Economic Impact of Electricity Market Price Forecasting Errors: A Demand-side Analysis

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***Abstract*—Several techniques have been proposed in the literature to forecast electricity market prices and improve forecast accuracy. However, no studies have been reported examining the economic impact of price forecast inaccuracies on forecast users. Therefore, in this paper, the application of electricity market price forecasts to short-term operation scheduling of two typical and inherently different industrial loads is examined and the associated economic impact is analyzed. Using electricity market price forecasts as the expected next-day electricity prices, optimal operating schedules and the associated costs are determined for each load. These costs are compared with those of a "perfect" price forecast scenario in which actual prices are used to determine the operating schedules. Numerical results and discussions are provided based on price forecasts with different error characteristics.**

***Index Terms*—Price forecasting, scheduling, forecasting error, economic value, economic benefit, demand-side management.**

I. Introduction

SHORT-term operation scheduling in a competitive electricity market is a challenging task because of the uncertainty associated with future electricity prices. One feasible approach to deal with this challenge is to generate and employ "accurate" forecasts of future prices. This approach is particularly efficient if the forecasts enjoy a high level of accuracy [1]. However, producing price forecasts with very low error levels is not always possible.

In recent years, several techniques have been applied to short-term electricity market price forecasting (e.g., [2]–[4]); a summary of the applied techniques is presented in [5]. Significantly different levels of forecast accuracy have been observed for the studied markets. For example, forecast errors ranging from about 5% to 20% were reported for the Spanish [2], PJM [6] and Ontario [7], [8] electricity markets. Such large variations in price forecasting errors mainly depend on the characteristics of the market under consideration and volatility of market prices [8], [9]. In addition, various approaches have been reported in the literature for improving the accuracy of electricity market price forecasts. For example, in [10], wavelet transforms were employed to improve the accuracy of an ARIMA model by about 2.7 percentage points. However, no works have been reported which either analyze the economic impact of using inaccurate price forecasts for operation scheduling, or study the economic benefits of improving price forecasting accuracy for forecasts users.

In this paper, electricity market price forecasts with different levels of accuracy are used to optimally schedule the next-day operation of two industrial loads: a process industry owning on-site generation facilities, and a municipal water plant with load-shifting capabilities. These two loads are inherently different in the way they respond to electricity prices, thus, the process industry produces electricity on-site when electricity market prices are high, whereas the water plant shifts its consumptions from high price hours to low price hours. Therefore, the main contribution of this work is to analyze and quantify the economic impact of employing imperfect electricity price forecasts for scheduling the short-term operation of typical demand-side market participants.

It should be noted that some approaches have been reported in the literature to deal with the problem of future price uncertainty in operation planning in competitive market environments. For example, in [11]–[13], market prices are modeled using time series models, and scenario-based techniques are employed to derive optimal operational strategies. On the other hand, the focus of the present work is on analyzing the economic impact of applying short-term price forecasts in operation scheduling from the demand-side's point of view.

The rest of this paper is organized as follows: A review of the relevant literature and the methodology employed for the analyses are presented in Section II. The industrial loads and their characteristics are discussed in Section III. Numerical results and discussions are provided in Section IV. Finally, Section V summarizes the methodology and main findings of this work.

II. Methodology

A. Review of Related Works

Forecasting future values of a variable and using the forecasts for planning purposes has been a common practice across a wide range of industries. Thus, evaluating the value of alternative forecasts and how improving forecasting accuracy could in turn improve the decision-making process has been studied in various applications. For example, the economic value of using probabilistic versus conventional weather forecasts in airline flight scheduling is analyzed in [14] showing potential cost reductions. Also, a survey of the economic value of improving seasonal climate forecast in agriculture is presented

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in [15], where it is argued that this value is limited when considering a wide range of circumstances.

In the electric power industry, studying the costs of load forecasting errors has been a topic of interest, given the importance of load forecasts for the daily operation of power systems. For example, in [16], a large number of daily load forecast scenarios with random errors ranging between zero and 15% are generated and the cost of meeting the demand under each scenario is determined; it is concluded that reducing the load forecast error to about 5% is adequate, and that lower error levels would only have a marginal economic value. In [17], the cost of load forecast inaccuracy for two typical power utilities are analyzed; the resulting economic values of reducing the error are reported to vary to some extent across the studied systems. Among several related studies, an approach to reduce the economic impacts of load forecasting errors in unit commitment is presented in [18]; a third cost component, i.e., the cost of expected energy not supplied, is considered in [19], in addition to the operation and start-up costs studied in [16] and [17]; a method to analyze the economic impact of forecasting errors in generation scheduling is proposed in [20] with an emphasis on forecasting horizon; and the economic value of improving weather forecast in electric load forecasting models is discussed in [21]. The findings of [19]–[21] are consistent with those in [17] and [16] in the sense that they generally report lower system costs when more accurate forecasts are used. In addition, a linearized model of the unit commitment problem is presented in [22] where the economic impact of uncertainty in wind is studied in the context of German power system; it is reported that the wind uncertainty mainly affect the start-up and shutdown costs, and hence, the impact was relatively small.

