Economic impact of price forecasting inaccuracy on self-scheduling of generation companies

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Abstract

This paper studies the economic impact of using inaccurate price forecasts on self-scheduling of generation companies (GenCos) in a competitive electricity market. Four alternative sets of price forecasts are used in this study which have different levels of accuracy. The economic impact of price forecast inaccuracies is calculated by comparing the economic benefits of the GenCos in two self-scheduling scenarios. In the first scenario, electricity market price forecasts are used to optimally schedule the GenCos’ next day operation. In the second scenario, perfect price forecasts, i.e., actual market prices, are used for self-scheduling of the GenCos. Two indices are utilized to quantify the differences in the economic benefits of the GenCos under the two scenarios. Simulation results are provided and discussed for two typical and inherently different GenCos, i.e., a hydro-based producer and a thermal-based producer.

1. Introduction

In competitive electricity markets, power suppliers are required to submit to the market operator their bid quantities and prices, usually one day before real-time operation. Suppliers generally optimize their bids by solving two problems. In the first problem, referred to as self-scheduling, a generation company (GenCo) needs to determine its optimal next-day operation schedules that, if implemented, maximizes its profit. In the second problem, generally known as strategic bidding, the GenCo sets an efficient bidding strategy that translates the determined optimal operation schedules into price-quantity bids and maximizes the likelihood that those bids are cleared in the market. The formulation and structure of the above problems may differ depending on many factors, including the technical characteristics of the GenCos, GenCos’ share of the market and market design. However, a common feature of all available approaches is that historical behaviour of market prices and a prediction of their future fluctuations need to be taken into account when solving these problems. A review of some of the available literature on the two mentioned problems can be found in [1].

Focusing only on GenCos’ self-scheduling problem, available approaches in the literature can be divided into two main groups with respect to the way they have considered future electricity market prices and the associated uncertainties. In the first group, optimal short-term operation schedules are derived solely based on a forecast of future prices. For example, in the pioneering work of [2], the next-day operation of a thermal GenCo is formulated assuming that the GenCo is price-taker, i.e., its behavior does not influence market prices. In this work, relatively accurate next-day electricity market price forecasts are assumed to be available and are the basis of self-scheduling. Similarly in [3], the self-scheduling problem is formulated for a hydro-based GenCo based on forecasted electricity prices for the next operating day. While the GenCo in [3] owns several units, its influence on price behavior is assumed to be negligible. In [4], a self-scheduling problem is formulated for a thermal GenCo when emission and fuel constraints are also included. Forecasts of locational marginal prices are employed in [4] to account for transmission congestion in the power system, and a method to derive optimal bids from the determined schedules is proposed. Self-scheduling of a price-taker hydro-thermal GenCo is formulated in [5] as a mixed integer linear programming problem where long-term bilateral contracts are also considered. While the prices of power under bilateral contracts are assumed to be known in [5], the revenue from selling power in the spot market is determined based on forecasts of next-day spot prices. In a recent work [6], the operation of a pumped-storage plant is formulated,
where forecasts of energy and reserve prices are used to determine the optimal operation schedules and bids for energy and reserve markets.

In a second group of approaches, the risks of trading under uncertain prices is also included in the formulated self-scheduling models. The objective in such approaches, generally referred to as risk-constrained self-scheduling methods, is to balance the trade-off between profit and risk. For example, in [7,8], the profit gained in the market is estimated based on the forecast prices. Furthermore, risk of trading in the spot market is formulated based on the estimated covariance matrix of the 24 hourly prices in a trading day. The objective of the self-scheduling optimization is to maximize the gained profit at a certain acceptable level of risk. In [9], a stochastic self-scheduling problem is formulated where the uncertainty of future prices are considered by generating a large number of electricity market price scenarios using a pre-determined price model. A risk-constrained bidding strategy is then proposed that takes into account the financial risk associated with each price scenario. In [10], a stochastic programming approach is proposed for profit maximization of a power producer who participates in day-ahead, automatic generation control and balancing markets. ARIMA and ETS models are used to generate future scenarios of market prices.

