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A Hybrid GA-Modified Harvey Model for Short-term Forecasting of Day-ahead Electricity Price and Electricity Load

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Abstract

The ability of different Harvey models has been proven for long-term forecasting of time series. In this paper, a new approach based on modified Harvey model tuned by genetic algorithm is proposed for short-term forecasting of electricity price and electricity load. To consider the fluctuate nature of electricity price and consumption, the model consists of some nonlinear terms of forecasts, which the optimal order of the nonlinear terms is determined based on T test and RMSE factor. The optimal order for hourly electricity price and electricity consumption is 3 and 2 nonlinear terms, respectively. The proposed model is applied to the hourly electricity consumption and power market price data for Iran from 22/12/2014-19/02/2015 using statistical analysis software EViews 5. The comparison revealed that the modified Harvey model is a very appropriate candidate for day-ahead simultaneous forecasting of electricity price and consumption.

Keywords: Harvey models, Short-term Forecasting, EViews, RMSE factor
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1. Introduction

Electricity price forecasting is a fundamental input to electric energy companies for decision-making mechanisms to participate in electricity markets. Electricity price can be considered as an effective input for load forecasting in electricity markets with the initiation of power systems restructuring and deregulation. On the other hand, accurate forecasting of electric power load is crucial to the operation and planning of power systems and aids an electric company to make imperative decisions on purchasing/ generating electric power, load switching, and etc. A lot of researches are involved in developing tools and algorithms for load and price forecasting. Most of these studies focused on only electricity price or electricity load. The techniques applied to the forecasting of electricity prices include multi-agent models [1-4], fundamental models [5-6], reduced-form models [7-8], statistical models [9-10], computational intelligence models [11-12] and hybrid models [13-14]. The methods used for electric load forecasting include regression method [15-16], exponential smoothing [17-18], adaptive load forecasting [19], autoregressive (AR) model, Autoregressive moving-average (ARMA) model, and autoregressive integrated moving-average (ARIMA) model [20], and artificial intelligence techniques [21]. However, there are a few studies conducted on simultaneous electricity price and load forecasting. In [22] a multi-input multi-output model has been presented consisting three components including wavelet packet transform (WPT), generalized mutual information and least squares support vector machine (LSSVM). Ref. [23] similar to [22] has proposed a three stage forecasting method employing 1) flexible WPT and conditional mutual information, 2) nonlinear LSSVM (NLSSVM) and ARIMA, and 3) a modified version of artificial bee colony algorithm to optimize NLSSVM parameters in a learning process. Also a combined method of support vector regression with an adaptive neuro-fuzzy inference system (ANFIS)

[24], and a model composed of autoregressive moving average (ARMAX), generalized auto regressive conditional heteroscedasticity (GARCH) and LSSVM [25] were suggested in literature.

Detailed review of the relevant literature reveals that the proposed methods for simultaneous electricity price and load forecasting need a time consuming calculations since they composed of some pre-processing stages. So, this paper aims to provide a general method for electricity price and load forecasting with a low and simple pre-processing stage. To this end, a high-accurate modified Harvey model (MHM) is proposed to simultaneous forecasting of electricity price and load. The paper is organized as follows. In section 2, the Harvey and modified Harvey model are described. Section 3 describes the Phillips–Perron unit root test used for assessing that the used data is generated by a stationary process and so, the ordinary least square (OLS) can be applied. Determining the optimal order of nonlinear terms of MHM method using root-mean-square error (RMSE) is studied in section 4. Analysis of the forecasting results and comparison of the methods are discussed in section 5, and finally section 6 concludes the study.

2. Model theory

A time series forecasting model based on the logistic curve was proposed by Harvey [26-27].The Harvey models do not require a saturation level to be estimated prior to estimation of the parameters. However, the model approaches a saturation level with time. There are two forms of Harvey models; a Harvey logistic model based on the general logistic model and a Harvey model based on general modified exponentials [26].