While the above studies employ different methods to generate forecast scenarios, the general approach to study the economic impact of forecast errors is to compare the costs incurred in exact and imperfect forecast price scenarios. This general approach is also followed in the present work, as explained next.

B. Forecast Inaccuracy Economic Impact Index

From the demand-side point of view, the optimal operation in a competitive electricity market environment concentrates on the minimization of total electricity costs. The problem of minimizing electricity costs over a K-interval planning period for a demand-side market participant can generally be formulated as:

$$\begin{aligned} \min_{\psi_k} \quad & \text{Cost} = \sum_{k=1}^{K} \rho_k \cdot \psi_k \\ \text{subject to:} \quad & \xi \end{aligned} \tag{1}$$

where ψ_k is the net power purchased from the market in planning interval k, ρ_k is the market price for electricity for interval k, and ξ represents the set of technical constraints. This optimization problem needs to be solved before the start of the planning period (e.g. the day before the operation day). However, market prices ρ_k are known only after the actual operation. Thus, (1) corresponds to an uncertain optimization problem.

By replacing the future prices ρ_k by their forecast values $\hat{\rho}_k$, the problem (1) turns into an *expected cost* minimization problem [1], [23], as follows:

$$\begin{aligned} \min_{\psi_k} \quad & E[\text{Cost}|I] = \sum_{k=1}^{K} \hat{\rho}_k \cdot \psi_k \\ \text{subject to:} \quad & \xi \end{aligned} \tag{2}$$

where E denotes the mathematical expectation, and I is the available information about electricity market price behavior at the time. Note that price forecasts are the *expected* values of future prices, i.e. $E[\rho_k|I]$=$\hat{\rho}_k$ [23]. The solution of problem (2) provides the demand-side market participant with optimal power purchase schedules which minimize the *expected* cost of electricity.

In order to analyze the economic impact of using imperfect price forecasts for demand-side short-term scheduling, two price scenarios are considered here. In the first scenario, it is assumed that the actual market prices are available; this is obviously a fictitious scenario. Let denote the solution of optimization problem (2) under this price scenario, i.e. actual prices, by $\psi_k^{\text{ap}}, k = 1, 2, ..., K$. Thus, if schedules ψ_k^{ap} were implemented in reality, the associated cost, denoted by Cost^{ap}, would have been:

$$E[\text{Cost}|\text{Actual Prices Available}] = \text{Cost}^{\text{ap}} = \sum_{k=1}^{K} \rho_k \cdot \psi_k^{\text{ap}} \tag{3}$$

In the second price scenario, it is assumed that imperfect price forecasts $\hat{\rho}_k$ are used to solve optimization problem (2). Let denote the solution of (2) when using this set of forecast prices by ψ_k^{fp}. Thus, if schedules ψ_k^{fp} are implemented in practice, the cost incurred by the market participant, denoted by Cost^{fp}, will be:

$$E[\text{Cost}|\text{Inaccurate Price Forecasts Available}] = \text{Cost}^{\text{fp}} = \sum_{k=1}^{K} \rho_k \cdot \psi_k^{\text{fp}} \tag{4}$$

Observe that the ψ_k^{fp} is determined based on forecast prices, but the final electricity cost is determined based on the actual prices ρ_k.

The Forecast Inaccuracy Economic Impact (FIEI) index over a K-interval planning period is defined here as:

$$\text{FIEI (\%)} = \frac{\text{Cost}^{\text{fp}} - \text{Cost}^{\text{ap}}}{\text{Cost}^{\text{fp}}} \times 100 \tag{5}$$

Here, a positive value of FIEI indicates the percentage of the actual cost attributable to price forecasting error. In other words, the final incurred electricity cost could have been lower by FIEI percent if the price forecasts were perfectly accurate. A value of zero for FIEI indicates that the incurred cost is the same for both the actual price and imperfect price forecasts scenarios, despite the error in the latter. When FIEI is negative, it basically means that the actual incurred cost is unexpectedly lower when using imperfect forecasts for scheduling. Two factors may contribute to negative FIEIs. First, if the global optimal solution is not obtained for (2), the cost under actual prices may be slightly more than the cost under imperfect forecast in unusual cases [17], which in turn leads to a negative FIEI. Second, considering (2) and (4), operating schedules are found using price forecasts whereas the actual incurred costs are determined based on actual prices; in rare cases, this may lead to a negative FIEI depending on how forecasts deviate from the actual prices.

The value of FIEI can only be found after "real-time", when the actual market prices are available. Therefore, it can only be used as an *after-the-fact* index to evaluate the overall economic efficiency of a certain price forecasting model. Note that this index deals with the overall economic loss associated with using inaccurate price forecasts for scheduling, and is not meant to measure forecasting error.

III. The Case Study Loads

Two main groups of bulk electricity consumers are able to respond to electricity prices: first, those having on-site generation facilities as an alternative source of electricity; and second, those having a controllable load that enables them to time-shift their operation. In the present work, two price-responsive large industrial electricity consumers representative of these two groups are considered for the analyses.