This paper studies the economic value of improving price forecast accuracy in a self-scheduling problem faced by a GenCo. The economic analyses in this paper are based on the first group of self-scheduling approaches, i.e., those that use forecasted prices to generate operating schedules without explicitly modelling the associated financial risks. The economic impact of price forecasting errors on large demand-side electricity consumers has been studied in [11]. A large water plant with the capability of shifting its pumping operation, and a process industry owning an on-site co-generation facility are studied in [11]. Two sets of alternative price forecasts with significantly different error measures are used to determine the lowest-cost operation scenarios of the loads. It is concluded that the economic value of accurate price forecasts is significantly different for the studied loads. In addition, it is demonstrated in [11] that popular error measures, such as the mean absolute percentage error (MAPE), may not always reflect the economic value of a forecasting method against another. In the present paper, the work in [11] is extended to the supply-side, i.e., for two typical hydro- and thermal-based GenCos. Four alternative sets of price forecast are employed in the process of optimal self-scheduling of the studied GenCos, and the economic benefit of using one set of forecasts against another is quantified. It is proposed and demonstrated in the present work that using profit-based measures, instead of typical error measures (e.g., MAPE), is more efficient in comparing the economic value of alternative forecasting methods.

The reminder of this paper is organized as follows: In Section 2, a brief review of the related works is presented and two indices for evaluating the economic impact of price forecasting errors on GenCos are introduced. In Section 3, the GenCo case studies and price forecasts used for the study are discussed. Numerical results and discussions are presented in Section 4, followed by the concluding remarks in Section 5.

2. Background review and methodology

2.1. Review of the related work

Evaluating the economic effect of inaccurate forecasts or the value of perfect information has been reported in several electric power-related applications. Among the reported works, in [12], the economic effect of inaccurate load forecasting in the unit commitment problem is investigated using Monte Carlo Simulation. It is concluded in [12] that reducing the error of load forecasting to about 5% is sufficient to optimize unit commitment schedules. In [13], Expected Cost Of Uncertainty (ECOU) is defined and used to study the value of perfect information in a short-term power system operation planning. The analysis in [13] is based on two planning scenarios, one based on available information (with load level uncertainty) which is called nature’s decision tree, and the second is based on perfect information and called ‘clairvoyant’s’ decision tree. The difference in the expected production costs between the two scenarios yields the expected cost of load forecast uncertainty and is the basis of the analysis. It is concluded that ECOU increases as the forecast lead time increases. In [14], the economic cost of inaccurate load forecasts is studied, where it is found that the value of improving load forecast accuracy is dependent upon generator and load characteristics. The economic benefits of more accurate temperature forecasts in electric demand forecasting problem is investigated in [15], where, on average, the value of 1 °C improvement in temperature forecast accuracy is estimated as $59 million per year. Randomly generated wind speeds are used in [16] as wind forecasts to evaluate the economic value of improving wind speed forecasts in the context of the UK electricity market. It is concluded that large size wind farms benefit from more accurate wind forecasts significantly more than the smaller ones. In [17] the impact of improved wind forecasting accuracy on system operation costs is studied for the German power system. It is observed in [17] that the costs associated with wind forecasting errors are mainly due to unnecessary start-ups and part-load operations, rather than increased operation costs.

2.2. Methodology

In general, a GenCo’s self-scheduling problem over a T-interval planning period can be formulated as follows:

\[
\max \text{Profit} = \sum_{t=1}^{T} f(P_t, X_t, \lambda_t) \quad \text{subject to: } \xi \tag{1}
\]

where \( f(P_t, X_t, \lambda_t) \) is the total profit over the planning period, \( P_t \) is the net output power sold in the market in planning interval \( t \), \( X_t \) is set of GenCo’s variables other than the output power, \( \lambda_t \) is the market price for interval \( t \), and \( \xi \) is the set of constraints. In a typical self-scheduling problem in practice, the GenCo solves (1) using forecasted prices \( \lambda_t^f \), since actual prices are not yet available at the scheduling time. Thus, problem (1) in fact is solved to maximize the expected profit based on the available expected prices \( \lambda_t^f \), and can be rewritten as:

\[
\max E[\text{Profit}|\lambda_t^f] = E \left[ \sum_{t=1}^{T} f(P_t, X_t, \lambda_t) \right] = \sum_{t=1}^{T} f(P_t, X_t, \lambda_t^f) \tag{2}
\]

subject to: \( \xi \)

