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Analysing the economic benefit of electricity price forecast in industrial load scheduling

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ABSTRACT

The current trend of electricity market deregulation ushers in increasingly dynamic electricity pricing schemes. The cost-optimal scheduling of industrial loads with accurate price forecasts is therefore important. However, results in the current literature suggest that mean absolute percentage error (MAPE) is poor at indicating the economic benefit of a forecast. This paper presents the economic benefit analysis of electricity price forecast on the day-ahead scheduling of load-shifting industrial plants. A coal-conveying system with storage is used as a case study. The research uses three price forecasting methods on the PJM's market prices over a period of two years. Rank correlation (RC) between the predicted price and the actual price is proposed as an indicator of economic benefit. The results show that RC is a better indicator of economic benefit than root mean square error (RMSE) and MAPE. They also show that potential economic benefit obtainable from forecasts depends on price volatility and not mean price. An artificial forecast is used to validate the superiority of RC over MAPE and RMSE. It is observed that the predictability of a forecast's economic benefit is largely dependent on how responsive the load is to electricity price changes.

1. Introduction

One of the currently dominant trends in the electricity markets is the move from fixed towards dynamic prices. This is driven by the introduction of price-responsive demand response (DR) in demand-side management (DSM) programs [1,2]. Eskom, the South African state-owned power utility, is also moving towards more dynamic pricing schemes [3]. One of Eskom's recent initiatives is the implementation of a critical peak pricing (CPP) pilot project currently under way.[1] DR is useful to a power utility since it improves the reliability of the power system [1]. However, this transition exposes electricity consumers to the risk associated with frequently changing prices [2]. The most appropriate strategy of mitigating the risk of high electricity cost is using cost-optimal scheduling with an accurate price forecasting method; that is, load-shifting.

There is significant interest in the accurate prediction of electricity prices [4–8]. The techniques used for prediction include game theory, simulation models, statistical analysis and data mining models [4]. The commonly used methods of quantifying forecasts' accuracy in literature are mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) [5–8]. A great deal of literature related to price forecasts tends to focus on improving the accuracy of forecasts with little regard for their practical application.

However, there is a growing interest in the economic assessment of price forecast accuracy for specific applications [5,6,9–11]. The authors in [9] and [10] consider the effects of price forecast errors on the supply-side of the grid, while [11] deals with the demand-side. The authors in [9–11] illustrate the inadequacy of MAPE in indicating the economic value of a forecast method. The main contribution of this paper extends this discussion by suggesting rank correlation (RC) as an alternative means of assessing economic impact and illustrating why the use of MAPE and RMSE is flawed.

Abbreviations: ANFIS, adaptive neuro-fuzzy inference system; FEBI, forecast economic benefit index; LSSVM, least squares support vector machine; MAE, mean absolute error; MAPE, mean absolute percentage error; MP, seasonal hourly mean price; OOC, on-off control; RC, Rank correlation; RMSE, root mean square error; SOS, amount of coal in storage; VSC, variable speed control.

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[1] http://www.eskom.co.za/c/article/975/critical-peak-day-pricing-pilot-project/.

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π_i	real-time hourly electricity price
ω, ω_{VSC}	trade-off weighting factors
v_j	price volatility
Ω	plants operational constraints
x_i	scheduling decision variables
s_i	conveyor start-up indicator
u_i	conveyor on-off switch status
D_i	conveyor hourly coal demand
F_i	sample conveyor feed rate
V_i	sample conveyor speed
N_p	number of samples per day
Δt	sampling time in hours

Subscript and superscript

AP	actual price
AFP	artificial forecast price
FP	flat price
PP	predicted price

This paper presents the economic assessment of electricity price forecast accuracy using day-ahead scheduling of load-shifting industrial plants. Two types of load-shifting loads are considered; one with on-off control and the other with continuous motor speed control via variable speed drives (VSDs). Three methods of forecasting day-ahead electricity prices are used to schedule the operation of a coal-conveying industrial plant in a real-time electricity market. The price forecasts and the costs of resulting schedules are compared over a period of two years using PJM market prices [12]. The results show that the economic benefit obtained from the forecast is highly dependent on the volatility of the electricity price being predicted. The ability of RC, MAPE and RMSE to rank the economic benefit of different forecasts is compared. As in [11], the assessment illustrates the weakness of common forecast accuracy indicators in assessing the appropriateness of a forecast method. However, the results in this paper further show that RC between the predicted and actual prices is a better indicator of the economic value of a forecast method. The paper uses an artificial forecast to illustrate why MAPE and RMSE are poor indicators of economic benefit.

The remainder of the paper is organised as follows: Section 2 briefly describes the price data and case study plant considered. Section 3 presents the methodology of assessing economic benefit. Section 4 summarises the forecast methods used. Section 5 presents and discusses the simulation results. Finally, Section 6 concludes the paper.

2. Price data, case study and benefit index

The data used in this paper are the real-time hourly locational marginal pricing data of the PJM, for a period of 24 months from September 2010 [12]. Due to seasonal changes in the electricity prices, data is divided into four seasons of three months each. For each season, the three prediction methods are trained with data of the first two months and performance is evaluated on the remaining month.

