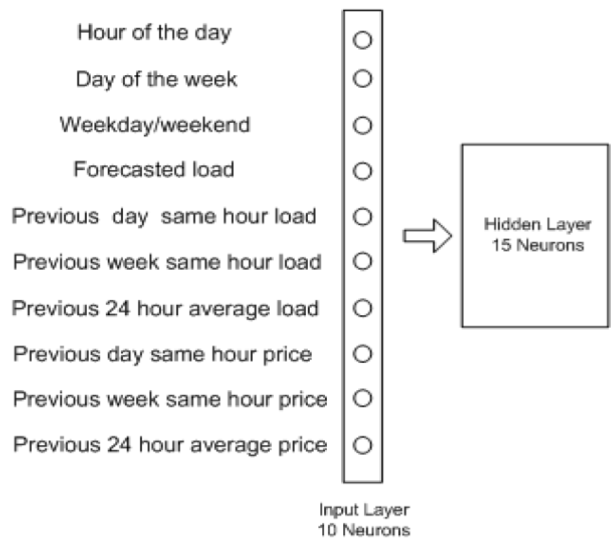

Figure 5. Proposed ANN model for SDAP forecasting.

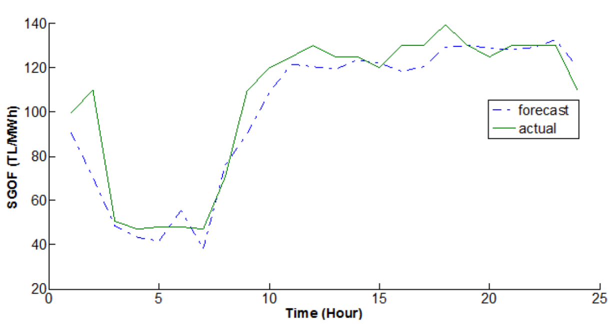

Figure 6. SDAP forecast for 20/02/11.

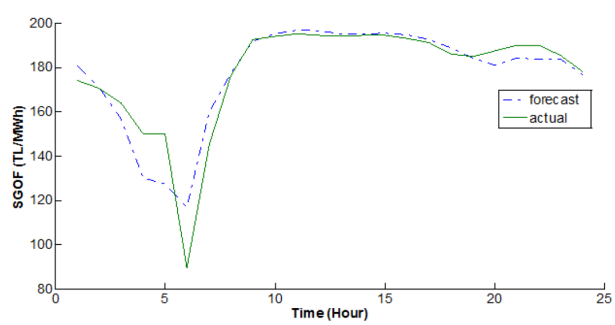

Figure 7. SDAP forecast for 28/07/11.

2.3. Application of the proposed ANN model

The proposed ANN model is applied to forecast the SDAP of the TEM for different days, such as week-ahead price forecasting during different seasons (winter, spring, summer, and autumn) of the year, weekdays, and weekend days. Table 1 represents the results for two different cases that reveal the impact of "type of the day" information. In Case 1, information about "type of day" (i.e., weekday or weekend) is not used as an input to the proposed ANN model. In Case 2, the “type of day” information is used as an input. Essentially, including the “type of day” information into the ANN model improves the forecasting performance. Since electricity prices on weekends are generally lower than that of weekdays due to the relatively lower demand training of the ANN model explicitly for weekends improve ANN performance [19].

Table 1. Impact of the “type of day” information on average MAPE.

Testing	Training	Average MAPE (%)	
		Case 1	Case 2
8 Aug (Monday)	4 July–7 Aug	9.09	8.53
9 Aug(Tuesday)	5 July–8 Aug	5.27	5.00
10 Aug (Wednesday)	6 July–9 Aug	3.57	3.26
11 Aug (Thursday)	7 July–10 Aug	11.97	11.66
12 Aug (Friday)	8 July–11 Aug	6.97	6.03
13–14 Aug (Weekend)	9 July–7 Aug	10.93	9.72