A) Harvey model (HM)

The general modified exponential function is of the form [26],

$$Y_t = \alpha\left(1+\beta e^{\gamma t}\right)^k \tag{1}$$

The value of k determines the form of the function and Y_t is the electricity price/load at time t, α is the saturation level, β and γ are parameters to be estimated. Differentiating and the taking natural logarithm as for the logistic model, leads to the Harvey model [26]:

$$\ln y_t = \rho \ln Y_{t-1} + \delta + \gamma t + \varepsilon_t \tag{2}$$

Where $y_t = Y_t - Y_{t-1}$, $\rho = (k-1)/k$, $\delta = \ln\left(k\beta\alpha^{1/k}\gamma\right)$ and ρ, β and γ are parameters to be estimated. Forecasts are obtained using:

$$\hat{Y}_t = \hat{Y}_{t-1} + \hat{Y}_{t-1}^{\rho} e^{(\sigma+\gamma t)} \tag{3}$$

It should be noted that for $\rho = 2$ in (2) and (3), the Harvey logistic model (HLM) [26] is obtained. In this study, the results of HLM only are presented in section 5 for comparison of the forecasting methods.

B) Modified Harvey model (MHM)

As understood form eq. (2) the Harvey model is an appropriate method for time series with linear time trend especially for annual data. Inasmuch as this paper aims to hourly forecast electricity price and load, the Harvey model is modified as follows to predict nonlinear and swinging trend:

$$\ln y_t = \rho \ln Y_{t-1} + \gamma t + \theta_2\left(\ln y_t\right)^2 + \theta_3\left(\ln y_t\right)^3 + \ldots + \theta_n\left(\ln y_t\right)^n + \varepsilon_t \tag{4}$$

The proposed model consists of a linear time trend as Harvey model and also a nonlinear trend of logarithm of differentiated forecasting variable (y_t). The $\theta_2, \theta_3, \ldots, \theta_n$ are the multipliers of nonlinear terms in (4) and n defines the number of nonlinear terms which is determined optimally based on regression RMSE.

3. Phillips–Perron Unit Root Test

Ordinary least square (OLS) method is based on the assumption that the studied variables are stationary. On the other hand, the prevailing belief is that most of time series are non-stationary due to a random process. In other words, the mean and variance of time series variables is not constant over time. Thus it is required to investigate that if the used variables in forecasting models are stationary or in the case of existence of unit root (non-stationary variables) the methods other than OLS, such as co-integration regression and etc. are used. In this paper the Phillips–Perron unit root test [28] is applied to assess that the used data is generated by a stationary process. This test assesses the null hypothesis of a unit root in a time series. The statistical analysis software EViews 5 is used to establish the studied models and also to run Phillips–Perron test. A sufficiently small value of the test result (i.e. the probability value at a specified significance level delivered by EViews 5) suggests that the null hypothesis is rejected and so, the studied variable is stationary. Therefore, the OLS regression can be applied. The hourly electricity consumption and power market price data for Iran from 22/12/2014-19/02/2015 [29] are used to investigate the effectiveness of the proposed forecasting model. Table I depicts the results of Phillips–Perron unit root test for the variables used in the forecasting models.

Table.1.
Phillips–Peron unit root test for the variables used in the forecasting models

Variable		t-statistic	Probability	Result
$\ln(y_t)$	Price	-17.87	<0.0001	Stationary
	Load	-47.59	0.0001	Stationary
$\ln(Y_{t-1})$	Price	-4.36	0.0004	Stationary
	Load	-6.77	<0.0001	Stationary
$(\ln(y_t))^2$	Price	-16.23	<0.0001	Stationary
	Load	-50.64	0.0001	Stationary
$(\ln(y_t))^3$	Price	-17.33	0.0004	Stationary
	Load	-52.14	0.0002	Stationary
$(\ln(y_t))^4$	Price	-19.25	0.0002	Stationary
	Load	-54.95	<0.0001	Stationary

Based on Table 1, the null hypothesis is rejected for all of the model variables and therefore, the variables used in the HLM, HM and MHM are stationary and their mean and variances will be constant over the time, thus the OLS regression method can be applied.