On-off control (OOC) or variable speed control (VSC) are two common alternatives used for controlling industrial plants with motors for the purposes of energy efficiency and energy cost optimization. Studies in [13] and [14] show the use of OOC in conveyor belt systems that transport coal. [15] shows both strategies for the control of pumping systems. [16] advocates the use of variable-speed drive technology for energy efficiency initiatives on cooling systems of 20 mines.

The case study industrial plant considered is a conveyor belt system transporting coal, as detailed in [14]. This industrial plant supplies a pre-determined series of hourly demand of coal D_i to a power station through storage bins. The coal-conveying system consists of a series of eight conveyor belts and 12 storage bins. The system's control inputs consist of hourly feed-rates F_i and belt speeds V_i for variable speed drives driving the conveyors. The total capacity of the storage bins is 5595 tonnes. In this case, the upper limits of the feed-rate F_{MAX} and speed V_{MAX} are taken to be 1500 tonnes/h and 2.5 m/s, respectively. The optimal scheduling algorithms for the VSC and OOC are given by (1) and (2), respectively.

2.1. Variable speed control

Apart from optimizing the cost of energy, (1) also attempts to reduce the stress on the belt and conveyor components by minimizing the velocity ramp $(V_i - V_{i+1})$. ω and ω_{VSC} are weighting parameters that control the amount of trade-off between the two objectives. The N_p sampling points are obtained by dividing a 24-h day into equal sampling periods of duration Δt. The power required by the conveyor is modelled as a four-parameter nonlinear function $P(F_i, V_i)$ described in [17]. The variable π_i represents the real-time hourly electricity price.

$$
\begin{aligned}
& L\min_{F_i, V_i} \Delta t \cdot \sum_{i=1}^{N_p} \pi_i P(F_i, V_i) + \omega \cdot \omega_{VSC} \sum_{i=1}^{N_p - 1} (V_i - V_{i+1})^2 \\
& \text{subject to :} \\
& F_i / 3.6 V_i \le Q_{Gmax}, \\
& \mathrm{LL} \le \mathrm{SOS}_0 + \Delta t \cdot \left(\sum_{i=1}^{m} F_i - \sum_{i=1}^{m} D_i \right) \le \mathrm{HL}, \\
& \forall m \in \{1, 2, \ldots, N_p\},
\end{aligned}
\tag{1}
$$

where $F_i \in [F_{MIN}, F_{MAX}]$ and $V \in [V_{MIN}, V_{MAX}]$.

To avoid spillages, the optimal schedule must ensure that the unit mass of material on the belt does not exceed the maximum Q_{Gmax}. It must also ensure that the amount of material in the storage, SOS, is constrained within the upper (HL) and lower (LL) storage limits. The optimization is initialised with the amount of material in the storage (SOS_0) equal to LL. The lower bounds of the F_i and V_i are set to zero. The VSC scheduling problem is a nonlinear optimization problem due to the conveyor power function and the nonlinear programming Matlab[2] toolbox is used to solve it.

2.2. On-off control

For the OOC in (2), the schedule is a series of the binary variables u_i that indicate by 1 when the plant is on and by 0 when it is off. In this case the objective is to minimize the cost of energy and the number of times the plant has to be switched on. Frequent on-off switching of motors is not advisable because it increases mechanical stress on the conveyor components. High start-up current of loaded motors also tends to reduce the motor's life span [14].

[2] http://www.mathworks.com/help/optim/.

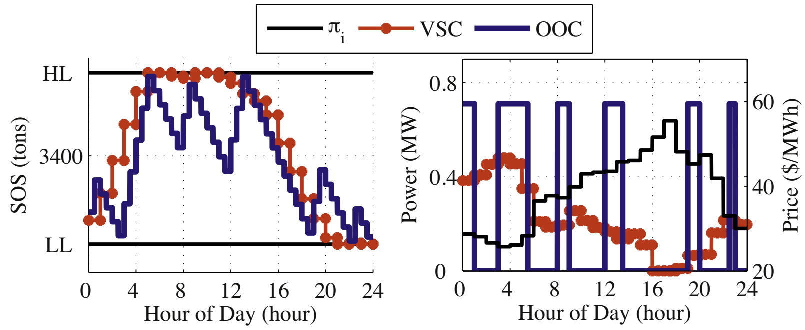

Fig. 1. Typical usage of storage bins and power schedules.