2.3.1. Seasonal effects

The performance of the proposed ANN model is checked for typical weeks in four seasons (i.e., winter, spring, summer, and autumn), as described below:

- The winter week is from 21 January to 27 January 2011 (testing set); the hourly data used to forecast this winter week are from 1 January to 20 January 2011 (training set).
- The spring week is from 6 April to 12 April 2011; the hourly data used to forecast this spring week are from 3 March to 5 April 2011.
- The summer week is from 25 July to 31 July 2011; the hourly data used to forecast this summer week are from 20 June to 24 July 2011.
- The fall week is from 13 September to 19 September 2011; the hourly data used to forecast this spring week are from 9 August to 12 September 2011.

In all four different periods, type of the day information is used as input to the ANN, both training and testing processes are repeated 10 times, and minimum, maximum, and an average MAPEs are obtained. Figures 8 and 9 show results for typical weeks in winter (maximum load period) and spring (minimum load period). The performance of the ANN model during the winter period is better than that of the spring period. When the load and price relationship in spring is investigated, it is observed that the load and price relationship shows a poor correlation for the training period and testing period when compared to the winter week. This correlation is illustrated in Figure 10. Table 2 presents the minimum, maximum, and average weekly MAPE values of the ANN-based week-ahead SDAP forecasting and MLR-based SDAP forecasting of the four weeks during the different seasons. Minimum MAPE value among 10 different training and test results is highest for the spring period (i.e. minimum MAPE is 11.76%). This result is obvious by comparing the regression analysis results of the spring period (Figure 10) and winter period (Figure 3). Correlation between the price and demand during the winter period is higher than that of the spring period. On the other hand, MAPE values during the fall period are 10% lower and less than that of the winter period. The main factor that differentiates the spring period from others could be the run-of-river hydraulic generators, whose generations depend on the water level. This essentially affects electricity prices during spring.

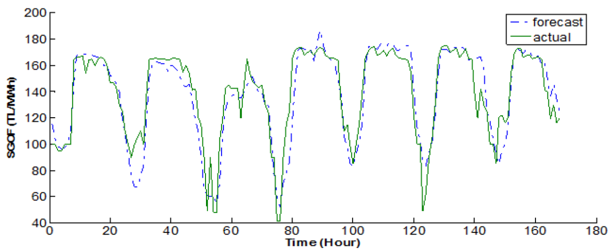

Figure 8. ANN-based SDAP forecast for a winter week (from 21/1/11 to 27/1/11).

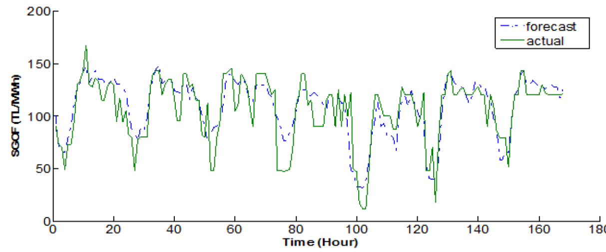

Figure 9. ANN-based SDAP forecast for a spring week (from 6/4/11 to 12/4/11).

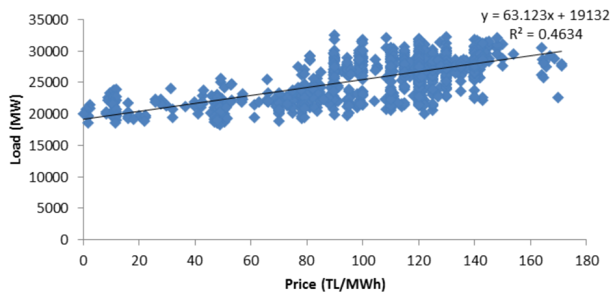

Figure 10. Load and price relationship from 2/3/11 to 12/4/11.

Table 2. Weekly MAPEs for week-ahead SDAP forecasting in different seasons.