4. Optimal Order of Nonlinear Terms of MHM

To determine the optimal order of nonlinear terms in the proposed model, first the nonlinear term of order 2 ($(\ln y_t)^2$) is inserted to MHM and the significance level of the variable $(\ln y_t)^2$ is evaluated by t-statistic. If the variable was significant, the time series is estimated and the value of RMSE is obtained. In the next stage, the nonlinear term of order 3 ($(\ln y_t)^3$) is considered and the t-statistic and RMSE value are evaluated. If the less RMSE is obtained, the $(\ln y_t)^3$ will be kept in the model. This procedure will continue until the optimal order of nonlinear terms is made. Table 2 shows the t-statistic and RMSE value for different orders of nonlinear terms for electricity price and consumption. As indicated, the optimal order of nonlinear terms is 4 and 3 for electricity price and consumption, respectively. That is, there will be 3 and 2 nonlinear terms for electricity price and consumption, respectively.

Table.2.
The results of optimal order of nonlinear terms for electricity price and consumption

Time series	Order *n*	t-statistic	Probability	RMSE (%)	Optimal order (*n**)
Electricity price	2	344.60	<0.0001	1.6202	*n**=4
	3	-419.75	<0.0001	0.0129	
	4	622.65	<0.0001	4.66e-5	
	5	-1.67	0.002	0.1427	
Electricity load	2	175.87	<0.0001	3.8808	*n**=3
	3	-88.88	<0.0001	0.5877	
	4	1.69	0.004	1.6322	

After attainment of optimal nonlinear terms, now the HM and MHM parameters (ρ , β , γ , θ_2 , θ_3 and θ_4) to be estimated. Since the forecasting models include natural logarithm (*ln*) and this function accept only positive arguments, so the variable y_t is replaced by $y_t+abs(min(y_t))+1$. For electricity price and load the $abs(min(y_t))+1$ is 51000 Rials/MW and 30 MW, respectively. The final HM for electricity price and load are as follows:

For price:

$$\ln(y_t + 51000) = \rho \ln(-y_t - 51000 + Y_t) + \delta + \gamma t \qquad (5)$$
$$\rho = -0.815,\ \delta = 2.988,\ \gamma = -5.889e^{-5}$$

For load:

$$\ln(y_t + 30) = \rho \ln(-y_t - 30 + Y_t) + \delta + \gamma t \qquad (6)$$
$$\rho = -0.187,\ \delta = 4.174,\ \gamma = -3.403e^{-5}$$

and the final MHM for electricity price and load are as follows:

For price:

$$\begin{aligned}\ln(y_t + 51000) &= \rho \ln(-y_t - 51000 + Y_t) \\ &+ \delta + \gamma t + \theta_2 (\ln(y_t + 51000))^2 \\ &+ \theta_3 (\ln(y_t + 51000))^3 + \theta_4 (\ln(y_t + 51000))^4\end{aligned} \qquad (7)$$

For load:

$$\begin{aligned}\ln(y_t + 30) &= \rho \ln(-y_t - 30 + Y_t) \\ &+ \delta + \gamma t + \theta_2 (\ln(y_t + 30))^2 \\ &+ \theta_3 (\ln(y_t + 30))^3\end{aligned} \qquad (8)$$

$$\rho = 5.0089e^{-3},\ \delta = 0.5303,\ \gamma = 5.6783e^{-7}$$
$$\theta_2 = 0.4493,\ \theta_3 = -0.0595$$

5. Comparison of Forecasts

Forecasts produced by the Harvey model for hourly power market electricity price and electricity load are depicted in Fig. 1. It should be noted that Fig. 1 shows y_t ($=Y_t$-Y_{t-1} i.e. the difference between two consecutive data of time series). Even though the long-term predictability of HM has been proven in literature, e.g. in [30] it has been shown that the Harvey Model is a very appropriate candidate for long- term forecasting of electricity consumption in New Zealand, but as can be understood the HM has a low capability in hourly forecasting. This could be due to high hourly fluctuations in electricity load and price which the annual data do not experience these fluctuations.

