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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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| | |
|---|---|
| $\pi_i$ | real-time hourly electricity price |
| $\omega$, $\omega_{VSC}$ | trade-off weighting factors |
| $\nu_j$ | price volatility |
| $\Omega$ | 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 |
| $\Delta t$ | 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 $(V_i - V_{i+1})$. $\omega$ and $\omega_{VSC}$ 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 $\Delta t$. The power required by the conveyor is modelled as a four-parameter nonlinear function $P(F_i, V_i)$ described in [17]. The variable $\pi_i$ represents the real-time hourly electricity price.

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

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 ($\mathrm{SOS}_0$) 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/.