Test week (2011)	Training period	Weekly MAPE (%)			
		ANN			MLR
		Min	Max	Average	Average
Winter: 21–27 Jan	1–20 Jan	7.10	9.13	8.12	9.14
Spring: 6–12 Apr	2 Mar– 5 Apr	11.76	14.22	12.08	12.88
Summer: 25–31 July	20 June–24 July	4.22	5.57	4.77	5.32
Fall: 13–19 Sept	9 Aug–12 Sept	5.29	9.17	7.69	7.82

The forecasting performance of the ANN model is better than that of the MLR in all of the seasonal weeks. This result is important, given the fact the ANN develops more accurate input–output relationships than the MLR due to its ability to capture nonlinear input–output mapping.

2.3.2. Price spikes

A preprocessor is added before the proposed price forecast approach in order to limit the price spike effects [1]. Figure 11 presents actual prices from 13/1/12 to 1/3/12 with price spikes. In preprocessing, if a price at the training set is higher than an upper limit, it will be set to that upper limit. The price profile of the TEM during 2011 shows that prices are lower than 200 TL/MWh unless power generation shortage occurs. Therefore, 200 TL/MWh is determined as the upper limit in this study. Figure 12 shows the price curve with preprocessing. The performance of the preprocessor approach is checked between 17/2 and 23/2. The hourly data used to forecast this week are from 13/1 to 16/2. Without any preprocessing, the average weekly MAPE for this week is 58.44% due to price spikes in the training data set, as illustrated in Figure 13. After the preprocessing, the average weekly MAPE is reduced to 6.43%, as illustrated in Figure 14. The forecasting performance is greatly improved by preprocessing the price spikes.

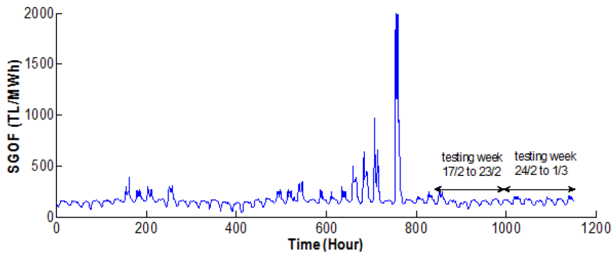

Figure 11. SDAP curve from 13/1/12 to 1/3/12 without preprocessing.

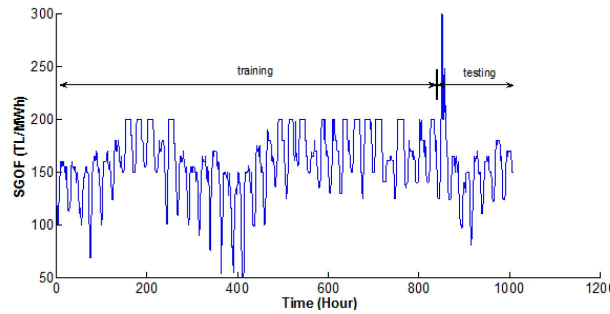

Figure 12. SDAP curve from 13/1/12 to 23/2/11 with preprocessing.

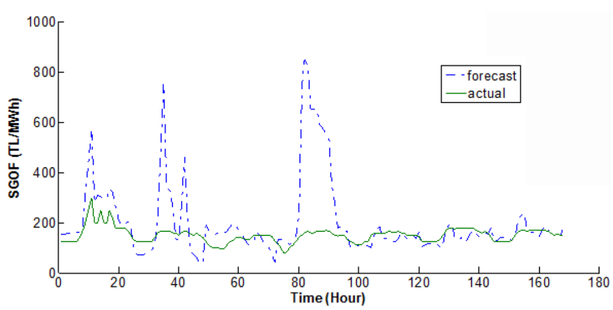

Figure 13. Week-ahead SDAP forecasting (17/2–23/2) without preprocessing.