To address this problem, there is a need to consider some modifications in Harvey model. As presented in equation (4) with considering a few nonlinear terms of $ln(y_t)$ the fluctuating nature of hourly electricity price and load can be modelled. Fig. 2 presents the modified Harvey model forecasting results for hourly power market electricity price and electricity load with 3 and 2 nonlinear terms, respectively. As the results show, the MHM has been able to accurately predict hourly electricity price and load. The hourly fluctuations of forecasts are well predicted using MHM as illustrated in the magnified plot.The forecasts (*Y*t not y_t) obtained by modified Harvey model (MHM) are compared with the Harvey (HM) and logistic Harvey models (LHM). Fig. 3 presents the 24-hour forecasts for electricity price and load. As it can be seen, the predicted values in the modified Harvey model are very close to the real observations compared to the other estimation models.

Considering that the accurate estimation of power market price and electricity consumption plays an important role in decision making of power market participants, knowing that which of the models can provide accurate estimates about forecast is of great importance. Therefore, in order to determine the best model, the root mean square error (RMSE) and the coefficient of determination (R squared) are provided in Table 3. The results reveal that the modified Harvey model including nonlinear terms of $ln(y_t)$ with a 99.95 coefficient of determination and a minimum RMSE has the highest accuracy and precision in comparison with LHM and HM.

6. Conclusion

This paper has proposed modified Harvey model for simultaneous forecasting of day-ahead electricity price and electricity consumption and compared with the previously developed logistic Harvey and Harvey model. The high accuracy and ability of Harvey model for long-term forecasting of electricity consumption has been proven, but for short-term (e.g. hourly) forecasting due to fluctuate nature of electricity market price and electricity load, it was necessary to apply some modification to Harvey model. To this end, a few significant nonlinear terms were added to HM. The optimal order of nonlinear terms was determined based on T test and RMSE of forecasting. The comparison of forecasts for three investigated models showed that the proposed MHM with a 99.95 coefficient of determination and a minimum RMSE has a high accuracy and generally is an appropriate method for day-ahead forecasting of electricity market price and electricity consumption to be used in decision making of power market participants.

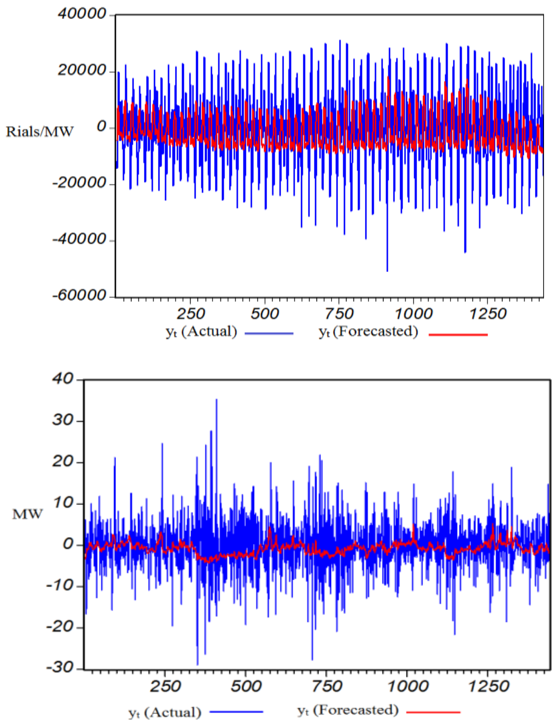


Fig.1. *Forecasts of the Harvey model for **(a)** electricity price and **(b)** electricity consumption*

Table.3.
RMSE and coefficient of determination for forecasting models

Forecasting Model	RMSE (%) Electricity price	RMSE (%) Electricity consumption	Coefficient of determination (R^2) Electricity price	Coefficient of determination (R^2) Electricity consumption
Logistic Harvey Model	3.1868	5.7835	86.73	87.93
Harvey Model	3.4182	5.6663	86.56	0.88
Modified Harvey Model	0.1893	0.2852	99.95	99.95

