Forecasting the Hourly Ontario Energy Price by Multivariate Adaptive Regression Splines

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***Abstract*— Multivariate adaptive regression splines (MARS) technique is an adaptive non-parametric regression approach which has been used for various forecasting and data mining applications in recent years. This technique is more useful when a large number of explanatory variable candidates need to be considered. In this paper, the MARS technique is applied to forecast the hourly Ontario energy price (HOEP). The MARS models are developed in this work considering two scenarios for the explanatory variables. In the first scenario, the model is build based solely on the lagged values of the HOEP. In the second scenario, current and lagged values of the latest pre-dispatch price and demand information, made available by the Ontario Independent Electricity System Operator (IESO), are also considered as explanatory variables. The forecasts generated by the developed models for high and low demand periods are significantly more accurate than the currently available forecasts for HOEP, demonstrating the MARS capability for electricity market price forecasting.**

***Index Terms*— Price forecasting, electricity markets, Multivariate Adaptive Regression Splines (MARS).**

I. Introduction

A prior knowledge of electricity market price fluctuations is essential for both the supply and demand sides. Price forecasting, with dependable accuracy, helps power suppliers in setting up rational offers in the short-term, as well as designing physical bilateral contracts in the medium-term. In addition, generation expansion plans are directly influenced by market price indicators for electricity in the long-term. For demand side entities, an insight into the market price fluctuations is crucial in order to decide between producing power locally or buying it from the spot markets in the short-term. Furthermore, market price forecasts can help the demand side to hedge against the risk of price volatility through physical bilateral contracts in the medium-term, and to plan their investment in distributed generation possibilities in the long-term. Hence, electricity market price forecasting has been the focus of several recent studies, and numerous methods have been reported applying artificial intelligence or time series based models.

Artificial intelligence based models have been employed for forecasting the PJM market prices [1]–[3] and the UK power pool prices [4]. Furthermore, a committee machine of neural networks [5] and a neural network based Kalman filter method [6] have been used for forecasting the on-peak average of New England market prices. Wavelet [3], [7] and input/output hidden Markov models [8] have also been used for forecasting the Spanish electricity market prices. On the other hand, ARIMA, dynamic regression and transfer function are the most popular time series models for electricity price forecasting. The ARIMA model has been used to forecast the Spanish market prices [7], [9], Californian market prices [9], Leipzig power exchange prices [10], and the PJM market prices [3]. The dynamic regression and transfer function models have been used for forecasting the Spanish and Californian market prices [11] and the PJM market prices [3]. The time series based GARCH models have also been used for forecasting the Spanish market prices [12]. Furthermore, some studies have combined the time series and artificial intelligence models [13], [14].

The multivariate adaptive regression splines (MARS) technique [15] is basically an adaptive piece-wise regression approach. This method has been employed for various prediction and data mining applications in recent years [16]–[24]. However, to the best of the authors' knowledge, MARS has not yet been applied for electricity market price forecasting.

In the Ontario market, the Independent Electricity System Operator (IESO) publishes forecasts for the Hourly Ontario Energy Price (HOEP) in the form of hourly-updated Pre-Dispatch Prices (PDPs). The PDP is calculated based on the most recent market information using the pre-dispatch version of Ontario's market dispatching and pricing algorithm [25]. The last published PDP for a given hour, called the 1-hour ahead PDP, is considered as the final price signal which is sent from the IESO to the market participants. Historical market data reveals significant deviation of the HOEP from the 1-hour ahead PDP [26], with an annual Mean Absolute Percentage Error (MAPE) of 26% for 2004. The only other study reported for forecasting the HOEP is [27], where a neuro-fuzzy model iss used and the daily MAPE of the generated 1-hour ahead forecasts are reported to vary between 19.83% to 24% across different scenarios.

In the present paper, the MARS model is considered for HOEP forecasting. Lagged values of the HOEP as well as the latest PDP and pre-dispatch demand (PDP) information are considered as explanatory variables in two separate scenarios, and 1-hour ahead HOEP forecasts are generated for six weeks over high and low demand periods.

The rest of this paper is organized as follows: In Section II, the MARS technique is described and a more detailed literature review of its applications is presented. The MARS models for the HOEP are developed in Section III and numerical

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results are discussed in Section IV. Section V summarizes the main contributions of this paper.