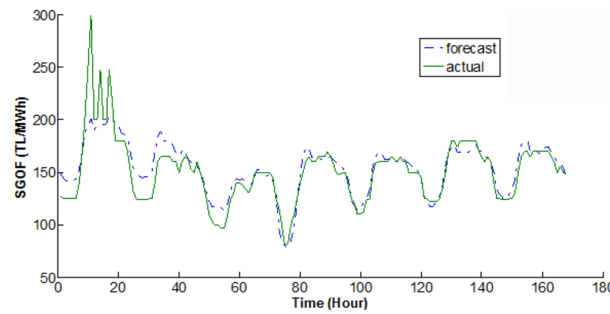

Figure 14. Week-ahead SDAP forecasting (17/2–23/2) with preprocessing.

3. System marginal price forecast

The computation of the SMP in markets where dual price mechanism is in effect is much more complicated than the SDAP since the SMP is related to real-time balancing of supply and demand in the system; therefore, it depends on unpredictable events such as congestion and generation outages that affect the evaluation of the SMP. Generally, information related to transmission congestion (or generator outages) and the SMP is not publicly available. The price planners should utilize publicly available information such as upward/downward regulation orders and system direction (i.e., generation surplus or deficit) to forecast the SMP. When the model already developed for system day-ahead MCP is utilized in forecasting the SMP, it is observed that MAPE values for the SMP price forecasts are much higher than those of the SDAP. Essentially, the model developed for SDAP forecasting should be revised for SMP forecasting, and new input parameters should be added to the proposed model in order to improve the forecasting performance.

The SMP in the TEM is related to system constraints and real-time balancing of supply and demand in the entire system. If there is an energy deficit in the system, generators starting from the lowest bid are ordered to increase their generation, and the SMP becomes greater than the SDAP. If there is an energy surplus, generators starting from the highest bid are ordered to decrease their generation, and the SMP becomes lower than the SDAP. Congestions in the system are also relaxed by increase/decrease orders to the generators that also result in the SMP values becoming higher than SDAP values given the fact that the bid for generation increase should be higher than the bid for generation decrease. If there is no energy deficit or surplus and no transmission constraints, the system is balanced, and the SMP is equal to the SDAP that was determined in the day-ahead market. Therefore, there is a correlation between the SMP, SDAP, system direction, and the amount of imbalances known as net volume of the instruction (NVI). Since NVI already includes system direction information (i.e., a positive NVI value means system direction with an energy deficit, a negative NVI value means system direction with an energy surplus, and a zero NVI value equals system balance), system direction information may not be used as an input parameter of the ANN.

3.1. Input parameters for SMP forecasting

In order to develop a proper ANN model for SMP forecasting, appropriate input parameters have to be reconsidered. Table 3 presents four models with factors that are considered in studying the impact of input vectors. Corresponding forecasting performances in terms of MAPEs are given in Table 4. As Table 4 shows, if the historical SDAP information is considered as input to the ANN (i.e., Model 2), the forecasting performance improves. Moreover, historical NVI information further improves the performance (i.e., Model 3). The best result is obtained when the NVI forecast is considered as an additional input to the ANN. This result is quite reasonable since the SMP highly depends on the amount of NVI. Essentially, NVI forecast information significantly improves price forecasting performance. Therefore, in this ANN model, day-ahead forecasting of the NVI is the most critical factor.

Table 3. Input factors considered in different model types for SMP forecasting.

Factors	M1	M2	M3	M4
Historical load	√	√	√	√
Forecasted load	√	√	√	√
Historical SMP	√	√	√	√
Historical SDAP		√	√	√
Forecasted SDAP	√	√	√	√
Historical NVI			√	√
Forecasted NVI				√

Table 4. Weekly MAPEs for week-ahead SMP forecasting with different models.

