PROVIDING OPTIMAL PRICING STRATEGY FOR BUYERS' ENERGY PACKAGES IN IRAN POWER EXCHANGE

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ABSTRACT

In contrast to the current existing whole-sale electricity market of Iran in that buyers may not impact the pricing strategy of the electricity, establishment of the energy exchange can enable both buyers and sellers to interact through a two-way bidding system until both parties agree to execute a deal. The significance of such a market for buyers (i.e. distribution companies) would be reflected in potentially reduced cost of energy ownership that is based on different energy offering packages. This paper deploy the 24-hours SARIMA model in order to predict the price of energy packages in the whole sale market and then presents a novel method based on minimisation of the cost function to achieve an optimal pricing strategy in various symbol of power exchange. Additionally, the effect of inflation has been specifically accounted. The overall solution would assist the buyer to determine the optimal price and amount of energy, it would require buying.

INTRODUCTION

After revising the structure of the electricity industry in Iran and the formation of the electricity market as a result, a whole-sale market based on the power pool was established. The electricity pool is one of the most essential coordination scheme used for short-term forward electricity markets. The main objective of such system is to utilize the society's resources optimally while accounting for engineering constraints that lead to minimizing the risks of costly blackouts. In this model, deals are being made based on the sellers' (i.e. electricity generators) capability of generation and their offered pricing as well as perdition of buyers for the next few days (normally three days). By establishing the bilateral power market, it is now possible for both parties to execute electricity deals based on a bidding system.

A given distribution company may have a number of available options to acquire its required electricity including a day-ahead market, 1-year long energy exchange and a 5-year long guaranteed pricing scheme from Distributed generations. Evidently, distributors seek to minimize their cost of ownership in order to maximise profitability. As mentioned earlier, a distributer may not impact the pricing offered in a wholesale scenario. In addition, due to the very small contribution of miscellaneous sources in proving electricity in Iranian market, they are not considered in this study. The paper investigates the problem of pricing optimisation from a practical point of view considering all effecting parameters in the Iranian electricity market and limiting itself merely to the known variables. Active contribution of distribution companies would result in lowering the ownership cost of energy when the 1-year long offerings are considered in an energy exchange market independent of the wholesale market. The Iranian energy exchange consists of three main markets: the physical delivery market, the derivatives market and the secondary market. The physical delivery market includes three main areas namely Electricity, Oil and Gas and other energy sources can be placed in this market. Also the derivatives market includes three main areas namely Standard parallel futures contract, Futures contract and Option contract [4]. Hereinafter in this paper we consider that energy exchange and power exchange are the same. In order to offer an optimal pricing for energy packages, one would first need to have acceptable estimation of hourly based demand. Such short term predictions are normally achieved by using neural networks [1]. After this step, information on the wholesale market price is required. Models based on time-series have shown to have an acceptable performance [2]. As an example of other possible methods, mention can be made to mixed fuzzy-neural network frameworks. Interested readers can consult [3] for more information on various price prediction methods. All these methods are offered as means of providing a pricing strategy for electricity sellers in the wholesale market. However, by introduction of the energy exchange that provides a way of competition between the distributers, it is now also vital for distributers to come up with an optimal pricing strategy when bidding. This is especially true considering fast transactions that are executed using online facilities. Normally, trades are executed with 5 timeframes namely: daily, weekly, monthly, seasonally and finally yearly. Each of the above can then be considered for various load conditions namely, low, medium, peak and base load levels. From the generators perspective, the pricing would depend on many factors including global energy price, short and long-term market fluctuations, weather conditions etc.

Since demand estimation is the first and critical step in defining the optimal pricing strategy, we will first investigate this aspect using neural networks. Subsequently, a time-series method based on SARIMA (Seasonal Auto Regressive Integrated Moving Average) model is deployed in order to estimate the energy price in the wholesale market. The predicted price value would be a function of previous values and past estimation errors. This would then be used to yield optimal pricing (based on cost function minimization) in various load condition markets. Since all trades, including long term deals, need to be paid upfront (normally within three days of deal execution [5]) the effect of inflation needs to be taken into account.