The auxiliary variable s_i indicates by a value 1 whenever a start-up occurs and is thus used to minimize the number of start-ups.

$$\begin{aligned}
&\min_{u_i, s_i} \Delta t \cdot P_{ON} \cdot \sum_{i=1}^{N_p} \pi_i u_i + \omega \sum_{i=1}^{N_p} s_i \\
&\text{subject to :} \\
&\mathrm{LL} \le \mathrm{SOS}_0 + \Delta t \cdot \left(F_{MAX} \cdot \sum_{i=1}^{m} u_i - \sum_{i=1}^{m} D_i \right) \le \mathrm{HL}, \qquad (2) \\
&u_1 - s_1 \le 0,\ u_{i+1} - u_i - s_{i+1} \le 0, \\
&\forall m \in \{1, 2, \ldots, N_p\}, \forall i \in \{1, 2, \ldots, N_p - 1\} \\
&\text{where} u_i, s_i \in \{0, 1\}.
\end{aligned}$$

The system is taken to deliver maximum feed rate and run at maximum speed when it is on. Thus, $P_{ON} = P(F_{MAX}, V_{MAX})$, when $u_i = 1$. A sampling time of 30 min is used for the simulations of OOC. The OOC is a linear binary optimization problem that is solved using a mixed integer solver called Coin-or branch and cut (Cbc) found in the OPTI[3] Matlab toolbox.

2.3. Typical plant schedules

Fig. 1 shows the price schedule and SOS obtained for the bi-annual hourly mean price series using the same daily coal demand [14]. The selected settings are $\omega = 2$ and $\omega_{VSC} = 0.1$. The VSC and OOC objective function costs are 192 and 172, respectively, both with the mechanical cost contributing less than 10%.

The high prices are avoided by both the VSC and OOC plants. During the first six hours of the day the power usage of the VSC cannot be increased any further to take advantage of the low prices because the storage reaches maximum capacity. Fig. 1 shows that the OOC scheduled plant is on in spite of a period of relatively high prices between 12:00 and 13:30, because otherwise the storage level would go beyond the lower limit. The schedules shown in Fig. 1 are able to avoid the price peak well because the real-time market energy price used for scheduling is fully known. This is practically impossible for real-time pricing, therefore in practice scheduling will have to rely on predicted prices.

2.4. Forecast economic benefit index

Generally, an accurate forecast produces low scheduling cost because it correctly predicts hours with high prices to be avoided and hours with low prices to be used. A bad-case scenario is when the day-ahead price is assumed to be constant and the resulting schedule merely attempts to meet the operational constraints. In such a case the schedule is developed without any information on the future prices. Thus, the cost of a schedule using a flat price profile throughout the day is used as a basis for comparison. For the purpose of comparison, the economic benefit of a forecasting method is quantified by creating a forecast economic benefit index (FEBI) adapted from [11] and defined by (3).

$$\mathrm{FEBI} = 100 \times \frac{\mathrm{Cost}^{FP} - \mathrm{Cost}^{PP}}{\mathrm{Cost}^{FP}} \qquad (3)$$

where Cost^{FP} and Cost^{PP} are the plant's operational costs determined using a flat price (FP) and predicted price (PP) schedules, respectively. The FEBI is a big positive value when the PP schedule is a lot cheaper than the FP schedule. In this case, the magnitude of the FEBI quantifies how beneficial the forecast is. On the contrary, the FEBI is negative when the PP is more expensive than the FP schedule. This indicates that the forecasting is in fact counter-productive. Thus, a positive value implies that there is a cost advantage in using the PP while a negative value implies a loss incurred owing to the PP.

3. Methodology

The methodology for calculating performance of forecasts using scheduling costs and FEBI is summarised in Fig. 2. For each day of operation the following three steps are carried out:

Step 1: Scheduling for a particular day k begins at the end of day $k-1$, at which time the actual prices (APs) of day k are unknown. The schedule is obtained by solving an optimization problem given by (4).

$$\left\{ \begin{array}{ll} \min & \mathrm{Cost}(\pi_i^{FP}; P(x)) \\ x_i & \text{s.t.} x_i \in \Omega, \forall i \in [1, N_p] \end{array} \right\} \qquad (4)$$

where x_i, $P(x)$ and π_i^{FP}, denote the scheduling decision variables, power used by the schedule and the predicted day-ahead prices, respectively. Ω denotes all the relevant operational constraints that must be satisfied by the schedule. In the current application, this step is carried out by solving (1) and (2) with predicted prices for the VSC and OOC plants, respectively. Let x_i^{PP} and $P_i^{PP} \doteq P(x_i^{PP})$ denote the solution to (4) and the corresponding power required by the schedule given the predicted price, respectively.

Step 2: The optimal schedule is then implemented throughout day k during which the actual prices are being revealed.

Step 3: At the end of day k, (5) is used to calculate the actual daily cost of the schedule derived from predicted prices, Cost^{PP}, since π_i^{AP} is known.

$$\mathrm{Cost}^{PP} = \Delta t \cdot \sum_{i=1}^{N_p} P_i^{AP} \cdot \pi_i^{AP} \qquad (5)$$

[3] http://www.i2c2.aut.ac.nz/Wiki/OPTI/.