II. Multivariate Adaptive Regression Splines

Multivariate Adaptive Regression Splines (MARS) was first introduced by Friedman [15] to efficiently approximate the relationship between a dependent variable and a set of explanatory variables in a piece-wise regression. Capability of MARS for modeling time series data was subsequently demonstrated in [28], where lagged values of the time series were treated as explanatory variables. In recent years, application of MARS has been reported for modeling a variety of data, such as, speech modeling [16], mobile radio channels prediction [17], and intrusion detection in information systems security [18]. In addition, MARS was employed to model the relationship between retention indices and molecular descriptors of alkanes [20], and to describe pesticide transport in soils [21]. MARS has also been applied to predict the average monthly foreign exchange rates [22], to model credit scoring [23], and for data mining on breast cancer pattern [24]. In all of the cited studies, promising results have been reported where MARS has been employed either for forecasting or for data mining purposes.

MARS is a non-parametric modeling approach versus the well-known global parametric modeling methods such as linear regression [15]. In global parametric approaches the underlying relationship between a target variable and a set of explanatory variables is approximated using a (usually simple) global parametric function which is fitted to the available data. While global parametric modeling methods are relatively easy to develop and interpret, they have a limited flexibility and work well only when the true underlying relationship is close to the pre-specified approximated function in the model. To overcome the weaknesses of global parametric approaches, non-parametric models are developed locally over specific subregions of the data; the data is searched for optimum number of subregions and a simple function is optimally fit to the realizations in each subregion. Recursive Partitioning Regression (RPR) is one of the most studied paradigms in the non-parametric modeling approaches.

RPR is an adaptive algorithm for function approximation with the capability of handling a large number of explanatory variables. Let consider a set of explanatory variables $X = \{x_1, x_2, ..., x_n\}$ over a domain $D \subset \mathbb{R}^n$, a target variable y and N realizations of the process $\{y_i, x_{1i}, x_{2i}, ..., x_{ni}\}_1^N$. The true relationship between y and X can be described as:

$$y = f(x_1, x_2, ..., x_n) + \epsilon \tag{1}$$

where f is an unknown function, and the error term ϵ is a white noise. Briefly, $f(X)$ is approximated in RPR as:

$$\hat{f}(X) = \sum_{m=1}^{M} a_m B_m(X) \tag{2}$$

where $\{a_m\}_1^M$ are the coefficients of the model which are estimated to yield the best fit to the data; M is the number of subregions $R_m \subset D$, or equivalently the number of basis functions in the model; and the basis function B_m is defined as:

$$B_m(X) = \begin{cases} 1 & X \in R_m \\ 0 & otherwise \end{cases} \tag{3}$$

Although RPR is a powerful method, it suffers from various shortcomings such as discontinuity at the subregion boundaries. MARS is a generalized version of RPR that overcomes some of the limitations of the original version.

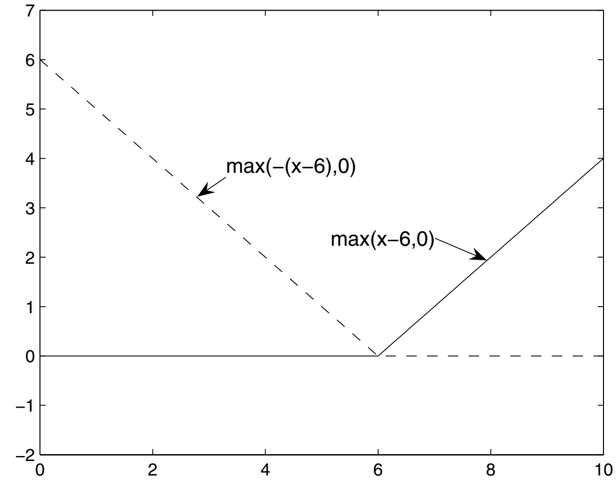

Fig. 1. Hockey stick spline basis function and its image for knot=6.

The main core of the MARS modeling approach is the hockey stick spline basis function, which maps a variable x to x^* as:

$$x^* = \max(x - c, 0) \tag{4}$$

where c is referred to as the basis function knot. The mirror image of the hockey stick spline basis function is also exploited in MARS to handle non-zero slope for values below the knot, and it can be expressed as:

$$x^* = \max(-(x - c), 0) \tag{5}$$

A hockey stick spline basis function and its mirror image are illustrated in Fig.1.