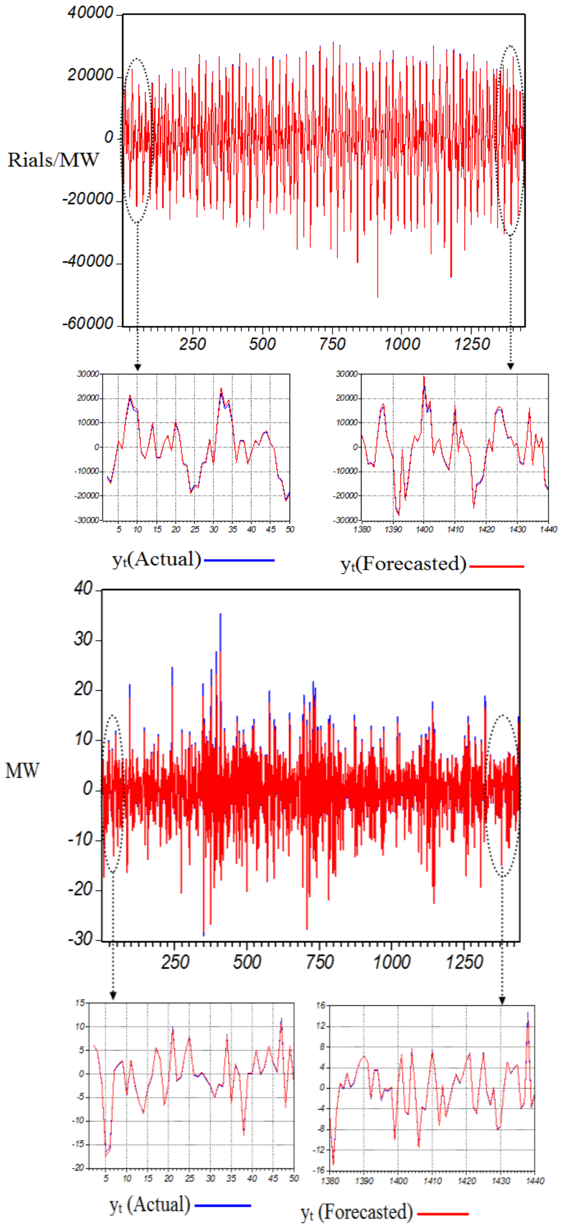
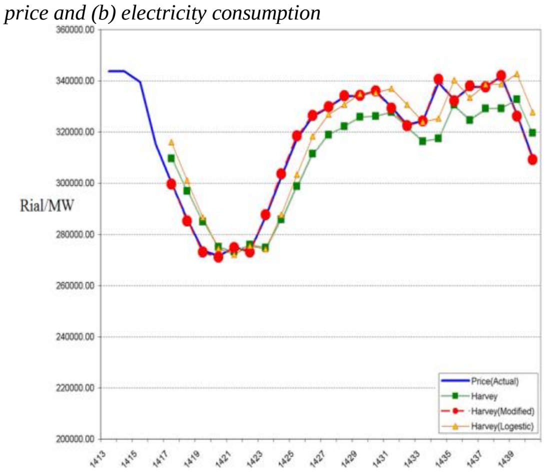


Fig.2. *Forecasts of the modified Harvey model for (a)electricity price and (b) electricity consumption*



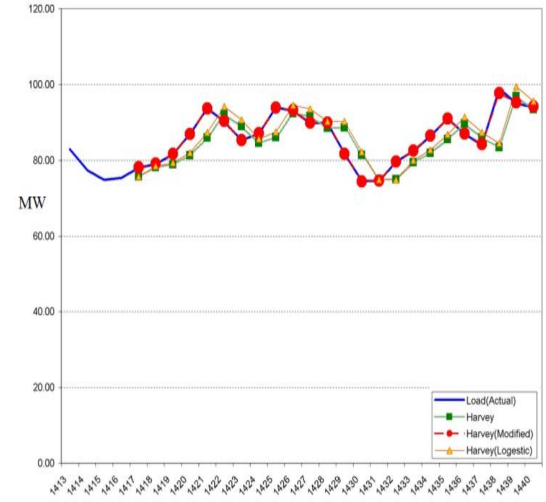


Fig.3. *Forecasts of the Logistic, Harvey and modified Harvey models for (a) electricity price and (b) consumption*

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