ESTIMATION OF BASE, LOW, MEDIUM AND PEAK LOAD FOR POWER EXCHANGE

To get an hourly-based estimation of demand load, a software package based on neural network is used. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation [6]. Figure 1 illustrates the architecture of the neural network with 3 neuron in the first layer of the network shown for illustration. The network consists of three layers: input layer, hidden layer and the output layer. The input parameters include the demand load on similar days of the previous week, previous day demand and the current temperature.

The transfer function used within the prediction module is of tangent hyperbolic type and the back propagation model was used to train the network. In addition the user can define the numerous parameters of the software including the learning rate as well as the number of days taken into account. To increase the prediction accuracy a separate neural network model is executed corresponding to each hour of a day.

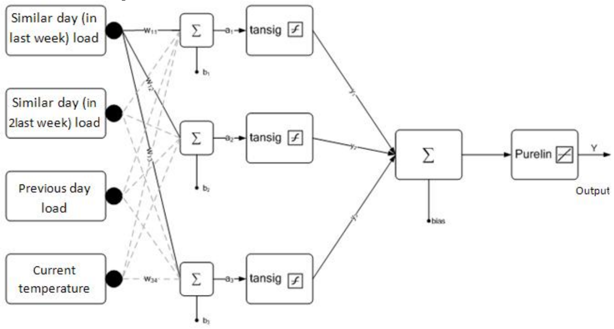

Figure 1: Neural network architecture used for demand estimation.

The calculated daily demand can be easily extended to a week, month and a season timeframe. Moreover, in order to avoid over-buying, it is necessary to consider the base load as a percentage of minimum of low load regime.

According to the following, the base load can vary from 0 to 100% of the l_min. If l_b, l_l, l_m and l_f to represent the base, low, medium and full (peak) load respectively, we would have:

$$L_b = x l_{l\_min} \qquad ,0 \le x \le 1 \qquad (1)$$

$$\begin{aligned} L_l &= (1-x) l_b \\ L_m &= l_{m\_min} - l_b \\ L_f &= l_{f\_min} - l_b \end{aligned} \qquad (2)$$

Subsequently, if there is a need for more electricity at any time during the day, it can be bought from the day-ahead market.

PREDICTION OF WHOLESALE MARKET PRICE

It is well known that the demand load may vary significantly during hours of a day resulting in price fluctuations. Studies show such fluctuations can have significance randomness making their prediction to be a challenging task [7]. Therefore, to increase the prediction accuracy, a separate model is used for each hour of the day. This study deploys an autocorrelation statistics analysis as well as a method based on Seasonal Auto Regressive Integrated Moving Average (SARIMA) model to optimally predict the wholesale market's price.

In this method, the unit price of the electricity is expressed based on the past values as well as previous error values and its only applicable to stationary time series. Therefore, a set of past pricing data are required and then one should investigate if the data behaves stationary over time or not. Since pricing data are stationary in variance and not mean, the delta of the data is calculated [8] and then the prediction model is derived based on autocorrelation and partial autocorrelation functions. During this process, the coefficients were calculated using minimum sum-of-squares estimation method. The estimation process is implemented individually for each hour of the day.

ESTIMATION OF ELECTRICITY PRICE ON THE POWER EXCHANGE

Evidently, the maximum offer for the electricity on the exchange for a daily buy should not exceed the price of the day-ahead market. The total cost of daily buy from the market can be calculated according to the following:

$$P = \sum_{i=1}^{24} p_i l_i \qquad (3)$$

Where P is the total cost of electricity for 24 hours and P_i is the unit cost of electricity for ith hour and l_i is the demand load for the ith hour. Then we would have:

$$\begin{aligned} P_{\mathrm{L}} &= \sum_{i=1}^{8} p_i (L_i - L_b - L_l) \\ P_{\mathrm{M}} &= \sum_{j=1}^{12} p_j (L_j - L_b - L_m) \\ P_{\mathrm{F}} &= \sum_{k=1}^{4} p_k (L_i - L_b - L_f) \end{aligned} \qquad (4)$$