Suppose the solution of (2) is referred to by \( \bar{X} \) and \( \bar{P} \). The actual expected profit of the GenCo after the prices are cleared, referred to here by \( \text{Profit}^{\text{exp}} \), can be calculated as:

\[
\text{Profit}^{\text{exp}} = \sum_{t=1}^{T} f(P_t, \bar{X}_t, \lambda_t^p) \tag{3}
\]

where \( \lambda_t^p \) is the actual after-the-fact market price for hour \( t \). Note that the GenCo is paid based on actual prices not forecast prices.

In a s scenario, if the actual after-the-fact prices, i.e., \( \lambda_t^p, t = 1, \ldots, T \), were available, the actual profit of the GenCo would be:

\[
\text{Profit}^{\text{act}} = \sum_{t=1}^{T} f(P_t, X_t, \lambda_t^p) \tag{4}
\]
where $\lambda^*$ and $P_i^*$ are the optimum solution of optimization problem (1) under this fictitious scenario, i.e., $\lambda^* = \lambda^P_i$.

In order to evaluate the economic value of improving price forecasts accuracy to the GenCos, two indices are proposed in this work. First, the Economic Loss Index (ELI) is defined as:

$$\text{ELI} = \frac{\text{Profit}_{\text{act}} - \text{Profit}_{\text{exp}}}{\text{Profit}_{\text{exp}}} \times 100$$

A positive value of ELI indicates the percentage of profit loss due to forecast inaccuracy. In other words, it means that the final profit using forecasted prices would be ELI percent lower than obtainable profit if perfect price forecasts were available. It should be noted that the absolute value of actual profit is used in the denominator of ELI definition to make it consistent in cases that actual profit is negative. Actual profit can sometimes be negative because of the ramp rate limits, and minimum up and down time constraints. A zero ELI indicates that the inaccuracy of the price forecasts has not resulted in any economic loss. A negative value of ELI means that profit obtained with forecasted price is ELI percent more than profit obtainable using perfect prices, unexpectedly. This case can occur when the global optimum solution of the optimization problem (1) is not obtained [14]. Furthermore, since the operating schedule is obtained using forecasted prices but the profit is determined using actual prices, in rare cases, ELI can be negative; this was also observed in [11].

Second, the Price Forecast Disadvantage Index (PFDI) is defined as follows:

$$\text{PFDI} = \frac{\text{Profit}_{\text{act}} - \text{Profit}_{\text{exp}}}{\sum_{t=1}^{T} P_i}$$

where $\sum_{t=1}^{T} P_i$ is the total energy in MWh sold in the market—without the loss of generality, it is assumed that each planning interval is 1 h. A positive value of PFDI shows the average profit loss of the GenCo as a result of price forecasting errors. The zero and negative values may occur similar to ELI. It is to be noted that the defined indices, i.e., ELI and PFDI, are used here to assess the economic value of improving price forecasts accuracy not to measure the accuracy of price forecasts.

3. Case study systems and price forecasts data

The self-scheduling problem employed in the analyses of the present paper is based on the works presented in [3,2]. The first studied GenCo is a hydro-based power producer with total capacity of 126.76 MW [3]. This GenCo has three cascaded units along a river basin, as follows: Units 1 and 3 are identical with a capacity of 28.62 MW and Unit 2 has a capacity of 69.5 MW. This GenCo is energy limited. In other words, it is supposed that the amount of water in reservoir at the end of 24-h planning period must be equal to its value at the beginning of the planning horizon. Thus, the GenCo’s objective is to maximize its profit given the limited water inflow and availability. The relationship between the power produced, the water discharged, and the head of the reservoir is non-concave in this work. Constant start-up costs considered as operation costs. The self-scheduling of the hydro-based GenCo is a Mixed Integer Programming (MIP) problem.