In MARS, the RPR model represented in (2) is modified as:

$$\hat{f}(X) = a_0 + \sum_{m=1}^{M} a_m H_m(X) \tag{6}$$

where a_0 is a constant, a_m and M are defined in (2) and the spline basis functions $H_m(X)$ are developed as:

$$H_m(X) = \prod_{k=1}^{K_m} [\max(s_{k,m}(x_{v(k,m)} - t_{k,m}), 0)] \tag{7}$$

where the explanatory variables associated with the basis function H_m are labeled by $v(k,m)$; K_m is the level of interaction between $v(k,m)$ variables; $t_{k,m}$ indicates the knot locations for H_m; and $s_{k,m}$ takes +1 for the hockey stick basis function and -1 for its mirror image.

MARS models are developed through a two-stage forward/backward stepwise regression procedure. In the forward stage, the entire domain D is split into overlapping subregions and the model parameters are estimated by minimizing a lack-of-fit criterion. If the maximum number of subregions is not specified, an over fitted model with basically one subregion (basis function) per realization is built in this stage, and all possible interactions among the explanatory variables are considered. In the backward stage, the basis functions which no longer contribute to the accuracy of the fit will be removed. To make the MARS algorithm computationally affordable, the level of interaction between variables, as well as the maximum number of basis functions in the model are specified by the user.

A modified version of the generalized cross validation criterion (MGCV) is used in the MARS algorithm as the lack-of-fit criterion:

$$\text{MGCV} = \frac{1}{N}\sum_{i=1}^{N}[y_i - \hat{f}(X_i)]^2/[1 - \frac{\tilde{C}(M)}{N}]^2 \tag{8}$$

where $[1 - \frac{\tilde{C}(M)}{N}]^2$ is a penalty factor accounting for the increased variance resulting from a complex model, and $\tilde{C}(M)$ is defined as:

$$\tilde{C}(M) = C(M) + d \cdot M \tag{9}$$

where $C(M)$ is the number of parameters being fit, and d is another penalty factor with 3 as a typical value [15].

III. Modeling the HOEP Using MARS

The electric power sector of the province of Ontario in Canada went through a process of transition from a government-owned vertically integrated system to a competitive wholesale electricity market on May 1, 2002. The Ontario electricity market consists of the real-time physical energy and operating reserves markets and a financial transmission rights (FTR) market, while a financial day-ahead forward market is under development. The uniform market clearing prices (MCPs) are determined every five minutes and the hourly average of five minute energy MCPs is defined as the HOEP. The market clearing algorithm is run in two time-frames, *i.e.,* the pre-dispatch and real-time (dispatch), and in two modes, *i.e.,* unconstrained and constrained. The pre-dispatch run is used to provide the market participants with the "projected" schedules and prices for advisory purposes in advance, while the final schedules and prices for financial settlement are determined in the real-time run. In the unconstrained algorithm, an economic gain function is optimized based on supply and demand bids to determine the energy and operating reserves MCPs, but most of the physical power system constraints are neglected. In the constrained algorithm, however, certain system security limits and a representation of the Ontario transmission network model are also included and final schedules are derived.

The pre-dispatch reports are first published by the Ontario IESO at 11:00 AM for the rest of hours of the current day and all hours for the day ahead, and are updated hourly. The pre-dispatch reports contain a variety of information including energy and operating reserves PDPs, the PDD, dispatchable load not served, system losses and some of the system security constraints [25]. Among the pre-dispatch variables, the PDP and PDD carry the latest information on market behavior in the coming hours. In practice, it takes the IESO about 15 minutes to generate and publish the pre-dispatch reports after each hour. Hence, at 1-hour before real-time, the 2-hour ahead PDPs/PDDs are the latest pre-dispatch information available and thus are considered in this work as explanatory variables. These data are publicly available on the IESO's web site at *www.ieso.ca.*

The MARS models for the HOEP are developed to generate forecasts for three time periods. The first period comprises two consequent weeks from April 26 to May 9, 2004, which are referred to as Week$_1$ and Week$_2$ respectively in this paper; the Ontario market presented its lowest spring demand during this period. The second period contains two consequent summer peak demand weeks from July 26 to August 8, 2004, which are referred to as Week$_3$ to Week$_4$, respectively. The last period includes two high demand winter weeks in 2004, starting on December 13, and ending on December 26; these weeks are referred to as Week$_5$ and Week$_6$, respectively. The models are built using 8 weeks of historical data and the Scientific Computing Associates (SCA) statistical system [29] is used here for model building procedures.