Test week	Average weekly MAPE (%)			
	M1	M2	M3	M4
Winter: 7/1–13/1/12	10.09	9.46	9.21	7.07
Spring: 11/5–17/5/12	19.73	18.97	18.60	12.00
Summer: 11/6–17/6/12	17.11	14.13	13.71	10.48

3.2. NVI forecasting

Since NVI is due to unexpected system imbalances in real-time system operation and occurs in case of imbalances such as energy deficit, energy surplus, congestion, or generation outages, NVI forecasting is a challenging task. The complexity of NVI forecasting is due to the number of influential random factors and the lack of information about some of these factors. Nevertheless, the most appropriate input parameters that are correlated with NVI should be determined. The correlation coefficient method is an approach that is utilized in order to understand the relationship between variables [20]. The correlation coefficient r is a measure of the strength and the direction of the relationship between two variables (x and y), as illustrated in (1), where n is the number of data pairs.

$$r = \frac{n * \sum x * y - (\sum x) * (\sum y)}{\sqrt{n * (\sum x^2) - (\sum x)^2} \sqrt{n * (\sum y^2) - (\sum y)^2}} \tag{1}$$

The value of r ranges from –1 to 1 and is a measure for determining how certain predictions can be made from a certain model. If x and y have strong positive correlation, r is close to 1. A correlation coefficient close to zero means that there is a random relationship between two variables. A correlation less than 0.5 is generally described as weak. The correlation coefficients between NVI and other variables are shown in Table 5. According to the results, it can be concluded that NVI is poorly correlated with the SDAP, while there is a strong correlation between NVI and other variables. This result is reasonable because NVI is related with real-time system balancing, and so the value of SDAP does not have a significant effect on the NVI value. However, variables such as SMP, delta, and system direction occur in the real-time balancing market, and the values of these variables show strong correlation with NVI values.

Table 5. Correlation coefficients of NVI.

Correlation pairs		Correlation coefficient (r)
NVI	Load	0.61
	SDAP	0.36
	SMP	0.67
	Delta = SMP–SDAP	0.74
	System Direction	0.75

A positive system direction (i.e., an energy deficit in the system) means positive NVI values, while a negative system direction (an energy surplus in the system) means negative NVI values. SMP values greater than SDAP (i.e., a positive delta value) occur when energy deficits exist in the system. Higher delta values also mean higher NVI values.

Considering these observations, input parameters that include historical and forecasted load, historical SMP, historical delta, and historical system direction data are utilized as inputs to ANN developed to forecast the SMP. Forecasted SMP results, as seen in Table 6, are still not satisfactory, particularly during the spring period. On the other hand, although the forecasted day NVI information improves SMP forecasting performance, NVI values are hard to forecast because NVI is related to real-time system imbalances and, therefore, it depends on some random events such as the energy deficit, energy surplus, and congestion or generation outages in real time. Considering this fact, an NVI forecast is performed probabilistically in the next section.

Table 6. Weekly MAPEs for week-ahead SMP forecasting.

Test week	Training period	SMP average weekly MAPE (%)
Winter: 7/1–13/1/12	3/12/2011–6/1/12	9.77
Spring: 11/5–17/5/12	6/4/12–10/5/12	21.81
Summer: 11/6–17/6/12	7/5/12–10/6/12	16.31

3.3. Probabilistic NVI forecasting

In order to better understand NVI variations over a period and to forecast future NVI values with probabilistic assumptions, volatility analysis is utilized. In general, price volatility depends on a large number of parameters such as fuel prices (often related to currency exchange rates), the availability of generating units, hydrogeneration production, demand elasticity and variations, network congestion, and the management rules of any specific electricity market [21]. With volatility analysis, the probability of future NVI values falling within a predefined range is estimated taking into account previous volatility values. The probable NVI range is utilized as an input to the proposed ANN model developed for SMP forecasting in order to forecast a future probable SMP range instead of a single SMP value forecasting, which is actually more reasonable for forecasting and risk analysis applications.

In economics and finance, volatility is basically a criterion used to study the risks associated with holding assets when there is an uncertainty associated with the future value of the assets [12]. A high volatility means the value of a variable has changed drastically over a period of time in either direction (increase or decrease). In contrast, low volatility refers to the fact that the value of a variable has not shown significant changes over a period of time and that the variations have been quite small.