The second system studied in the present work is a GenCo with one coal-fired unit with a capacity of 294 MW. The self-scheduling formulation, unit specifications, data and initial condition are adopted from [2]. However, the Minimum Up Time (MUT) and Minimum Down Time (MDT) of the unit are chosen to be 4 and 3 h, respectively, in the present study. MUT and MDT are the constraints that limit the flexibility of unit in responding to price changes. Ramp-up and ramp-down limit of unit are 60 MW/h and 50 MW/h, respectively. Also, the start-up and shut-down ramp limits are selected as 170 MW/h and 160 MW/h, respectively. The stair-wise start-up cost and constant shut-down cost considered beside the production cost as operation cost. The maximum marginal production cost of the unit is $43.33/MWh. The formulated self-scheduling problem for this GenCo is also a MIP problem. In comparison with the hydro producer, the studied thermal producer is not fuel constrained and will produce power as long as it is profitable.

The objective of both GenCos is to optimally schedule their operation over a 24-h scheduling period in order to maximize their profit. It is assumed that the GenCos are price takers, i.e., their self-scheduling do not change the hourly market clearing price. It is also assumed that GenCo’s bids for selling energy to market are always completely cleared, and thus, no strategic bidding is considered in line with [3,2]. GenCos are not allowed to reschedule or change the submitted bids. Note that although the formulated self-scheduling problems include operating reserve prices, those prices are assumed to be known. The self-scheduling optimization problems of the two GenCos are solved using the CPLEX [18] and SBB solvers [19], in GAMS [20] environment. Further analysis is done using GAMS and MATLAB interface [21].

The case market is selected to be the Ontario electricity market [22], where the Hourly Ontario Energy Prices (HOEPs) are uniformly applied to all market participants. Four alternative sets of HOEP forecasts are used in this study to evaluate the economic benefits of improving forecasts accuracy. The forecasts are reported in [23] where further details and discussions regarding the forecasting methods can also be found. The forecasts are generated for six typical weeks in year 2004 as follows: two weeks from April 26 to May 9, two weeks from July 26 to August 8, two weeks from December 13 to 26. Three sets of the price forecasts are generated using data-driven time series models, i.e., Transfer Function (TF) models, Auto Regressive Integrated Moving Average (ARIMA) models and Dynamic Regression (DR) models. The fourth set of price forecasts is the 24-h-ahead Pre-Dispatch Prices (PDPs) provided by Ontario’s ISEO [22] for the same mentioned time periods. These prices are calculated based on most recent market information using the pre-dispatch version of Ontario’s market dispatching and pricing algorithm [24]. The after-the-fact HOEPs for the six studied weeks are used in this study as the perfect price forecasts.

Mean absolute percentage error $^1$ is the most popular error measure for assessing the inaccuracy of electricity market price forecasts and is used in this work to measure forecasting errors. Mean Absolute Error $^2$ was also considered in this work but the numerical results and conclusions for both measures were observed to be consistent, and hence, only the MAPE measure is used onward. The price forecasts generated by the TF, DR and ARIMA models have the six-week MAPEs of 16.09%, 16.53% and 17.65%, respectively, which are significantly lower than the six-week MAPE of the PDPs (39.32%).

4. Simulation results and discussions

4.1. Hydro-based GenCo

Economic impact of using the four previously discussed sets of price forecasts on the operation of the hydro power producer is evaluated using ELI and PFDI. The results are presented for the TF forecasts with the lowest MAPE and the PDPs with the highest MAPE with greater details.