The HOEP models were developed considering two scenarios. In the first scenario (SCN1), the MARS models are developed based on the lagged values of the HOEP time series. This scenario can be imagined as an adaptive non-linear autoregressive modeling paradigm. In the second scenario, current and lagged values of the 2-hour ahead PDP (HA2PDP) and 2-hour ahead PDD (HA2PDD) time series are also added to the set of explanatory variables; this can be thought of as an adaptive non-linear dynamic regression modeling scenario.

The lags $l \in L = \{1, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168, 169, 336, 337\}$, of the HOEP, HA2PDP, and HA2PDD were initially considered to account for possible correlations between the current value of the HOEP and historical values of the HOEP, HA2PDP, and HA2PDD. However, it was found that lags 336 and 337 of the HOEP, and lags 2, 3, 48, and thereafter from both the HA2PDP and the HA2PDD do not contribute to the developed models. Therefore, the set of final explanatory variables for SCN1 is:

$$X_{\text{SCN1}} = \{\text{HOEP}_{t-l_1} | l_1 \in L_1\}$$
$$L_1 = \{1, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168, 169\}$$

and the set of final explanatory variables for SCN2 can be presented as:

$$X_{\text{SCN2}} = \{\text{HOEP}_{t-l_1}, \text{HA2PDP}_{t-l_2}, \text{HA2PDP}_{t-l_2} | l_1 \in L_1, l_2 \in L_2\}$$
$$L_2 = \{0, 1, 24, 25\}$$

where lag 0 in L_2 represents the current value of the associated variables.

In this work, the maximum number of basis functions was selected to be 100, and interaction between variables were

TABLE I
WEEKLY MAPES (%)

	MARS		IESO
	SCN1	SCN2	1-hour ahead PDP
Week_1	13.3	12.5	25.8
Week_2	12.9	12.3	22.6
Week_3	9.4	8.6	12.5
Week_4	14.4	11.7	14.9
Week_5	12.9	11.8	21.7
Week_6	15.5	13.9	25
Average	**13.1**	**11.8**	**20.4**

examined up to level 3; however, while the models with interactions took much longer time to be generated, they were not found to be more accurate than the models developed considering no interactions, in terms of out-of-sample accuracy. Hence, the maximum number of basis functions in the final model building processes are reduced to 45, and no interactions are assumed among the explanatory variables. All final models took less than one minute to be built on a Pentium(R) 4 CPU 2.53 GHZ, 1.0 GB of RAM computer.

The final MARS models generally take the following form:

$$\text{HOEP}_t = a_0 + \sum_{m=1}^{M} a_m \max(s_m(x_m - t_m), 0) + \epsilon \qquad (10)$$

where HOEP_t is the value of the HOEP at time t to be forecasted; M is the final number of basis functions in the model; s_m takes either +1 or -1, x_m represents an explanatory variable from X_{SCN1} for SCN1 and from X_{SCN2} for SCN2, which contributes to the m^{th} basis function; and t_m is the knot location for the m^{th} basis function. As examples of (10), the developed model to forecast the HOEP during Week_1 in SCN1 and SCN2 are presented in the Appendix; the models developed for the other weeks are generally similar to what is presented in the Appendix and hence are not presented here.

IV. NUMERICAL RESULTS AND DISCUSSION

Daily forecasts are generated for seven days of each week using the developed models, and weekly MAPE is used to assess out-of-sample forecast accuracy of the models as follows:

$$\text{MAPE} = \frac{100}{168} \sum_{t=1}^{168} \frac{|\text{HOEP}_{f,t} - \text{HOEP}_{a,t}|}{\text{HOEP}_{a,t}} \qquad (11)$$

where $\text{HOEP}_{f,t}$ and $\text{HOEP}_{a,t}$ are the forecast and the actual values of the HOEP for hour t, respectively. The weekly MAPEs of the generated forecasts, using the models developed in this paper for the six weeks under study, are presented in Table I. For comparison purposes, the weekly MAPEs of the 1-hour ahead PDPs (the IESO-generated 1-hour ahead HOEP forecasts) are also presented in this table.