The first load considered in this work is a typical process-industry having both thermal and electrical energy demand. The process industry owns an on-site gas-engine electricity generator equipped with a heat recovery boiler for combined heat and power production. A traditional oil-boiler is also available to generate thermal energy. The gas-engine is employed for electricity generation when electricity market prices are expected to be high. Thermal energy, a by-product of the gas-engine that increases the overall energy efficiency, makes on-site generation a viable option. It is assumed that reliable forecasts of the thermal demand and electrical energy demand are available. The objective of this load is to use electricity market price forecasts to optimally schedule a combination of the gas-engine, the oil-boiler, and electricity from the grid to minimize the total expected energy costs over a planning period (e.g., over 24 hours). This case study is based on the system presented in [24] with some modifications. The process-industry load's detail formulation and data are provided in [23].

The second load is a municipal water-plant which has an obligation to meet its hourly water demand day-by-day. The water plant has an inexhaustible potable water source, a number of pumps, an elevated reservoir, and a main pipeline to convey water from the pumping station to the elevated reservoir. The water plant is modeled using a simplified mass-balance model, in which the nodal pressure requirements are assumed to be satisfied if the water level in the elevated reservoir remains within a desired range [25]. The constant-velocity centrifugal pumps work in parallel and their pumping capacity is assumed to be constant during each 1-hour interval. The water plant is assumed to have access to a reliable hour-by-hour forecast of water demand for the K-interval operating period. The objective in this case is to minimize the total expected electricity cost by scheduling the pumping operation at low price hours based on the available price forecasts. The water-plant load's formulation and parameters are mostly taken from [26], and further details are provided in [23].

The next-day operation of each load is modeled over a planning period of 24 hours, equally divided into 24 1-hour planning intervals. The following assumptions are made for the simulations:

- All optimization variables are assumed to be constant over the 1-hour intervals.
- No rescheduling or revision of the initially obtained schedules are considered during the operating period.
- The case studies are price-taker customers who cannot impact market clearing prices by any strategic behavior; price-maker customers are not considered here.
- The participants' bids (offers) to purchase (to sell) electricity from (to) the market are always cleared.
- The scheduling is based on only one set of market prices in the case of two-settlement markets, i.e., either real-time market prices or day-ahead market prices.

IV. Numerical Results and Discussion

The Ontario electricity market is selected as the case-market in this study, and the Hourly Ontario Energy Price (HOEP) forecasts are considered as the expected future electricity market prices [27]. The Ontario electricity market is a single-settlement real-time market, and the HOEP is a province-wide uniform market price applicable to most demand-side wholesale electricity customers in Ontario.

Two alternative sets of HOEP forecasts are considered here for the analyses. The first set is the 24-hour-ahead HOEP forecasts generated by the Transfer Function (TF) models in [8] for a 42-day period (six typical but different weeks in 2004); these forecasts have a MAPE[1] of 16.1% over the six-week period. The second set is the 24-hour-ahead Pre-Dispatch Prices (PDPs) generated by Ontario's IESO [28] for the same period, but with a significantly higher six-week MAPE of 40% [8]. The corresponding ex-post HOEPs are used as the "perfect" HOEP forecasts.

The cumulative distribution of the percentage errors for the TF and PDP forecasts are presented in Fig. 1. As it is reflected in this figure, the percentage error of the PDPs is higher than 50% on more than 25% of the days; this level of error is obsrved only on 3% of the days for the TF forecasts. The unusually high PDP errors are generally because they are being generated by mimicking the market using the available bids and forecasts of intermittent suuply and load; these bids and forecasts, however, are usually subject to change when approaching real-time operation [27]. In addition, observe from Fig. 1 that the PDPs exhibit an over-forecast tendency compared to the TF forecasts. The over-forecast tendency in PDPs is due to the use of hourly peak-load forecasts, while the HOEPs are calculated using the 5-minute actual load values.

The next-day operating schedules of the two loads are determined for each day of the 42-day study period using the

[1]MAPE=average(|actual price - forecast price|/actual price)

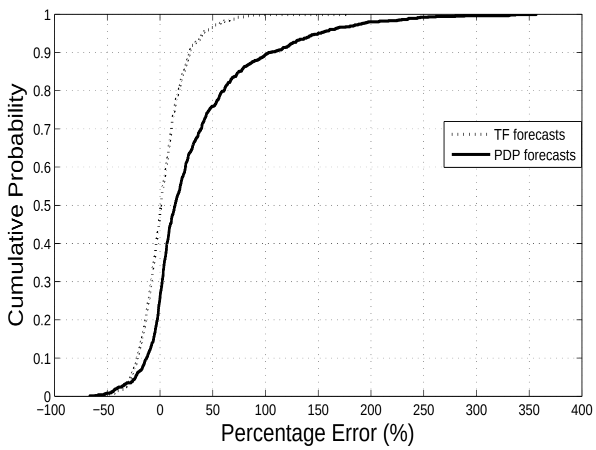

Fig. 1. Cumulative distribution of percentage errors for the TF and PDP forecasts.