\[ MAPE = \frac{100 \times \text{average}\left(\frac{\text{actual price} - \text{forecast price}}{\text{actual price}}\right)}{\text{forecast price}} \]

\[ MAE = \text{average}\left(\frac{\text{actual price} - \text{forecast price}}{\text{actual price}}\right) \]
The daily values of PFDI and ELI for the 42-day period for the TF forecasts are depicted in Fig. 1. In this figure, the daily pairs of ELI (PFDI) and MAPE are sorted in descending order with respect to MAPEs. In Fig. 2, the daily ELI (PFDI) and MAPE pairs, sorted in descending order with respect to MAPEs, for the PDPs are presented. It can be observed from these figures that the high values of ELIs can occur on both high and low levels of MAPEs. For example, in Fig. 1, event 6 which corresponds to Day 40 has a low ELI of 0.82% and a PFDI of 0.36 $/MWh, while in this day the TF forecasts MAPE has the relatively high value of 26.27%. In contrast, in Fig. 2, events 8 and 39 have similar ELI values (1.17% and 1.30%, respectively) but the corresponding MAPEs of the PDPs on these days are significantly different (55.63% and 14.55%, respectively). Overall, in 60% of the days, a higher value of MAPE for PDP prices, compared to that of the TF forecasts, resulted in a higher value of ELI. However, in the other 40% of the days, PDPs with higher MAPEs, compared to those of the TF forecasts, resulted in lower ELIs.

To discuss how forecast errors affect the operation of the GenCo and explain the above observation, the simulation results were further analyzed. As an example, for Day 33, the PDPs had a MAPE of 103.52% and the TF forecasts had a MAPE of 16.31%, which resulted in the daily ELIs of 14.45% and 6.66%, respectively. Event 21 in Fig. 1 and event 2 in Fig. 2 correspond to Day 33 and have relatively high values of ELI and PFDI. It was observed that the TF price forecasts ranging from $47.63/MWh to $59.54/MWh (at hours 7–17) resulted in the same power output schedules with a unique value of 34.38 MW. Similarly, the PDPs ranging between $72.5/MWh and $105.19/MWh (at hours 17–22) also resulted in unique schedules. Note that this range of price variations, compared to the actual prices, could result in significantly different values of MAPE while the economic effects were the same. Thus, in some operating hours, the optimal schedule did not significantly change by the changes in price forecasts which was mainly due to the hard constraints (e.g., MUT and MDT). It was also observed that the maximum output of
Table 1
Total six-week indices for hydro producer using forecasted prices and PDPs.

<table>
<thead>
<tr>
<th></th>
<th>MAPE (%)</th>
<th>ELI tot (%)</th>
<th>PFDI tot ($/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDPs</td>
<td>39.33</td>
<td>4.46</td>
<td>2.53</td>
</tr>
<tr>
<td>ARIMA forecasts</td>
<td>17.65</td>
<td>3.08</td>
<td>1.73</td>
</tr>
<tr>
<td>DR forecasts</td>
<td>16.53</td>
<td>3.88</td>
<td>2.17</td>
</tr>
<tr>
<td>TF forecasts</td>
<td>16.09</td>
<td>3.57</td>
<td>2.00</td>
</tr>
</tbody>
</table>

the GenCo was limited to 89.68 MW at Day 33. The water limitation and the non-concave unit performance curves that result in working on the knee points of the performance curves for a wide range of prices cause such behaviour for this GenCo.

To assess the overall economic impact of price forecasting error, the total ELI over the 42-day period, referred to here by ELI tot, is defined as follows:

\[
\text{ELI}^{\text{tot}}(\%) = 100 \times \frac{\sum_{i=1}^{42} (\text{Profit}^{\text{act}}(i) - \text{Profit}^{\text{exp}}(i))}{\sum_{i=1}^{42} |\text{Profit}^{\text{act}}(i)|} \tag{7}
\]

Also, the total PFDI, denoted here by PFDI tot, is defined as the weighted average of daily PFDIs, as follows:

\[
\text{PFDI}^{\text{tot}} = \frac{\sum_{i=1}^{42} \sum_{l=1}^{24} (\text{Profit}^{\text{act}}(i) - \text{Profit}^{\text{exp}}(i)) P_{i,l}}{\sum_{i=1}^{42} \sum_{l=1}^{24} P_{i,l}} \quad (\$/\text{MWh}) \tag{8}
\]

where \( P_{i,l} \) indicates the energy sold in time interval \( t \) of Day \( i \). Table 1 summarizes the six-week ELI tot and PFDI tot indices for the hydro producer, calculated using the TF, DR, ARIMA forecasts and the PDPs; the forecast MAPEs are also provided for reference. Observe from this table that although TF forecasts have the lowest MAPE among the four sets, the economic loss associated with using the ARIMA forecasts is the lowest. Thus, based on the results presented in this table and in Figs. 1 and 2, it can be concluded that MAPE may not always reflect the economic advantage of a set of forecasts against another when comparing alternative forecasting methods, especially when the difference in error measures is not that significant.