As presented in Table I, except for the forecast for Week_4 in which the MARS forecasts are similar to the 1-hour ahead PDPs, it is generally observed that MARS forecasts are far more accurate than the IESO-generated forecasts in the other 5 weeks. The average weekly MAPEs of the forecasts in SCN1 and SCN2 are 13.1% and 11.8%, much improved than the 20.4% of the IESO-generated forecasts. Furthermore, note that including the pre-dispatch information in SCN2 improves the average weekly MAPE of the forecasts.

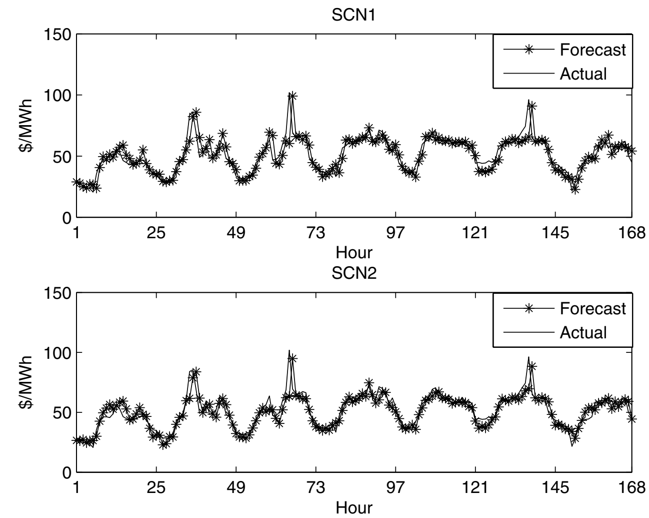

Fig. 2. Forecasts and actual values of the HOEP during Week_3.

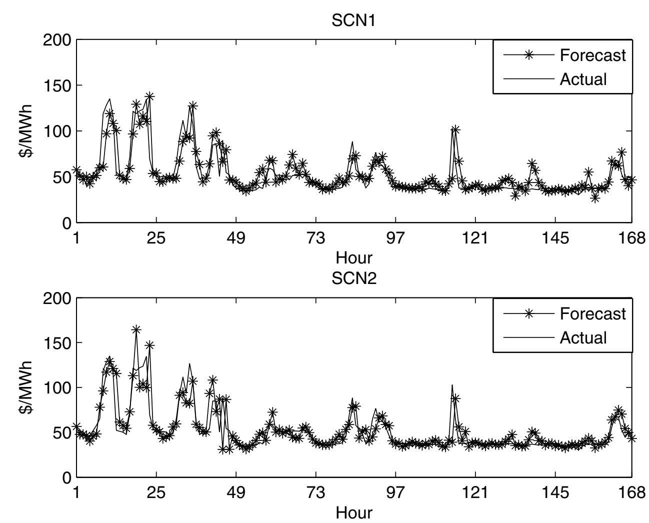

Fig. 3. Forecasts and actual values of the HOEP during Week_6.

The best results were achieved for Week_3 which was one of the high demand weeks of 2004 summer (Fig. 2). Despite the high demand, prices on all seven days were in the normal expected range during this week, with the exception of three unusual price spikes. Although the general price trend is forecasted with a good accuracy for this week in both scenarios, the three price spikes are not properly forecasted by any of the models.

The highest forecast errors occurred during Week_6 in both scenarios. The HOEP forecasts generated by MARS models in SCN1 and SCN2 are plotted against the corresponding actual values for this week in Fig. 3. In this week, the prices were unusually volatile for the first two days of the week and unusually steady for the rest. Furthermore, some price spikes happened during the 4^{th} and 5^{th} days of this week.

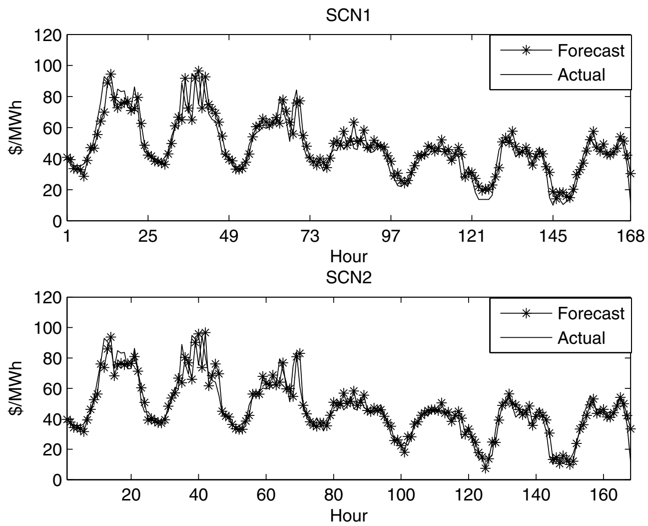

Fig. 4. Forecasts and actual values of the HOEP during Week$_4$.