TF forecasts, the PDPs and the ex-post HOEPs. The daily FIEI values are calculated according to (5). In addition, the overall economic impact is quantified using the following six-week FIEI index:

$$\text{FIEI}_{6w}(\%) = 100 \times \frac{\sum_{\text{day}=1}^{42}(\text{Cost}_{day}^{\text{fp}} - \text{Cost}_{day}^{\text{ap}})}{\sum_{\text{day}=1}^{42}\text{Cost}_{day}^{\text{fp}}} \quad (6)$$

where $\text{Cost}_{day}^{\text{fp}}$ and $\text{Cost}_{day}^{\text{ap}}$ are the daily operation costs based on forecast prices and actual prices, respectively.

Two popular error measures in the price forecasting literature, i.e. MAPE and MAE[2] are considered in this work. The numerical results and conclusions for both measures were observed to be consistent, and hence, only the MAPE measure is used here.

A. The Process-industry Load

The daily FIEI and MAPE values for the 42-day period are presented in Fig. 2 for both forecast sets. In this figure, the daily pairs of MAPE and FIEI are sorted in a descending order with respect to MAPEs. It can be observed from this figure that high values of FIEI can occur at both high and low levels of MAPEs. For example, in the case of TF forecasts in Fig. 2-(a), the second event which represents Day 27 has a FIEI of zero despite a MAPE of 27.5%. Similar behavior can be observed for the 5^{th}, 15^{th}, 21^{th}, 24^{th}, 31^{th}, and 37^{th} events. Also, it can be observed from Fig. 2-(b) that the FIEI values are very close for the 2^{nd} and the 25^{th} events despite the significant difference in their MAPEs. These results imply that a high (low) value of MAPE for a given set of forecasts does not always mean a high (low) economic loss.

Cross-examining the daily MAPE and FIEIs, i.e., comparing the relative differences in the MAPEs of the two forecast sets with the relative differences in the resulting FIEIs on different days over the 42-day period, reveals that on about 80% of the days, a higher MAPE for the PDPs has translated into a higher FIEI compared to those of the TF forecasts. However, on about

[2]MAE=average(|actual price - forecast price|)

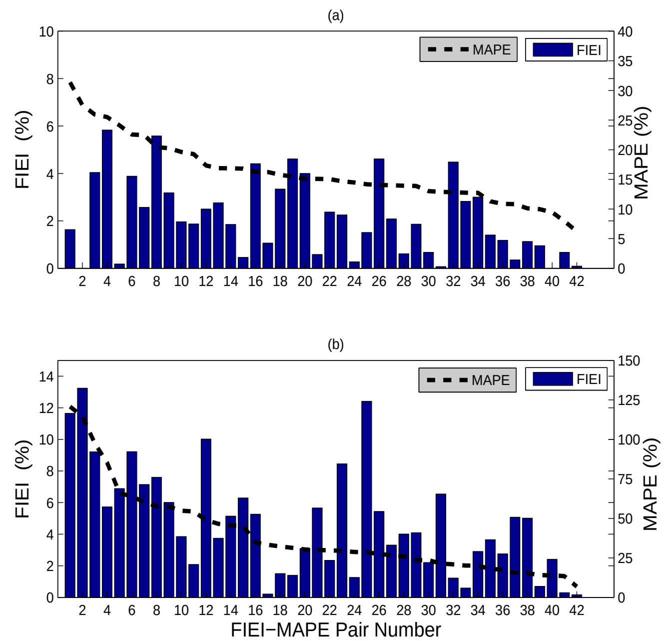

Fig. 2. Daily MAPEs versus the corresponding FIEI for the process industry: (a) TF forecasts, and (b) PDPs.

TABLE I
DAILY MAPES AND FIEIS FOR THREE TYPICAL DAYS

	MAPE (%)		FIEI (%)	
	TF Forecasts	PDPs	TF Forecasts	PDPs
Day 5	16.3	28.5	0.6	12.6
Day 11	16.9	28.7	2.81	1.7
Day 39	9.4	15.6	0	5.18

20% of the days, the opposite holds true, i.e., a higher MAPE for PDPs has actually resulted in a lower FIEI. Furthermore, there are some instances for which the FIEI is zero or very close to zero despite a relatively high MAPE. To discuss these observations, one typical day of each category, namely, Day 5, Day 11, and Day 39, is selected and the corresponding forecast MAPEs and the associated daily FIEI indices are presented in Table I.

Observe from Table I that on Day 5, the MAPE of the TF forecasts is 12.2 percentage points lower than that of the PDPs. The daily FIEI index has also significantly improved on this day, i.e., from 12.6% for the PDPs to 0.64% for the TF forecasts. On Day 11, on the other hand, although the MAPE of the TF forecasts is 11.8 percentage points lower than that of the PDPs, the daily FIEI resulting from using the TF forecasts (2.81%) is actually higher than that of the PDPs (1.7%). In addition, despite a MAPE of 9.4% on Day 39, the FIEI associated with the TF forecasts is zero.