3.3.1. Volatility analysis

In volatility analysis studies, time periods are selected according to the need to observe variable fluctuation over a period of time. We can define variable r_k as the difference between real and expected NVI values at hour k with Eq. (2), where NVI_k is the real NVI value at hour k, and $NVI_{k,\exp}$ is the expected NVI value at the same hour k.

$$r_k = NVI_k - NVI_{k,\exp} \tag{2}$$

Historical volatility is defined as the standard deviation of r_k, and it can be estimated by using the r_k variables as in Eq. (3), where σ is the estimated value of historical volatility and $\hat{r}$ is the mean of r_i's. If a two-week observation is selected for the historical NVI fluctuation, two-week (i.e. 336 h) volatility is defined. It is common to define two-week volatility price in ANN-based approaches [21]. The forecasting results are summarized in Table 7. Figure 15 illustrates ANN-based NVI forecast for a typical two-week period in winter.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(r_i - \hat{r})^2}{N-1}} \qquad \sigma_{k,336} = \sqrt{\frac{\sum_{i=k}^{k+335}(r_i - \hat{r})^2}{335}} \tag{3}$$

Table 7. Two-week historical volatility for different seasons.

Test week	Mean of r_k	Volatility (Std dev. $\sigma_{k,336}$)
24/12/2011–6/1/12	22.87	548.61
27/4/12–10/5/12	–67.54	650.3

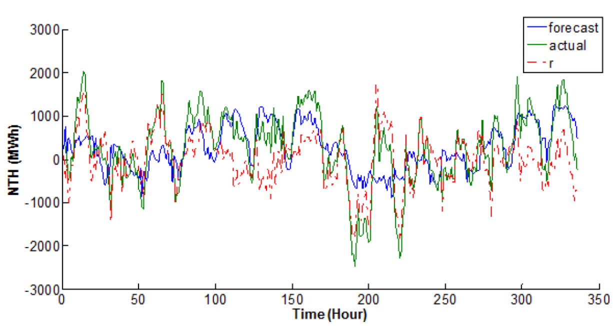

Figure 15. NVI forecast for 24/12/11 to 6/1/12 (rk = actual forecast).

3.3.2. Probability distribution of NVI

Taking historical volatility values into account, future NVI values falling within a predefined range with a predefined probability can be estimated by utilizing the Bienayme–Chebyshev inequality, frequently used in statistical studies and probability theory. The Bienayme–Chebyshev inequality states that in any data sample or probability distribution, the probability that a random variable differs from its mean by more than n times the standard deviation is less than or equal to $1/n^2$. According to this inequality, the probability that a value will be more than two standard deviations from the mean ($n = 2$) cannot exceed 25%.

Let X_i be a random variable with a finite expected mean value μ and a finite standard deviation σ. For any chosen n^2, the Bienayme–Chebyshev inequality is then noted as follows:

$$Pr(-n < X_i - \mu < +n) \geq 1 - \frac{\sigma^2}{n^2} \tag{4}$$

Using Eq. (4) and replacing X_i with r_k and μ with $\hat{r}$, the inequality then becomes

$$Pr(-n < r_k - \hat{r} << n) \geq 1 - \frac{\sigma^2}{n^2} \tag{5}$$

Using Eq. (2) for r_k variables and after arranging Eq. (4), the inequality becomes

$$Pr(NVI_{k,336} + \hat{r} - n < NVI_k < NVI_{k,\exp} + \hat{r} + n) \geq 1 - \frac{\sigma^2_{k,336}}{n^2} \tag{6}$$

where $\sigma_{k,336}$ is two weeks volatility as defined in Eq. (3).