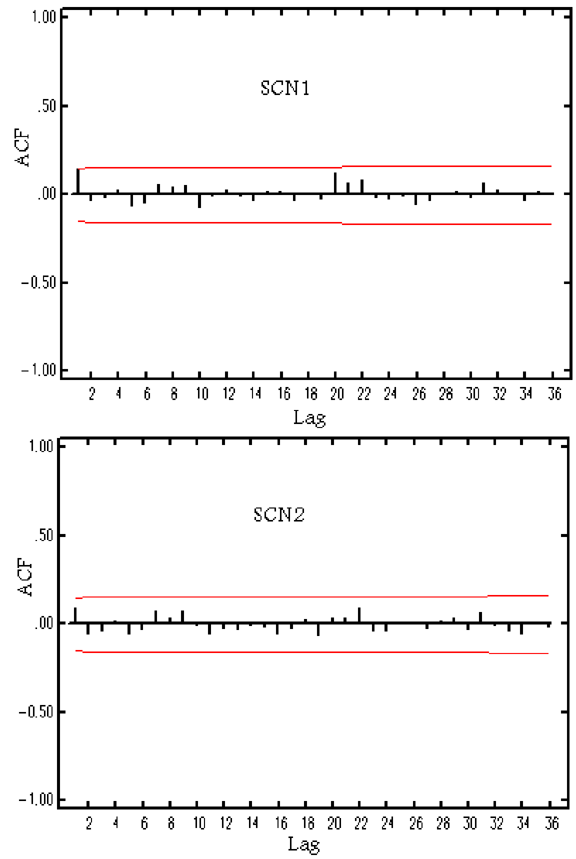

Fig. 5. Residuals ACF of the forecasts generated by the models in SCN1 and SCN2 for Week$_1$.

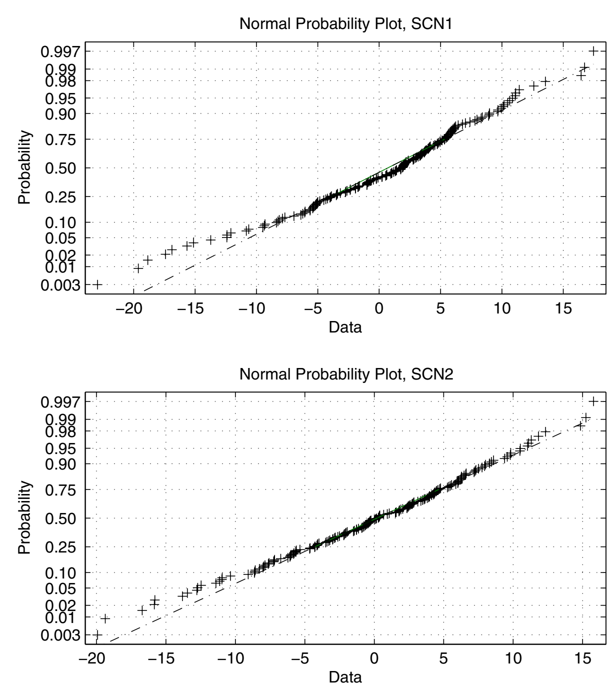

Fig. 6. Normal probability plots of the residuals of the models decveloped for Week$_1$.

None of the models can reasonably forecast the unusual prices, although the MARS model is SCN2 predicts prices relatively better.

The HOEP forecasts generated by MARS models in SCN1 and SCN2, along with the actual HOEP values for Week$_4$ are plotted in Fig. 4. During the firs two days of this week, the Ontario market experienced its highest summer demand and prices were unusually high. However, market demand decreased over the next days of the week and the prices declined as well, sometimes to unusually low values. In this week, the weekly MAPE of the forecasts from the MARS model in SCN2 improved in comparison to SCN1. Hence, it can be inferred that including the pre-dispatch information in the models can be considered as an important factor when market demand is close to its maximum.