The inconsistency in the relationship between the MAPE and FIEI when two alternative sets of forecasts are considered can be explained based on the operational characteristics of the process industry. Thus, the process industry purchases electricity from the market if the market price is lower than a certain threshold. This threshold price can simply be found

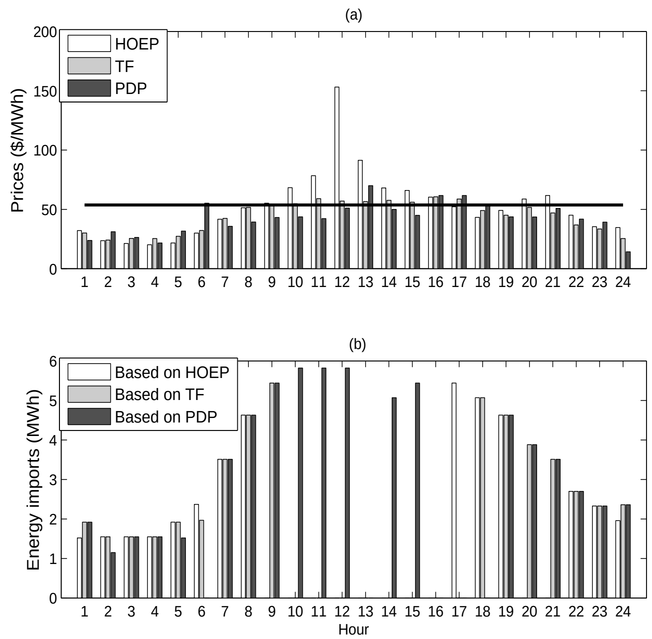

Fig. 3. Day 5: (a) actual and forecast prices, and (b) energy import schedules for the process-industry based on the TF and PDP forecasts.

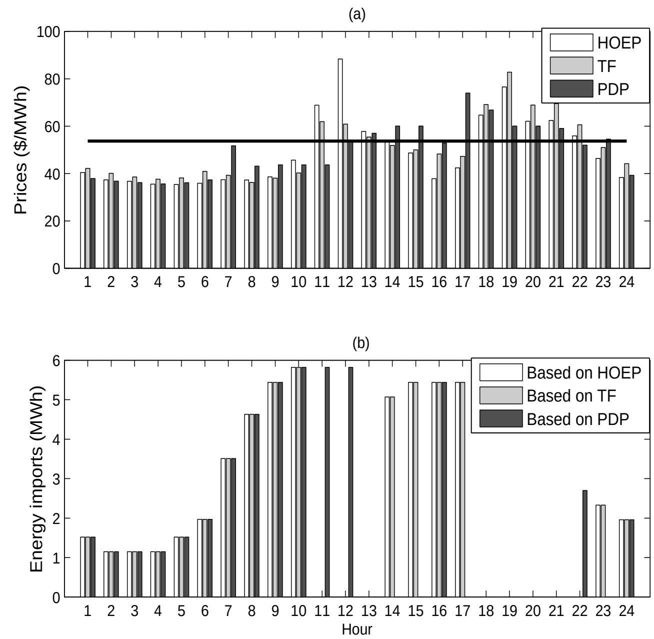

Fig. 4. Day 39: (a) actual and forecast prices, and (b) energy import schedules for the process-industry based on the TF and PDP forecasts.

by gradually increasing the electricity market prices in the optimization problem from zero to a value beyond which no electricity is purchased from the market. For the system under study, this value is found to be $53.7/MWh. Therefore, if the electricity market prices are forecasted to be higher than the threshold price, it would be economical to produce the required electricity locally. Hence, forecasting the future electricity market prices with respect to this threshold is a crucial factor for the process-industry load.

The scheduled energy imports on Day 5 when using the TF forecasts, the PDPs forecasts and the HOEPs as expected future prices are shown in Fig. 3; the actual and forecast prices are also depicted against the threshold in this figure. Observe in Fig. 3-(a) that the relative value of the future prices with respect to the threshold are predicted incorrectly by the PDPs for 10 hours. For example, at Hour 10, the price forecast is lower than $53.7/MWh whereas the actual price is higher than $53.7/MWh; in contrast, at Hour 17, the price forecast is higher than $53.7/MWh but the actual price is lower than $53. The TF forecasts, on the other hand, miss the relative value of prices with respect to the threshold for only four hours (e.g. Hour 21 in Fig. 3-(a)). Thus, on Day 5, the prices are predicted accurately with respect to the threshold on more hours by the TF forecasts than by the PDPs; this has resulted in a lower FIEI index for the TF forecasts on this day.

For Day 11, on the other hand, it was observed that the TF forecasts wrongly predicted the market price with respect to the threshold for five individual hours; however, the PDPs did so for only three hours. In other words, despite the higher MAPE of the PDPs, they performed better than the TF forecasts in predicting the relative value of the prices with respect to the threshold; hence, the FIEI value associated with using the PDPs was lower on this day.