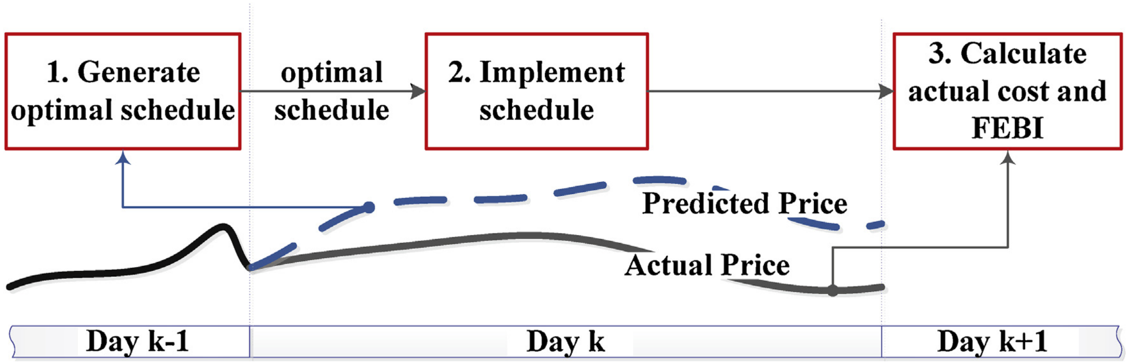

Fig. 2. Methodology for calculating benefit of a day-ahead forecast.

The FP schedule is then calculated using (4), with a FP whose value is the mean of the price during day k. Let the power required by the FP schedule be P_i^{FP}, then the cost, Cost^{FP}, is calculated as shown in (6). This is considered as a baseline cost.

$$\mathrm{Cost}^{FP} = \Delta t \cdot \sum_{i=1}^{N} P_i^{FP} \cdot \pi_i^{AP} \tag{6}$$

The FEBI for day k can then be calculated using (3). Unlike Cost^{FP}, Cost^{PP} is obtained with information about future prices, that is the predicted price. Therefore Cost^{PP} is normally smaller than Cost^{FP} and FEBI is normally a positive value. A good forecasting methodology should have large positive values of FEBI.

3.1. Rank correlation as an indicator of economic benefit

Refs. [11] and [6] criticize the use of MAPE and RMSE for evaluating the economic benefit of forecasts for demand-side applications but do not explore alternative methods of evaluation. They proposed the use of price classification instead. These price classification methods rely on assigning thresholds whose values are said to be dependent on specific applications [6,18,19]. Selection of thresholds is straightforward for electrical loads with co-generation since the threshold is simply set to equal the cost of internal generation. However, this is difficult for load-shifting applications such as those considered in this paper because the schedule depends on the relative difference of the hourly prices and not the absolute values. For example, 40.06 $/MWh can be considered as expensive on 12 October 2012 where it is the maximum price, but cheap on 30 October 2012 where the mean price is 58.62 $/MWh. Thus, setting threshold values is not easy.

Since a good forecast only needs to distinguish between high and low prices, one plausible alternative is to use the correlation between the actual price and the predicted price as an indicator of a forecast method's economic benefit. The most commonly used correlation coefficient is the Pearson product-moment (PPM) coefficient, which measures the linear dependence between two variables. However, since the electricity price series is nonlinear with a lot of spikes, an RC would be the most appropriate to use [7]. The RC measures statistical dependence without the assumption of linearity and it is considered a robust measure of correspondence [20,21]. The Kendall RC between a predicted (π_i^{PP}) and actual price (π_i^{AP}) series is used in this paper. The fact that RC is based on ranks, it only measures the ability of a forecast to correctly identify peaks and valleys in the price series and disregards the absolute value of the prices. A detailed explanation of how RC is calculated is provided in Appendix A.

The Spearman and Kendall correlations are the most commonly used methods of calculating RC, but the Kendall RC is selected because it has been shown to be more robust and simple to compute [20]. One of the more robust proposed methods of calculating RC is the median correlation coefficient [20]. However, our preliminary analysis has indicated that this method is inferior because it treats the price spikes as outliers, thereby underestimating the correlation coefficient. The limitation of correlation is that a small sample size can only calculate large correlation values with enough confidence level. For example, only values above 0.28 can be calculated with a commonly used standard of 95% confidence level using our 24-h samples of daily prices, for the PPM [22] .

4. Electricity price forecasting

Forecasting electricity prices is conducted using three methods, namely; seasonal mean prices (MP), least-square support vector machine (LSSVM) and an adaptive neuro-fuzzy inference system (ANFIS). For MP, the hourly average prices of the training data are calculated and used as the day-ahead price prediction. In the cases of both the LSSVM and ANFIS, one-step ahead models are trained and used to recursively predict prices 24 h ahead. The details of this procedure are outlined in [23] using wind speed data. The LSSVM and ANFIS predictors use selected price lags over the past 48 h as model inputs.

LSSVM is a form of SVM that simplifies the formulation of SVM, resulting in a set of linear equations. The advantage of LSSVM is that it requires less training effort than the normal SVM. The LSSVM model employed here uses a Gaussian kernel. The details about training an LSSVM regression model are available in [24,25]. ANFIS is an adaptive multi-layered network that maps multiple inputs to an output using fuzzy logic constructs. A comprehensive introduction to ANFIS is available in [26]. ANFIS has been used successfully in a number of recent publications [27–29]. The ANFIS model implemented in this paper uses the Sugeno-type structure with three triangular windows on the best three price lags.