In that P_L, P_M and P_F represents the costs associated to the extra electricity acquisitions corresponding to the low, medium and full demand regimes. As stated before, trading in exchange would makes sense only if the maximum cost of ownership is the same as the daily market. Formally speaking:

$$Max\{P_2\} = P - (P_L + P_M + P_F) \qquad (5)$$

On the other hand, the cost of ownership by buying from the exchange can be written as:

$$P_2 = 24 L_b p_b + 8 L_l p_l + 12 L_m p_m + 4 L_f p_f \qquad (6)$$

Combining (5) and (6) reveals that p_b,p_l,p_m, and p_f are the upper bounds of price for base, low, medium and full load regimes which makes the electricity accusation through the exchange economical if the bidding prices are lower than those. Subsequently the above equation can be split into the followings:

$$\begin{aligned} P - P_{\mathrm{L}} &= 8(L_l p_l + L_b p_b) \\ P - P_{\mathrm{M}} &= 12(L_m p_m + L_b p_b) \\ P - P_{\mathrm{F}} &= 4(L_f p_f + L_b p_b) \end{aligned} \qquad (7)$$

Of course the above set of equations can have infinite answers as there are more variables there than the equations. One could assume a value for one of the quantities and drive the rest but this may not lead to the total cost minimization. If F to represents the total costs of daily trades on the exchange, according to (1), (2) and (6), it can be expressed as:

$$F = 24xL_ip_b + 12(L_j - xL_i)p_m + 8(L_i - xL_i)p_l + 4(L_k - xL_i)p_f \quad (8)$$

To find the function's minimum point the roots of derivative of the function in respect to x should be found.

$$\frac{dF}{dx} = 24L_ip_b - 12L_ip_m - 8L_ip_l - 4L_ip_f = 0 \quad (9)$$

$$p_b = \frac{p_m}{2} + \frac{p_f}{6} + \frac{p_l}{3} \qquad (10)$$

By replacing these into (7) we would have:

$$\begin{pmatrix} L_l + \frac{L_b}{3} & \frac{L_b}{2} & \frac{L_b}{6} \\ \frac{L_b}{3} & L_m + \frac{L_b}{2} & \frac{L_b}{6} \\ \frac{L_b}{32} & \frac{L_b}{2} & L_f + \frac{L_b}{6} \end{pmatrix} * \begin{pmatrix} P_l \\ P_m \\ P_f \end{pmatrix} = \begin{pmatrix} c_L \\ c_M \\ c_F \end{pmatrix} \quad (11)$$

Where the fixed coefficients are:

$$C_L = \frac{P - P_L}{8} \quad , C_M = \frac{P - P_M}{12} \quad , C_F = \frac{P - P_F}{4}$$

If A represents the coefficient matrix, we have:

$$\begin{pmatrix} P_l \\ P_m \\ P_f \end{pmatrix} = A^{-1} * \begin{pmatrix} c_L \\ c_M \\ c_F \end{pmatrix} \quad (12)$$

Using this method, the impact of pricing of each load regime would be proportional to the duration of that load regime. This method gives the maximum price by which buying from exchange is economical. Any bidding below this threshold results in cost savings. Otherwise, buying from day-ahead market could be more beneficial. This method can be easily applied to longer term buying schemes including weekly, monthly and yearly.

EFFECT OF INFLATION ON LONG TERM TRADES

Since all trades ought to be cleared within few days after deal executions, longer term trades need to account for inflations as well. If PV represents the current value of a good, with an annual inflation rate of I, the value after D days, FV, would be:

$$FV = PV \times (1 + i)^{\frac{D}{365}} \quad (13)$$

Therefore, if P_{fo} illustrates the predicted price and for example, the 10% deposit to be paid immediately, the total cost of ownership at the time when the good is delivered is:

$$p_{fo} = 0.9 \times p_{ac} + FV(0.1 \times p_{ac}) \quad (14)$$

Accordingly, the actual biding price should be calculated as:

$$p_{ac} = \frac{p_{fo}}{0.9 + 0.1 \times (1 + i)^{\frac{D}{365}}} \quad (15)$$

Of course the above is the upper bound of bidding price and distributers should try to bid lower than this bound to maximize their profitability compared to the day-ahead market buyouts.