TABLE II
SIX-WEEK MAPES AND ASSOCIATED FIEIS FOR THE PROCESS INDUSTRY

MAPE_{6w} (%)		FIEI_{6w} (%)	
TF Forecasts	PDPs	TF Forecasts	PDPs
16.1	40.0	2.0	4.0

The scheduled energy imports on Day 39 when using the TF forecasts, the PDPs and the HOEPs are presented in Fig. 4. Observe that the relative value of prices with respect to the threshold are perfectly predicted by the TF forecasts despite its MAPE of 9.4%. This has resulted in identical schedules for the TF forecasts and the ex-post HOEPs, and thus a zero FIEI.

The six-week MAPEs of the two forecast sets and the associated FIEI indices are presented in Table II. From this table, the overall six-week FIEI index associated with the TF forecasts is 2%, which is half the FIEI value associated with the PDPs (4%); this is, on average, a 0.08% cost reduction for a 1% lower MAPE for the TF forecasts over the PDPs.

In order to study how improving the accuracy of a given forecasting model could economically benefit the user, an experiment based on the TF forecasts is discussed next. Thus, a set of hourly artificial forecasts, denoted by AF, are generated as follows:

$$\text{AF}_t = \text{HOEP}_t + a(\text{TF}_t - \text{HOEP}_t) \quad (7)$$

where HOEP_t and TF_t are the hourly values of the HOEPs and TF forecasts, respectively. By varying the value of a between 0 and 1.6 with 0.1 increments, 15 sets of daily forecasts were generated for each day of the 42-day study period. If the value

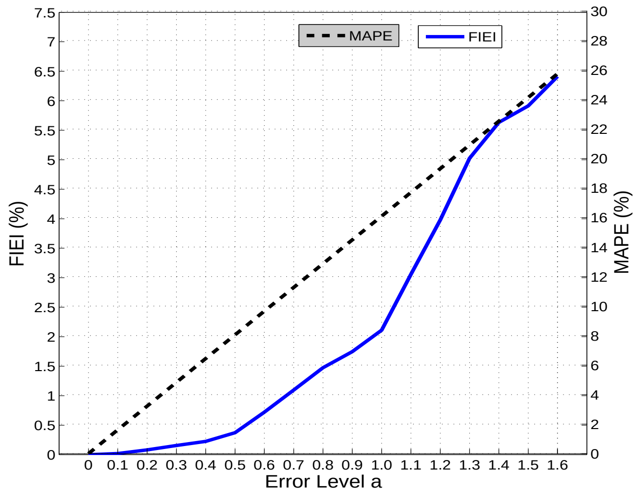

Fig. 5. Six-week averages of the MAPEs for various simulated forecasts, and the corresponding FIEIs.

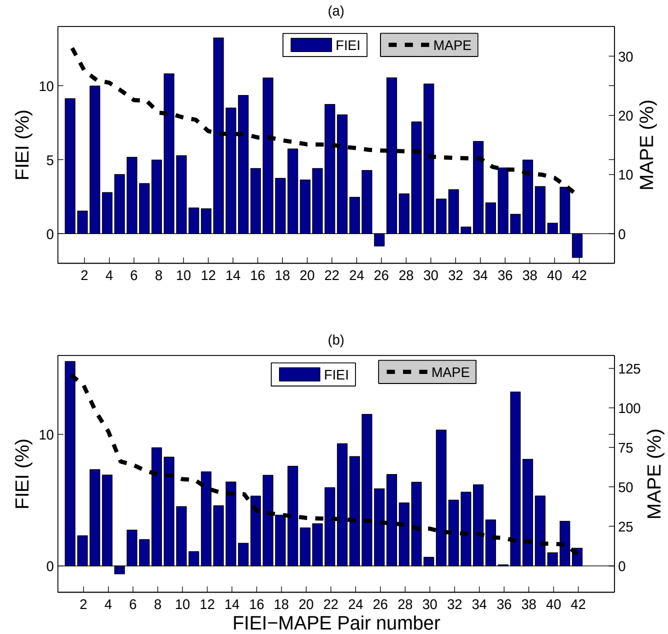

Fig. 6. Daily MAPEs versus the corresponding FIEI for the water plant: (a) TF forecasts, and (b) PDPs.

of AF fell below zero, that value was replaced with \$1/MWh. A value of $a < 1$ would imply improving the TF forecast errors, whereas a value of $a > 1$ would simulate degrading the TF forecasts. An $a = 0$ yields the HOEPs, i.e., perfect forecasts, and $a = 1$ yields the TF forecasts. Due to the unusually high errors of the PDPs, these were not considered for this experiment.

The six-week MAPEs of the artificial forecasts AF for each of the error levels a and the corresponding six-week average FIEIs are presented in Fig. 5. Observe from this figure that for errors less than about 5%, the FIEI is negligible; this is also consistent with findings reported in [16] and [17] for demand forecasting errors. When MAPE falls between 6 to 16%, a 1% improvement in MAPE would result in about 0.2% reduction in operation costs; this reduction is higher when the forecast MAPE falls within the 16 to 24% range (the error level in most published works on electricity market price forecasting falls within a 5 to 15% MAPE range). Observe that this 0.2% cost reduction is significantly higher than the aforementioned 0.08% cost reduction when using the TF forecasts instead of the PDPs.