The maximum average values of MAPE, RMSE and RC are 27.1%, 15.2% and 0.59, for all three forecast methods over the eight-months testing period. The prediction saves up to 16.6% and 14.6% of the cost when compared to scheduling without any price information (FP schedule). A review of price forecasting mechanisms shows that MAPE accuracy reported in many papers is within the range of 1–36% [4,6,7]. The RMSE error on the Spanish market is reported to be in the range of 5–10% [5]. Therefore, the performances of the considered forecast methods are good enough because they give comparable ranges of accuracy to those reported in literature. It is also worth noting that prediction accuracy varies with price volatility so prediction performance of the same method may vary with price data [6].

Table 1
A seasonal summary of forecasting performances.

Season	Forecast method	VSC FEBI	OOC FEBI	MAPE	RMSE	RC
Autumn 2011	MP	3.9	4.9	28.5	12.2	0.40
	LSSVM	10.7	11.3	16.6	9.1	0.44
	ANFIS	9.7	11.1	18.9	10.2	0.39
Winter 2012	MP	10.2	9.7	17.5	7.9	0.65
	LSSVM	8.6	5.5	13.0	6.3	0.50
	ANFIS	6.9	2.0	12.2	6.2	0.48
Spring 2012	MP	2.3	8.6	21.9	13.9	0.43
	LSSVM	20.3	17.1	20.1	13.0	0.63
	ANFIS	12.0	11.5	22.2	14.0	0.52
Summer 2012	MP	24.4	20.5	24.5	13.2	0.80
	LSSVM	22.8	15.9	19.8	12.0	0.76
	ANFIS	19.9	11.9	21.4	13.1	0.67

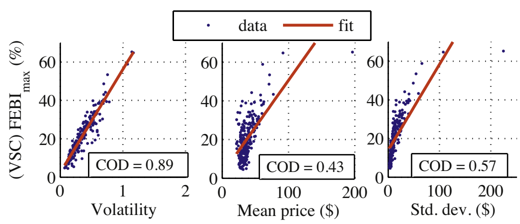

Fig. 3. Dependence of daily maximum economic benefit on three factors for VSC.

5. Simulation results and discussions

5.1. Effect of price volatility on economic benefit

The electricity price modelling, forecasting as well as the simulation of the plants are carried-out in the Matlab environment. A perfect prediction must give the exact value of the actual price. Therefore, ideally when the optimal solutions of (4) are reached, the FEBI of the actual price is always equal to or bigger than that of any other forecast method. This means that the FEBI calculated using the actual price represents the upper limit of the economic benefit ($FEBI_{MAX}$) that can be achieved by any forecast method.

In this paper, price volatility (ν_j) is defined as the ratio of the standard deviation (Std. dev) to the mean of daily prices [25]. Figs. 3 and 4 show the dependence of $FEBI_{MAX}$ on mean price, Std. dev and volatility for each of the 241 days of testing. They also show the coefficient of determination (COD) for a linear fit. The strong linear dependence of volatility on economic benefit is clearly visible. This result is intuitive, since it implies that price forecasting is mostly required when the variability of the hourly prices in a day is high. However, it also means a forecasting method derives varying amounts of benefit on each day even when the forecasting method's accuracy is constant. A comparison between Figs. 3 and 4 shows a particularly higher number of days with high volatility and low $FEBI_{MAX}$ values for the OOC plant than the VSC plant. This indicates a distinct difference in the behaviour between the two methods of control. This behaviour is explained in Section 5.3. It is worth noting that the prediction of $FEBI_{MAX}$ by the volatility cannot be perfect because the plants are scheduled not only to reduce the operating cost, but also to minimize mechanical stress in the components.

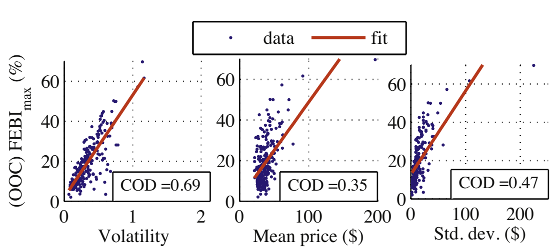

Fig. 4. Dependence of daily maximum economic benefit on three factors for OOC.

5.2. Indicators of economic benefit

A summary of the performances of economic benefit indicators and forecasting methods is given in Table1. For the sake of brevity only the last four seasons are shown.

For winter and summer 2012, Table 1 shows that the values of MAPE and RMSE for MP are higher than those of ANFIS. This wrongly suggests that ANFIS's predictions are more accurate than those of MP. A comparison of FEBI values clearly shows that MP provides a better forecast method than ANFIS in terms of the economic benefit. On the contrary, the higher values of RC for the MP compared to ANFIS indicate that MP is able to forecast more accurately the relative difference in hourly prices in a day than ANFIS; as a result it gives higher values of FEBI. In fact the comparison of RC values is able to rank the forecast methods in a correct order of average economic benefit for six seasons out of a total of eight. That is, excluding the two autumn seasons. By comparison MAPE is successful in only two.