IMPLEMENTATION FOR A SIMPLE AND PRACTICAL CASE STUDY

This section presents a simple case study in that the proposed method of this study is used to predict the low, medium, full and base price of elasticity unit for a distribution company in November 2011. Figure 2 shows the real and the estimated demand load calculated on an hourly basis for Nov. The estimation is based on the neural network and accounts for weather conditions too.

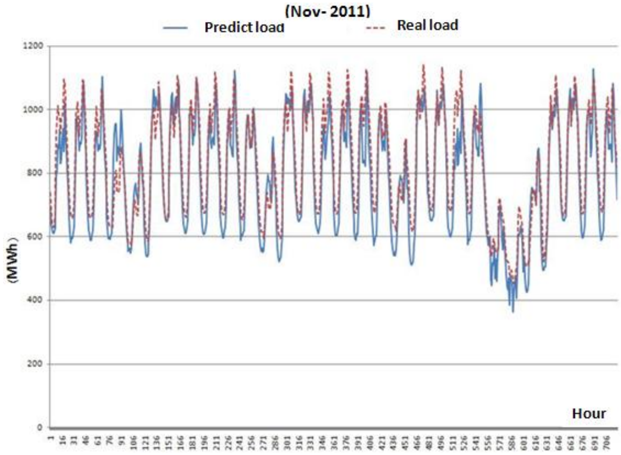

Figure 2: Load predictions and real load of Nov 2011 for wholesale market.

After minor modifications and taking into account special occasions such as national holidays, the estimation error is shown to be below 3% that is a good indication. Subsequently, using the method described in earlier section, the base, low, medium and full load demands can be calculated as the followings for days of Nov 2011.

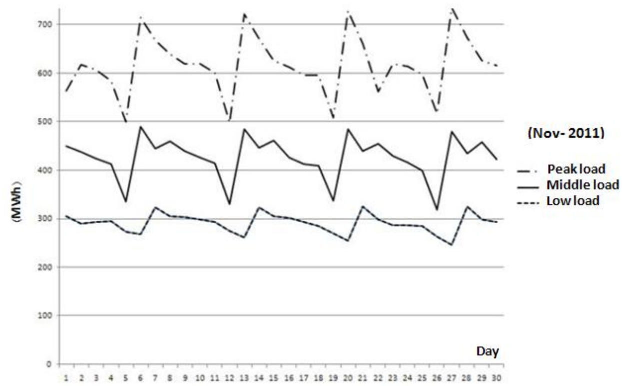

Figure 3: Predicted loads of Nov 2011 for power exchange.

Since minimization of the cost function is independent of the x values, x is considered to be equal to 0.5 resulting a match between the base and low regime load. To predict the price on the wholesale market, hourly rates of electricity during days of Sep and Nov 2011 are considered. In this method it is first checked weather the data is stationary or not and if not then deferential values of data are considered and the model coefficients are calculated according to the autocorrelation and fractional autocorrelation functions. Figure 4 shows an example of energy price for 19:00 in Sep and Oct. Table 1 surmises the model parameters used.

Parameter	AR=MA	Ordinary Difference	SAR= SMA	Seasonal Difference	Period
Value	1	0	1	0	7

Table 1: Parameters and values used in proposed model.

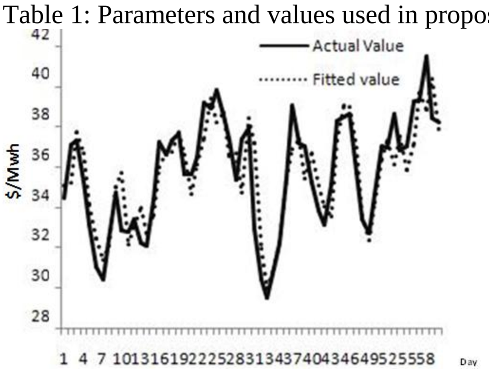

Figure 4: Actual and fitted value of hours19 in Sep and Oct.