The error term ϵ in (10) is presumed to be a white noise. The forecasts residuals are the best estimated values of actual ϵ for the forecasting period, and were found to fairly pass the popular white noise diagnostic checking tests, such as autocorrelation functions (ACF) and the normal probability plots [30]. The ACFs of the forecasts residuals for the models developed in SCN1 and SCN2 for Week$_1$ are presented in Fig. 5, where acceptable autocorrelation values are shown. The normal probability plots of the residuals for Week$_1$ are presented in Fig. 6, and demonstrate their normal distributions. The forecasts residuals for the other studied weeks behave similarly and are not presented here.

V. Conclusions

In this paper, the MARS modeling approach is applied to model the short-term behavior of the HOEP. The models are developed in two scenarios. Thus, historical values of the HOEP are considered as the models explanatory variables in the first scenario. In the second scenario, the pre-dispatch price and demand information which are made available by the Ontario IESO just-in-time are also added to the set of explanatory variables. The 1-hour ahead HOEP forecasts generated by the models in both scenarios significantly outperform the IESO-generated and previously published HOEP forecasts. Furthermore, the weekly MAPEs of the forecasts from the models in the second scenario are better in comparison to the models in the first scenario, specially during the summer peak-demand week.

APPENDIX

1) SCN1, Week_1:

$$\begin{aligned}\text{HOEP}_t = {} & 59.84 - 0.5303 \max(93.64 - \text{HOEP}_{t-1}, 0) \\ & + \max(\text{HA2PDP}_t - 20.34, 0) \\ & + \max(\text{HOEP}_{t-120} - 93.13, 0) \\ & - 0.1671 \max(93.13 - \text{HOEP}_{t-120}, 0) \\ & + \max(43.79 - \text{HOEP}_{t-121}, 0) \\ & + \max(\text{HA2PDD}_t - 20649.0, 0) \\ & - 0.0012 \max(20454.0 - \text{HA2PDD}_{t-1}, 0) \\ & - 0.0070 \max(\text{HA2PDD}_{t-25} - 19407.0, 0) \\ & + \max(19407.0 - \text{HA2PDD}_{t-25}, 0) \\ & + \max(\text{HA2PDD}_{t-24} - 18201.0, 0) \\ & - 1.3862 \max(\text{HOEP}_{t-169} - 93.13, 0) \\ & + \max(\text{HOEP}_{t-48} - 17.83, 0) \\ & - 0.4436 \max(\text{HOEP}_{t-144} - 69.7, 0) \\ & - 0.1621 \max(\text{HOEP}_{t-120} - 57.41, 0) \\ & + \max(\text{HOEP}_{t-144} - 58.5, 0) \\ & - 0.0650 \max(\text{HOEP}_{t-49} - 17.83, 0) \\ & - 0.4402 \max(\text{HA2PDP}_t - 93.0, 0) \\ & + \max(97.0 - \text{HA2PDP}_{t-1}, 0) \\ & + \max(\text{HOEP}_{t-1} - 71.21, 0) \\ & - 0.4350 \max(\text{HOEP}_{t-24} - 46.72, 0) \\ & + \max(\text{HOEP}_{t-24} - 39.94, 0) + \epsilon \end{aligned} \tag{12}$$

2) SCN2, Week_1:

$$\begin{aligned}\text{HOEP}_t = {} & 24.47 - 0.3959 \max(\text{HOEP}_{t-1} - 94.92, 0) \\ & - 0.1269 \max(104.91 - \text{HOEP}_{t-168}, 0) \\ & + \max(\text{HOEP}_{t-24} - 23.49, 0) \\ & + \max(106.24 - \text{HOEP}_{t-25}, 0) \\ & - 0.1870 \max(106.24 - \text{HOEP}_{t-48}, 0) \\ & - 0.11 \max(\text{HOEP}_{t-49} - 23.49, 0) \\ & + \max(\text{HOEP}_{t-144} - 23.49, 0) \\ & + \max(99.44 - \text{HOEP}_{t-145}, 0) \\ & - 0.6786 \max(\text{HOEP}_{t-1} - 39.64, 0) \\ & + \max(\text{HOEP}_{t-1} - 30.14, 0) \\ & + \max(51.7 - \text{HOEP}_{t-121}, 0) \\ & + \max(\text{HOEP}_{t-120} - 23.49, 0) + \epsilon \end{aligned} \tag{13}$$

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