4.2. Thermal-based GenCo

Unlike the hydro-based GenCo where the main limitation was availability of water, the MUT, MDT, ramp-up and down, start-up and shut-down ramp rates limit the operation of the thermal-based GenCo. These constraints may lead to negative profit (loss) not only with forecasted prices but also with actual prices. Gaining a negative profit, i.e., loss, mainly depends on the unit initial status in the beginning of scheduling horizon and its marginal cost. Note that optimal self-scheduling approaches only guarantee a maximum profit or a minimum loss, and they do not eliminate the possibility of incurring a loss.

The daily MAPEs and the corresponding ELIs and PFDIs for the thermal-based GenCo are presented in Fig. 3a and b, respectively, based on TF forecasts. In these figures, the values of PFDIs and ELIs are sorted in a descending order with respect to MAPE values. It should be noted that in Fig. 3a, there are very high peaks in events 9 and 17, which correspond to Days 26 (180%) and 41 (25,670%)—to make the figures visually acceptable, these large values are capped in these figures. These peaks are mainly due to the small values of the obtainable profit when using the actual prices and high values of loss when scheduling using forecasted prices. For example, in Day 41, if the perfect prices are used by the GenCo for self-scheduling, GenCo’s profit will be only $62, but if the TF forecasts are used for scheduling, it will lose $15,956. Also note that, as it can be seen in Fig. 3, there are some events with small negative ELIs and PFDIs, the reason of which discussed earlier in Section 2. Similar to the hydro-based GenCo, it can be observed from Fig. 3 that high (low) values of ELI can occur when the forecast MAPEs are low (high). In fact, the first three events which happen to have the highest MAPEs have resulted in very low economic losses.

The MAPEs and the corresponding daily ELIs and PFDIs, sorted in a descending order with respect to MAPEs, for the PDPs are presented in Fig. 4a and b, respectively. Similar to Fig. 3, events 18 and 33, which correspond to Days 26 and 41, have very high ELI values (743.18% and 17572%) and are capped to fit into the fig-

![Fig. 3. Daily MAPEs versus the corresponding (a) ELI and (b) PFDI for the thermal GenCo, based on TF forecasts.](image-url)
ure. To explain these results, it was observed that on Day 26, the actual prices were higher than the maximum value of the unit cost function or the unit marginal cost ($43.33/MWh) only at 6 h. However, the PDPs were higher than the unit marginal cost for 23 h. Thus, the GenCo self-scheduling model found very optimistic operating schedules when using the PDPs and hence, incurred significant losses in practice. The high value of ELI on Day 41 was resulted from the low obtainable profit based on the actual prices. Using the PDPs has similarly resulted in some negative ELIs, as observed for the TF forecasts.

The values of $ELI^{tot}$ and $PFDI^{tot}$ for the thermal GenCo are presented in Table 2 based on the four price forecast sets. Observe that the total ELI and PFDI values are very close for the PDPs and the three other sets of forecasts despite the significant differences in their MAPEs. In addition, the high MAPE values of PDPs in events 1–12 resulted to the low ELI and PFDI values. To explain these observations, the prices on the days corresponding to events 1–12 of Fig. 4 were further investigated. The actual prices for those days were higher than the unit marginal cost in most of the hours. These high prices resulted in maximum output schedules in those hours. In other words, regardless of the value of the forecast prices, which in some cases were very off, the economic outputs were the same. Thus, the high difference in MAPE of the PDPs, compared to the other sets, did not translate into significantly different operating schedules and hence, the corresponding economic impacts were very close for all the price sets.