The last two-week volatility value calculated for the winter week is 548.61 MWh, as given in Table 7. If this value is applied to Eq. (6), assuming a 80% probability for NVI interval forecast, then

$$Pr(NVI_{k,\exp} + \hat{r} - n < NVI_k < NVI_{k,\exp} + \hat{r} + n) \geq \left(1 - \frac{548.61^2}{n^2}\right) = 0.8 \tag{7}$$

This equation represents the fact that the probability of $|(NVI_k\, NVI_{k,\exp}) - Mean\,(NVI_k\, NVI_{k,\exp})| \geq n$ is equal to 80% for each n > 0 under two-week volatility of 548.61 MW between 24/12/2011 and 6/1/12. Essentially, n is equal to 1227 MWh. This means that real NVI values for the winter week, from 7/1/12 to 13/1/12, should fall within the interval $NTH_{\exp} + \hat{r} \pm n$ with a probability of 80%. That is,

$$Pr(NVI_{k,\exp} + 22.87 - 1227 < NVI_k < NVI_{k,\exp} + 22.87 + 1227) \geq \left(1 - \frac{548.61^2}{1227^2}\right) = 0.8 \tag{8}$$

The NVI forecast band for a typical winter week is given in Figure 16. The figure verifies that the real NVI values are within the probability band.

3.4. Probabilistic SMP forecasting

NVI forecasting values, together with the lower and upper boundaries, are utilized as inputs to Model 4 (given in Table 3) for week-ahead SMP forecasting. NVI boundary values are given as inputs to the ANN to forecast SMP boundary forecasts. The results of this method are shown in Figure 17 for the winter week, from 7/1/12 to 13/1/12. Figure 17 shows that all of the actual SMP values fall between upper and lower boundaries.

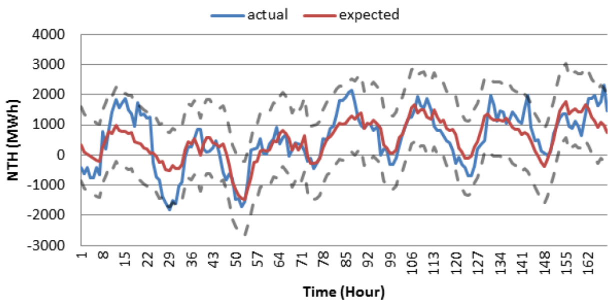

Figure 16. NVI values with lower and upper bounds for 7/1/12–13/1/12.

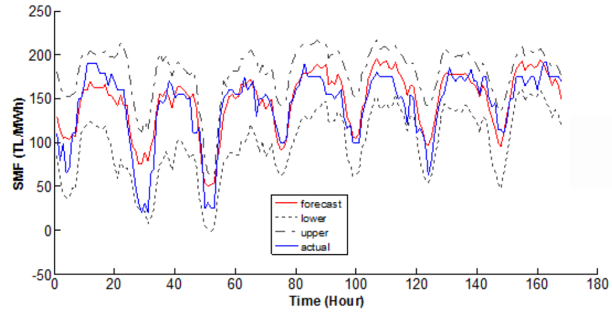

Figure 17. SMP values with lower and upper bounds for 7/1/12–13/1/12.

4. Conclusion

ANN-based day ahead Market Clearing Price (MCP) forecast forecast and real-time market SMP forecast tools were developed and tested on the actual data obtained from TEM TEM. The ANN model proposed for MCP forecasting is revised for SMP forecasting, and new input parameters were added to the proposed model in order to improve forecasting performances. The forecasting performance of the ANN model improves significantly when the forecasted day NVI information is considered as an input to the ANN model. Volatility analysis and the Bienayme–Chebyshev inequality are considered in order to estimate the probability of future NVI values falling within a predefined range with a predefined probability. The NVI range forecast is utilized as input to the proposed ANN model developed for SMP forecasting in order to forecast a future probable SMP range instead of single SMP value forecasting, which is actually more useful for forecasting and risk analysis applications.

Although the price forecast results presented in this study are not very close to actual values in some cases (i.e., MAPE $>$ 10%), the proposed ANN approach can be effectively utilized for price-based unit commitment problems and bidding strategies in electricity markets. Future studies may include hybrid price forecasting techniques such as fuzzy logic and ANN combinations in order to improve forecasting performances.

Data of the TEM utilized in the study for 2011 were publicly available during the study. However, the proposed approach is independent from the year as the correlation between the price and factors (load, temperature, and day index) is still valid in the TEM.

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