The failure of average RC in predicting the right order (ranking) of economic benefit between MP and LSSVM during the autumn of 2011 may be attributed to two possible reasons. The first reason is that the accuracy of correlation coefficients is low because only 24 samples are used per day [22]. Therefore, the average values of RC given by forecast methods during these seasons are too close to distinguish between the methods confidently. Thus RC performs poorly when correlation values are low. Another reason is the variation in volatility during the season. It has already been established in Section 5.1 that high volatility tends to present bigger opportunities for scheduling cost reduction. A forecast may have higher correlations during periods of high volatility even though the average value of RC is low. This would give such a forecast disproportionately high benefits since a forecast is more beneficial

Table 2
Ranking error sensitivity to storage size.

Type	Ranking Index	Storage size (% of 5595 tonnes)			
		75	100	150	300
VSC	MAPE	41.4	41.6	43.0	43.0
	RMSE	38.5	39.3	42.6	41.5
	RC	23.9	20.9	23.4	24.2
OOC	MAPE	51.7	48.3	43.6	48.7
	RMSE	48.8	43.7	43.7	49.4
	RC	43.4	34.7	33.3	42.3

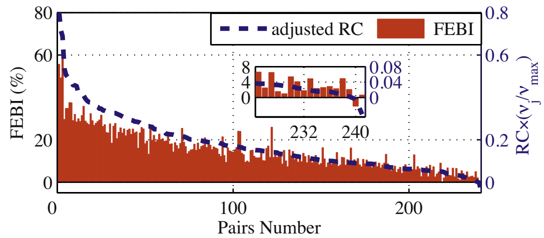

Fig. 5. Dependence of economic benefit on RC for LSSVM forecasts.

during periods of high volatility. To investigate this, correlation values adjusted by volatilities can be used. The total volatility-adjusted RC can be calculated by,

$$\text{Total volatility} - \text{adjusted RC} = \left(\sum_{j=1}^{M} \text{RC}_j \cdot \frac{v_j}{v_{\max}}\right) \quad (7)$$

where M is the number of days, 30 days in the case of Autumn 2011. v_{max} is the maximum volatility value during Autumn 2011. Using (7) the Autumn of 2011 gives the values 6.34, 6.99 and 6.45 corresponding to MP, LSSVM and ANFIS, respectively. These values are in agreement with the values of FEBI. Therefore, it is prudent to do a comparison based upon a volatility-adjusted RC whenever the RC values are very close to each other, as is the case with Autumn 2011, in Table 1.

Fig. 5 shows the ordered pairs of FEBI and volatility-adjusted RC, for the LSSVM forecasting method. As expected, Fig. 5 shows that adjusted RC values are visibly proportional to the FEBI. The pair with the smallest FEBI and adjusted RC correctly appears towards the end, as pair number 240. However, the volatility adjustment does not improve the performance of MAPE and RMSE. Scatter plots of adjusted values for RC, MAPE and RMSE give linear fits to FEBI with COD values of 0.91, 0.58 and 0.31, respectively. These again show the superiority of RC in indicating the magnitude of economic benefit.

The three indicators (without adjustment) are further tested on their ability to rank the performance between any two of the three prediction algorithms used. The summary of the ranking errors is shown in Fig. 6. The average ranking error for RC is 20.1% and 34.7 % for the VSC and OOC plants, respectively. This indicates that it is harder to predict the economic benefit of an OOC plant than that of a VSC.

5.3. Using an artificial forecast

In order to validate the observation that RC, but neither MAPE nor RMSE is important when assessing the benefit of a forecast

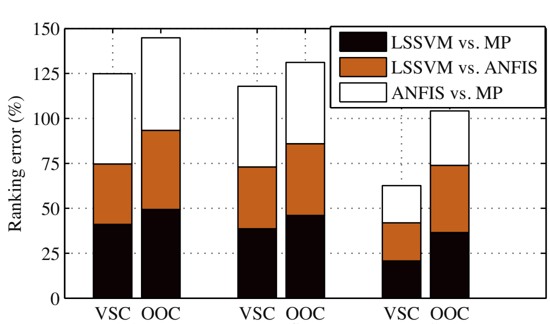

Fig. 6. Ranking error when comparing the benefit between forecasts.

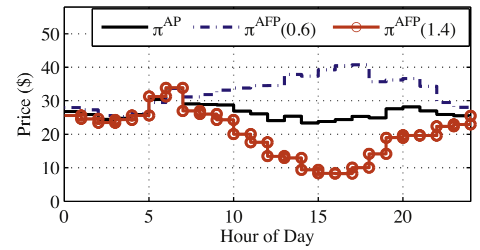

Fig. 7. Actual price and artificial forecast over a 24-h period.

method in a load-shifting application, a set of artificial forecasts (AFs) is created using (8).

$$\pi_i^{\text{AFP}}(c_{\text{mean}}) = c\pi_i^{\text{AP}} + (1-c)\pi_i^{\text{dist}}$$
$$\text{where} c = c_{\text{mean}} + \mathbf{U}[-0.2, +0.2] \quad (8)$$

where π_i^{AFP} and π_i^{AP} denote the AF prices generated and the AP forecast, respectively. π_i^{dist} is a disturbance price that is negatively correlated to AP. The mean of the uniformly distributed parameter c_{mean} is varied between 0 and 1.6 in steps of 0.2 so as to generate multiple forecasts.