By comparing the predicted and real price of the electricity for days of Nov, it is revealed that the estimation error is below 2%. Figure 5 illustrates the real and estimated price of all 720 hours of Nov.

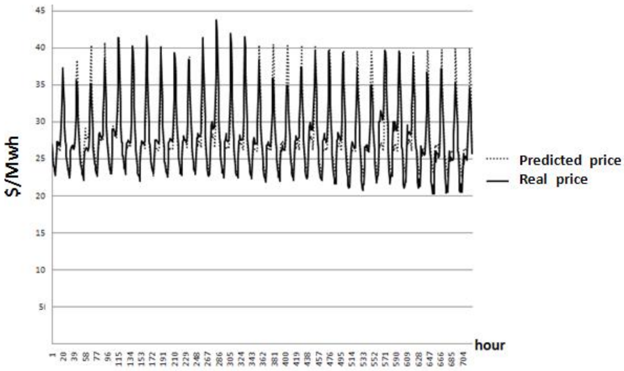

Figure 5: Hourly Real and estimated price of Nov.

Finally, the prices are corrected by considering the annual inflation rate effect (that is 15.2% in Iran [9]). Figure 7 shows an example case for estimating the bidding price for duration of 3 weeks to one year. Subsequently, the minimum sum-of-squares estimation method is used to evaluate the maximum price of low, medium, full and base load regimes for Nov. (See Figure 6)

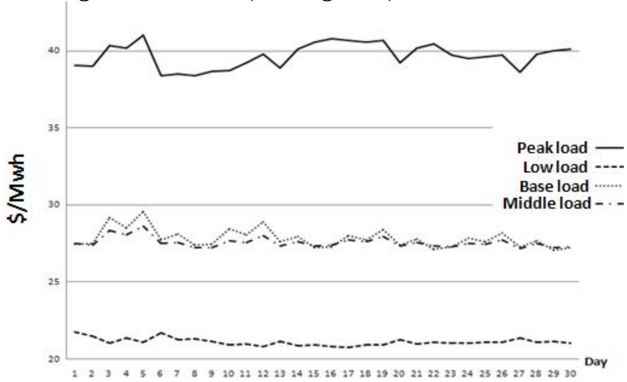

Figure 6: Estimation maximum price of low, medium, full and base load regimes to order in power exchange.

Any bidding price below the above threshold will results in financial gains for the distribution companies compared to buying from the wholesale market. Using this strategy a distribution company can save up to 1.2 $ per megawatt hour of electricity. (See Figure 7)

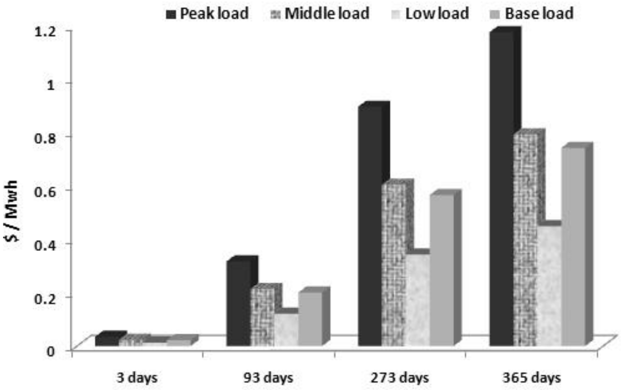

Figure 7: Reduction bidding price considering inflation rate effect in various load regimes according to delivery time.

CONCLUSION

Considering the importance of electricity price prediction in the wholesale day-ahead markets and energy exchange, this study propose a novel method based on combination of time-series of 24 hours model and function minimization methods to evaluate the upper bound of price that a distribution company should bid on in the power exchange. The proposed method considers various regimes of demand load and additionally account for inflation rates when long term trades are considered. The results from the case study confirm high accuracy of the method and that the estimation errors are marginal.

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