B. The Water-Plant Load

The daily MAPE and FIEI pairs over the 42-day period for the water-plant load, sorted with respect to MAPE values in a descending order, are presented in Fig. 6. It can be observed from this figure that, similar to the results presented in Fig. 2, high (low) values of FIEI may occur despite the low (high) values of forecast MAPE for the water plant. In addition, the FIEI values turned out to be negative on three occasions. Negative FIEI values imply that using forecast prices actually resulted in lower operations costs; these negative values are all small and are justified in Section II-B. A common pattern in the forecasts on these days was a small under-forecast for low-price hours and a relatively high over-forecast for the high-price hours.

TABLE III
THE MAPES AND FIEIS OF THE TF FORECASTS AND PDPS FOR SOME TYPICAL DAYS

	MAPE (%)		FIEI (%)	
	TF Forecasts	PDPs	TF Forecasts	PDPs
Day 1	16.9	54.8	8.5	4.5
Day 32	15.5	45.2	5.7	1.7

Cross-examining the results of the PDP and TF forecasts for this case study reveals that on 88% of the days, the differences in MAPE values of the TF and PDP forecasts are not consistent with the differences in the corresponding FIEI values. In other words, if TF forecasts have a lower MAPE than the PDPs for the day, the FIEIs resulting from the TF forecasts are actually higher than those of the PDPs (see Table III for some examples). In order to explain this phenomenon, the nature of the water-plant optimization should be considered. The solution of the water-plant optimization problem is such that the pumping operation is mainly scheduled over low price hours rather than high price hours. Thus, the ability of a forecasting model to predict the general trend of price fluctuations is an important feature for the water plant.

The six-week FIEI values associated with using the TF and PDP forecasts for water-plant scheduling, and the corresponding forecast MAPEs, are presented in Table IV. Observe that despite the significant difference in the MAPE values, the economic losses resulting from both the TF and PDP forecasts are very close, which is a counter-intuitive observation. Examining the TF and PDP forecasts showed that despite having different levels of errors in predicting the exact values of prices, the TF and PDP prices performed very closely when it came to predicting the general trend of prices.

TABLE IV
SIX-WEEK MAPES AND ASSOCIATED FIEIS

MAPE_{6w} (%)		FIEI_{6w} (%)	
TF Forecasts	PDPs	TF Forecasts	PDPs
16.1	40.0	4.9	5.5

TABLE V
THE MAPES AND FIEIS FOR DAY 5 FOR BOTH CASE STUDIES

	MAPE (%)		FIEI (%)	
	TF Forecasts	PDPs	TF Forecasts	PDPs
Water Plant	16.3	28.5	10.5	11.5
Process Industry	16.3	28.5	0.6	12.6

It can be observed from the numerical results that a particular set of forecasts may result in significantly different economic benefits when used by inherently different users. For example, the MAPE of the TF forecasts and the PDPs and the associated FIEIs for Day 5 for both case study loads are presented in Table V. Observe that using the TF forecasts for the process industry has a marginal economic loss (FIEI=0.6%); however, the very same set of forecasts results in a very high economic loss for the water plant (FIEI=10.5%). In addition, the relative accuracy of a set of forecasts versus another may be significantly different from the view points of different users. From example, as it is shown in Table V, while using the TF forecasts instead of the PDPs is highly beneficial to the process industry (FIEI=0.6% versus FIEI=12.6%), the water plant's loss from using the PDPs instead of the TF forecasts is not that significant (FIEI=11.5% versus FIEI=10.5%). These results highlight that while a set of forecasts may be considered accurate enough by one user, the very same forecasts may be graded as inaccurate by another.

The numerical results presented for the two case study loads in this section and Section IV-A also imply that when comparing the economic value of two alternative forecasting models for a particular user, the popular error measures may not give the full picture. Specific forecasting capabilities may be critical (e.g., the ability to forecast the prices with respect to a threshold in the case of the process industry) depending on the nature of the operation of the user. If a forecasting model outperforms another in terms of such capabilities, it would result in more economic benefits. Superior capabilities, however, may not always be captured by the popular error measures, such as MAPE.

Using the artificial set of price forecasts AF in (7), a similar analysis was repeated for the water plant to determine the average value of improving the forecasts errors for a given forecasting model; the results are presented in Fig. 7. Observe from this figure that the economic losses resulting from a forecast error of 5% or less is negligible for the water plant, similar to the process-industry load. Furthermore, when MAPE is within a 5 to 14% range, a 1% improvement in forecast accuracy would result in about 0.35% cost reductions for this case study. Beyond this range, the rate of reduction is higher.