The AFs become closer to the AP as c_{mean} increases from 0 to 1 and decreases from 1.6 to 1, but from opposite sides, as illustrated by Fig. 7. When c_{mean} is 0 the AF is almost equal to π_i^{dist}. Thus, the indicators are at their worst values, as shown in Figs. 8 and 9 . When c_{mean} is 1 the AF is almost equal to the AP. As a result, the MAPE and RC values are close to 0% and 1, respectively.

Fig. 8 shows that the economic benefit of $\pi_i^{\text{AFP}}(1.4)$ is far better than of $\pi_i^{\text{AFP}}(0.6)$ even though their respective MAPE of 25.1% and 23.7% are close. This is because the forecasts are equidistant from the AP, even though they lie on opposite sides, as shown in Fig. 7. It is worth noting that the values of RMSE for both forecasts are also close, with values of 9.1 and 8.4, respectively.

The forecast $\pi_i^{\text{AFP}}(1.4)$, which tends to follow the trend of the AP in identifying periods of low prices, is more correlated than $\pi_i^{\text{AFP}}(0.6)$, which opposes the trend. Therefore $\pi_i^{\text{AFP}}(1.4)$ should perform better than $\pi_i^{\text{AFP}}(0.6)$, as correctly indicated by RC in Fig. 9. This result agrees with the observations made in [11], that the PP trends and not specific values are important when scheduling a load-shifting plant.

Fig. 9 shows that the RC performs better for the VSC than the OOC plant. This is because the OOC plant tends to be more insensitive to small changes in RC. For example, $\pi_i^{\text{AFP}}(0.2)$ and $\pi_i^{\text{AFP}}(0.4)$ as well as $\pi_i^{\text{AFP}}(1.2)$ and $\pi_i^{\text{AFP}}(1)$ have almost equal economic benefit. The reason for this behaviour becomes clear when comparing the typical schedules in Fig. 1. The power usage of the VSC plant can vary flexibly between 0 and the maximum value, while it is restricted to either full/no power for the OOC plant. Thus the OOC becomes insensitive to small variations in the price forecast's RC.

Another observation for the OOC plant in Fig. 9 is that there are cases where AF with a slightly smaller RC result in better economic benefits. This is due to the fact that the scheduling problem defined in (2) optimizes both energy cost and a mechanical objective. Therefore the very low prices of AF(1.4) and AF(1.6) encourage the OOC to have more start-ups, thereby enabling the plant to reduce more cost compared to AF(1). The number of start-ups in AF(1), AF(1.4) and AF(1.6) are 4, 6 and 6, respectively. This is also the reason why comparing Fig. 4 shows a particularly high number of days with high volatility and low values of FEBI$_{MAX}$ when compared to the VSC plant in Figs. 3.

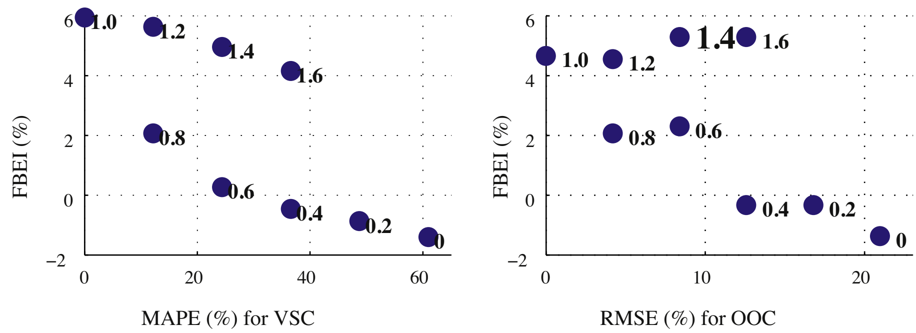

Fig. 8. Dependence of economic benefit on MAPE and RMSE for the artificial forecast.

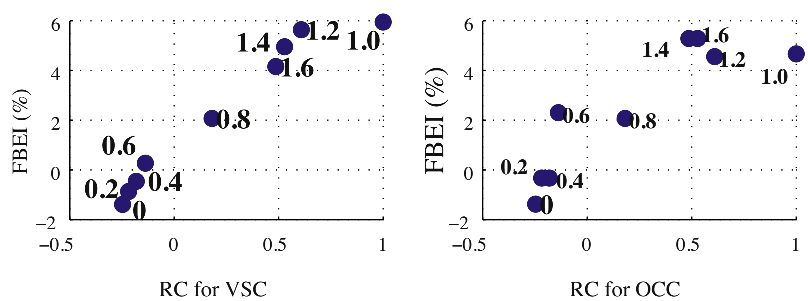

Fig. 9. Dependence of economic benefit on RC, for the artificial forecast.