Comparing the results presented in Tables 1 and 2 for the thermal and hydro GenCos, the values of $PFDI^{tot}$ are generally lower for the thermal GenCo compared to the hydro GenCo. This is mainly because of the higher capacity and traded energy of the thermal GenCo. Also observe that ARIMA prices resulted in the lowest economic loss for the hydro GenCo whereas the TF forecasts are preferred by the thermal GenCo. Verifying the findings of the previous literature, this observation indicates that economic value of a forecasting model may be different across different power suppliers.

### 4.3. Profit-based error measures

As discussed earlier in this section, using MAPE as the basis of selecting a forecasting method against another is not always effective, especially when the forecasting errors are close. To investigate if the defined indices in the present work, i.e., ELI and PFDI, can provide a consistent measure of the economic value of a forecasting model versus another, the first four weeks of the 42-day test period were selected as ‘model-selection data’ and their values were calculated based on the four sets of price forecasts for the two GenCos. A forecasting model was selected as the ‘preferred model’ based on those results for each GenCo. The last two weeks of the 42-day period were used as the ‘verification data’, to assess whether the selected models in the model-selection stage perform consistently for out-of-sample data. The numerical results are presented in Tables 3 and 4.

Observe from Table 3 that the ARIMA forecasting model is preferred by the hydro GenCo based on the ‘decision-making’ stage.

### Table 2

Total six-week indices for thermal producer using forecasted prices and PDPs.

<table>
<thead>
<tr>
<th></th>
<th>MAPE (%)</th>
<th>ELI (%)</th>
<th>$PFDI^{tot}$ ($/MWh$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDPs</td>
<td>39.33</td>
<td>4.82</td>
<td>0.68</td>
</tr>
<tr>
<td>ARIMA forecasts</td>
<td>17.65</td>
<td>4.46</td>
<td>0.71</td>
</tr>
<tr>
<td>DR forecasts</td>
<td>16.53</td>
<td>4.28</td>
<td>0.69</td>
</tr>
<tr>
<td>TF forecasts</td>
<td>16.09</td>
<td>4.22</td>
<td>0.67</td>
</tr>
</tbody>
</table>

### Table 3

Results of profit-based measure verification for hydro producer.

<table>
<thead>
<tr>
<th>Prices</th>
<th>Decision-making</th>
<th>Verification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAPE</td>
<td>ELI</td>
</tr>
<tr>
<td>ARIMA</td>
<td>17.83</td>
<td>2.63</td>
</tr>
<tr>
<td>DR</td>
<td>16.28</td>
<td>3.44</td>
</tr>
<tr>
<td>TF</td>
<td>15.72</td>
<td>3.20</td>
</tr>
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</table>

### Table 4

Results of profit-based measure verification for thermal producer.

<table>
<thead>
<tr>
<th>Prices</th>
<th>Decision-making</th>
<th>Verification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAPE</td>
<td>ELI</td>
</tr>
<tr>
<td>ARIMA</td>
<td>17.83</td>
<td>3.62</td>
</tr>
<tr>
<td>DR</td>
<td>16.50</td>
<td>3.48</td>
</tr>
<tr>
<td>TF</td>
<td>15.72</td>
<td>3.42</td>
</tr>
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</table>
Table 5
Total six-week indices for hydro producer with different capacities and ARIMA prices.

<table>
<thead>
<tr>
<th>No. of units</th>
<th>Capacity (MW)</th>
<th>ELI(^{tot}) (%)</th>
<th>PFDI(^{tot}) ($/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>98.14</td>
<td>5.09</td>
<td>3.15</td>
</tr>
<tr>
<td>3</td>
<td>126.76</td>
<td>3.08</td>
<td>1.73</td>
</tr>
<tr>
<td>4</td>
<td>155.38</td>
<td>1.98</td>
<td>1.07</td>
</tr>
<tr>
<td>5</td>
<td>184</td>
<td>1.53</td>
<td>0.79</td>
</tr>
<tr>
<td>6</td>
<td>212.62</td>
<td>1.19</td>
<td>0.62</td>
</tr>
</tbody>
</table>

This selection remains preferred in the ‘verification’ stage where it provides the lowest economic losses. Similarly in Table 4, the TF forecasting model is preferred by the thermal GenCo, based on the ELI and PFDI values, in both decision-making and verification stages. Note that these indices, i.e., ELI and PFDI, do not measure forecasting errors, but they represent the economic impact of forecast accuracy on a given forecast user. These measures depend on the characteristics of the system for which price forecasts are used for optimal self-scheduling.