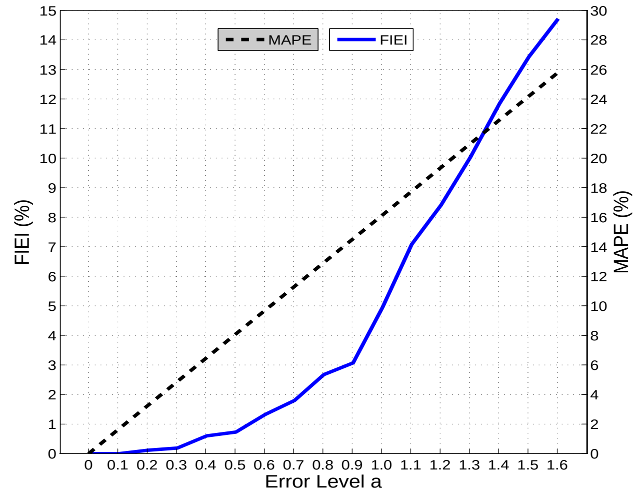

Fig. 7. The six-week averages of the MAPEs for various simulated forecasts, and the corresponding FIEIs.

C. Sensitivity Analysis

In order to study how simulation parameters may impact the above numerical results, sensitivity analyses were carried out for the two case studies.

1) The Process-Industry Load: Considering the fact that most of the technical parameters are fixed in practice for a given gas engine and oil boiler, only the sensitivity of the results with respect to fuel prices is analyzed. Fuel price fluctuations were assumed to have no impact on electricity market prices in the short term.

A change in fuel prices affects the operation of this load since higher fuel prices naturally result in a reduction in on-site electricity production and the purchase of more electricity from the market; in fact, for very high fuel prices, this load will import all its electricity from the grid and turn the gas engine off. On the other hand, if fuel prices drop, this load will produce more electricity on-site; as a matter of fact, for very low fuel prices, the process industry will generate all its electricity locally and export the excess electricity to the market. Note that for very low fuel prices, the market price threshold beyond which on-site generation of electricity is economical would be very low, whereas for very high fuel prices, this threshold would be very high; thus, no price-based optimization would be required in either of the two extreme cases. However, if the threshold falls within the range of minimum and maximum electricity market prices, this load will optimize its operation accordingly. Therefore, the economic value of improving forecast accuracy would depend on how this threshold is predicted by the forecasting models.

The prices of oil and natural gas were increased by 20% in the first scenario and the economic value of improving the forecast accuracy was analyzed using the artificial forecasts AF. It was observed that the new threshold was moved up to about \$63/MWh, and a 1% reduction in forecast MAPE would result in an about 0.16% reduction in costs for MAPEs ranging from 5 to 15%. In a second scenario, the fuel prices were decreased by 20% which resulted in a new threshold of about \$40/MWh. In this case, and for the aforementioned MAPE range, the average cost reduction was about 0.1% for a 1% improvement in forecast errors. Comparing these results with those presented in Section IV-A shows that the economic savings resulting from improving forecast accuracy depends on fuel prices for the process-industry load.

2) The Water-Plant Load: For the water plan, the sensitivity analysis was carried out by increasing (decreasing) water demand, power consumption and water discharge capacity of the pumps by 100% (40%); the area of the reservoir was also changed accordingly. The average cost reductions resulting from improving the forecast accuracy were analyzed based on the artificial forecasts AF. No significant changes were observed, compared to the results presented in Section IV-B. Thus, the results presented for the water plant does not depend on simulation parameters. One should note that optimal pumping schedules are determined considering market price fluctuations and water-demand patterns. Hence, such schedules will not significantly change as long as the price and water-demand patterns do not shift significantly. A significant shift in water-demand fluctuations in the short-term, however, is not realistic and thus was not studied.

V. Conclusions

This work examined the economic impact of electricity market price forecast errors on demand-side market customers. Two typical price-responsive loads, i.e., a process industry and a municipal water plant were considered. These two case studies have different load management capabilities: the process industry has access to an on-site source of electricity, and the water plan can shift its demand over a planning period to some extent. Alternative sets of imperfect electricity market price forecasts with significantly different error characteristics were used as the expected electricity prices. The corresponding ex-post prices were then used to study the economic impact of using imperfect price forecasts for operation scheduling, comparing the costs of operation under exact and imperfect forecast price scenarios. A sensitivity analysis was also performed to asses how the operation parameters could influence the numerical results.

It can be concluded from the presented results and discussions that while the popular error measures such as the MAPE could reflect the overall economic value of improving accuracy level of a particular forecasting model, they may not yield the full picture when used to compare alternative forecasting models. Other considerations, such as how the models meet the specific forecasting requirements of the forecast users, should also be taken into account. This observation implies that "accurate" price forecasting may have different meaning for different forecast users. The interpretation mainly depends upon the nature of the operation of the forecast users and their specific forecasting needs; for example, while some customers, such as the process industry in this study, need to predict future prices with respect to a certain threshold, some others, such as the studied water plant, need to predict the general trend of prices over the planning period. However, the ability of a model in meeting such specific needs may not always be captured by the popular error measures.

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