5.4. Sensitivity analysis

The preceding discussion implies that the success of RC as an indicator of economic benefit is dependent on the weighting parameter (ω) in (1) and (2). Fig. 10 shows the values of COD for the plots of the FEBI versus RC for different values of ω. Increasing the value of ω decreases the emphasis of the resulting schedule towards optimizing energy cost and increases the impact of the mechanical cost. As expected, the results in Fig. 10 show that the usefulness of RC decreases with decreasing emphasis on optimizing the energy cost. It is also worth noting that the COD of the OOC plant falls faster than that of the VSC plant as ω increases.

Table 2 compares the abilities of RC, MAPE and RMSE in ranking the forecast methods according to their economic benefit for varying amounts of the plant's storage size, as percentage of its original value. The results show that RC remains a better indicator regardless of the storage size. The results for the VSC plant are fairly stable across all storage sizes. However, increasing the storage size in OOC increases the possibility of multiple start-up and this makes the performance of forecasts more unpredictable. This explains the large error values when the storage size is above 200%. Also, the binary problem of the OOC becomes too difficult for the optimizer to solve quickly when the storage size decreases. As a result many of the solutions become sub-optimal. This is why the ranking error of RC is large when 75% storage size is used.

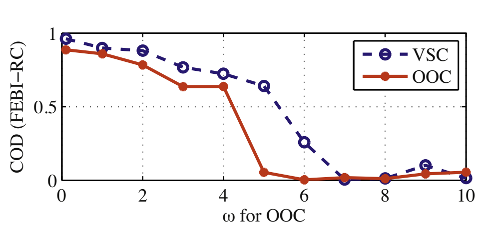

Fig. 10. Predictability of economic benefit as ω changes.

6. Conclusion

This paper presents an assessment of the economic impact of price prediction on a load-shifting industrial plant. Rank correlation between forecast and actual prices is found to be a suitable indicator of economic performance of a forecast in day-ahead scheduling of load-shifting applications. The suitability of RC is attributable to its ability to capture the similarity between the trends in the actual and forecast prices. The analysis shows that MAPE and RMSE are not suitable indicators of the economic benefit because they merely measure the absolute error of a prediction. These results are in agreement with current literature, which declares that the prediction of relative price trend and not the actual value, is useful for load-shifting applications [11]. The economic benefit increases with increasing price volatility in the day-ahead scheduling of load-shifting applications. The results show that the economic benefit obtained from price forecasts becomes less predictable when more emphasis is placed on other operational requirements, such as mechanical stress of components, apart from cost reduction. The results also indicate that it is easier to predict the economic performance of a forecast for a plant controlled using variable speed drives than one controlled by an on/off switch.

Appendix A. Calculating Kendal's rank correlation

The Kendal RC between a predicted (π_i^{PP}) and actual (π_i^{AP}) price series is calculated using (9). N_C and N_D are the number of concordant and discordant pairs respectively. The pair of observations (π_i^{PP},π_i^{AP}) and (π_j^{PP},π_j^{AP}) are said to be concordant when $rank(\pi_i^{PP}) > rank(\pi_j^{PP})$ and $rank(\pi_i^{AP}) > rank(\pi_j^{AP})$, or $rank(\pi_i^{PP}) < rank(\pi_j^{PP})$ and $rank(\pi_i^{AP}) < rank(\pi_j^{AP})$. N_{TA} and N_{TP} represent the number of rank ties for actual prices (i.e. $rank(\pi_i^{AP}) = rank(\pi_j^{AP})$) and predicted prices (i.e. $rank(\pi_i^{PP}) = rank(\pi_j^{PP})$), respectively. The number 24 used in (9) accounts for the number of hours in the daily price series.

$$\mathrm{RC} = \begin{cases} \dfrac{2}{24(24-1)} \cdot (N_C - N_D) & \text{(generally, or)} \\ \dfrac{(N_C - N_D)}{\sqrt{(N_C + N_D + N_{TA}) \cdot (N_C + N_D + N_{TP})}} & \text{(when there are ties)} \end{cases} \tag{9}$$

As an example, consider the 4-h long predicted price series {24.5, 25.0, 32.6, 52.1} \$/MWh and corresponding actual prices {26.3, 22.2, 40.7, 28.9} \$/MWh. The ranks of the series are {1,2,3,4} and {2,1,4,3} and the 4 sets of observations are A (1, 2) ≡ (24.5, 26.3), B (2, 1) ≡ (25.0, 22.2), C (3, 4) ≡ (32.6, 40.7) and D (4, 1) ≡ (52.1, 28.9). The concordant pairs are (A,C), (A,D), (B,C) and (B,D), while (A,B) and (C,D) are the discordant pairs. Thus, $N_C = 4$, $N_D = 2$ and there are no ties. Using the 4-h long series, the first condition of (9) applies, therefore RC = 2 · (4 − 2)/4(4 − 1) = 1/3.

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