4.4. Sensitivity analysis

In order to study how GenCo parameters affect the economic value of price forecast accuracies, a sensitivity analysis is presented in this section with regard to some of the GenCo parameters.

4.4.1. Hydro-based GenCo

Several parameters impact the operation of the hydro-based GenCo, such as water inflow, initial water level, unit capacities and the number of units cascaded on the river basin. Among those, the impact of the latter on economic impact of forecasting errors on this GenCo is studied here. Note that this case resembles the coordinated scheduling of a number of units on a river basin versus independent scheduling. By changing the number of units from 2 to 6, the total capacity of the GenCo varies from 98.14 MW to 212.62 MW. Table 5 shows the six-week ELI and PFDI values for the hydro GenCo based on ARIMA prices. Observe that as the capacity of the GenCo increases, the economic impact of forecast errors on the GenCo decreases. In other words, coordinated scheduling of units on a river basin hedges the uncertainty in price forecasts. The reason for this is that the units are cascaded and the discharged and spillage water of upper-level reservoir will be added to natural inflow water of lower-level reservoir. In this particular case study, since the upper-level unit (the second unit) has a greater capacity (69.52 MW) compared to lower level units (units third to sixth) which have a capacity of (28.62 MW), coordinated scheduling and having more cascaded units has led to a more efficient usage of the limited available water.

4.4.2. Thermal-based GenCo

For the thermal GenCo, ramp-up and down rates, MDT, MDT, start-up and shut-down ramp rates, start-up and shut-down costs, and operation cost functions can influence the operation of this GenCo. Among these parameters, the sensitivity of the results to the values of MDT and MDT is studied here by changing these limits from their base values to 10 h. A wide range of MUT and MDT are reported for thermal units in the literature, from 3 h [25] to 10 h [2].

The total six-week values of ELI and PFDI are calculated based on the TF forecasts for each value of MUT and MDT. The ELI and PFDI results were found to be consistent and thus, only the PFDI results are presented in Fig. 5. As it can be seen from this figure, the PFDI values increased for the MDT values up to 6 h and then the trend reversed. This phenomenon can be justified based on the fact that the flexibility of the unit decreases as the MDT value increases, resulting in higher economic losses from inaccurate prices. However, after a certain value of MDT (6 h in this case) the unit is unable to respond to the changes in prices and thus, is more robust to forecast errors. In other words, the unit cannot change its status even if the prices are forecasted to be favourable.

Also from Fig. 5, it can be observed that sensitivity of the analysis to the MUT is negligible. Investigating the operation schedules over various days, not presented here, showed that the unit is on for most of the time and thus, MUT has no impact on its operation.

5. Conclusion

In this paper, the economic value of improving price forecasting accuracy in GenCo's self-scheduling problem was presented. Four sets of forecasts, generated using alternative forecasting methods, were used to determine the optimal next-day schedules of a hydro-based GenCo and a thermal-based GenCo. The economic gains associated with the resulting schedules were compared with those of the schedules determined based on perfect price forecasts, i.e., actual market prices. Two indices were employed to quantify the economic impact of price forecasting errors on a studied GenCo.

The results of this study showed that the economic loss associated with a set of price forecasts may significantly vary across different power suppliers. Furthermore, a forecasting model having significantly higher errors based on traditional error measures (e.g., MAPE) compared to other models may not always result in significantly higher economic losses. These findings are consistent with the results reported in the previous literature about the demand-side market participants. In addition, traditional error measures such as MAPE or MAE are not always efficient when used to select among alternative models, especially when the errors levels of the models are close. In other words, a model with higher MAPE may in fact result in lower economic losses compared to another model having a lower MAPE. Instead, it was demonstrated that other operation-based measures, such as the indices defined in the present paper, are more reliable for being used as a basis for selecting a forecasting model.

References
