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Prediction of Hydropower Energy Price Using Gómes-Maravall Seasonal Model

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ABSTRACT

The present research is aimed at investigating the possibility of predicting average monthly electricity prices and presenting a model for predicting electricity price in Iranian market considering unique characteristics of electricity as a commodity. For this purpose, time series data on average monthly electricity price during 2006–2015 was used. Firstly, unit root test was used to investigate stationarity of time series of electricity price. Then, using Gómes-Maravall model, an ARIMA model was estimated for predicating electricity price in Iranian market using energy purchase data from a hydropower plant. The model was run utilizing SEATS (Signal Extraction in ARIMA Time Series) and TARMO ("Time Series Regression with ARIMA Noise, Missing Observations, and Outliers") programs. For this purpose, energy purchase data from three Karun river hydropower plants (Khuzestan Province, Iran) was used.

Keywords: Electricity Prices, Hydropower, Seasonal Gómes-Maravall Model
JEL Classifications: Q41, Q43

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1. INTRODUCTION

In many countries, structure of power industry is evolving from an exclusive environment to a competitive one. However, different countries are experiencing different models of restructuring of power industry toward privatization of this industry and making it competitive. Despite the differences between electrical energy and other commodities, which root in unique characteristics of this type of energy such as inability to store it in large amounts, the main idea behind the process of making competitive the power industry is to consider the electric energy as a commodity which can be traded via bilateral or multilateral agreements or electricity market.

With the restructuring of electricity market from a governmental monopoly to competitive market where average price is determined by market forces, modeling and prediction of price has been accompanied with uncertainty and become particularly important for stakeholders of electricity market. In order to perform modeling and prediction in such a competitive market, one should consider characteristics of electricity as a commodity, such as storage limitations, low elasticity, seasonal nature of supply and demand, and the necessity of a continuous balance between supply and demand.

Today, electricity market exhibits further harmony with other markets such as ancillary services market, thereby remarkably complicating decision-making toward enhanced profitability for market's stakeholders. Success in the novel competitive electricity market requires possessing an acceptable deal of skill in estimation based on scientific criteria. Players of energy market are uncertain about the profit to be gained from long-term energy delivery contracts in the future, because there are chances that production, demand, and prices change compared to the contract requirements; as such, energy suppliers and consumers may act better should they perform more accurate predictions. With increasing the demand for electricity, the motivation toward optimized use of resources and economic competitions lead companies and economic firms toward investing on and participation in electricity industry. In a competitive electricity system, customers are free to select sellers. Accordingly, more customers can be attracted by providing better services and cheaper energy, bringing about more profits for energy producers and sellers while presenting more interests to the customers. Energy sellers or suppliers are representatives who sell energy to customers; they may not be original producers, but rather have bought shares of plant productions. In such a case, prediction of electricity prices offered by electricity market for purchasing the electricity generated by plants or supplied by energy suppliers become very important. Meanwhile, being engaged with production limitations in terms of water input and seasonal changes, hydropower plants consider predicting trend of prices in longer runs.

In order to predict and model the behavior of electricity prices in short- and mid-term using time series data on electricity prices and considering particular characteristics of electricity, numerous econometric tools and artificial intelligence-based methods (e.g. neural networks) have been adopted. In most of modeling practices, various possible methods have been used for estimating the models followed by comparing the methods based on statistics indicating the power of predictions. In the present research, however, Box-Jenkins and Gómes-Maravall model are investigated and compared using seasonal data.

Electricity price follows a seasonal pattern, because the demand for electricity depends on the level of economic activity in different days, weeks, and months in a year and also on weather conditions. When the demand for electricity decreases, producers tend to use the units with minimal final production cost. During summer or peak hours, however, the units of higher final cost are also brought in service. Prices tend to move along an average price determined by the competitive market forces. In electricity market, the production unit with the lowest efficiency will be the last unit to respond to the demand for electricity. Moreover, as an effective factor in determining prices, air temperature follows a periodic pattern which returns to the average price. This pattern is commonly used to explain the autocorrelation of electricity price time series. As such, some sort of mean reversion model is expected for electricity prices.

There are limiting values in electricity price time series. The solution which makes the model able to predict these data is to include the variable of time scattering variable into the mean reversion model. These models can further take into account intense fluctuations in the values of variables, making them suitable for modeling electricity price data which can be influenced by network interruptions, meteorological factors, sudden rise of demand, and production fluctuations. Fluctuations in electricity prices are commonly not stable, so that the prices reverse to the mean rapidly. ARIMA and seasonal ARIMA models introduce effect of the information received from common and uncommon states into the model. Some of the received information are of the type of normal events and result in smooth changes in prices; these changes are explained by the mean reversion model. Some other received information is uncommon and lead to fluctuations in prices. These models express market prices as a function of preceding prices and previous error terms.

2. RESEARCH BACKGROUND

Analysis of seasonal changes in economic time series has a background almost identical to that of the theory of macro-economics. However, despite such a great deal of background, only little consensus can be seen in empirical research on the way to deal with seasonal nature of fluctuations in economic variables. Considering the studies performed so far, advances have been achieved in reducing electricity price prediction error. In the following, some of the most important studies on price predication time series are briefly reviewed.

Samer et al. (2001) predicted demand for electricity using single-variable ARIMA models. In this paper, once finished with making the data reliable, the demand for electricity was predicted using different ARIMA models such as MA and AR at various orders. Finally, AR(1) model was selected as the best model for this purpose.

Darbellay and Marek (2000) predicted short-term demand for electricity in Czech Republic. In this paper, the demand was firstly predicted using a nonlinear model (artificial neural networks), followed by predicting the same demand using a linear model (ARIMA). It was finally concluded that, short-term demand for electricity follows a linear model, so that the artificial neural network may not be regarded as a better model for predicating the demand for electricity.

Darbellay and Slama (2000) presented a combination of artificial neural network and ARIMA as an optimum solution for predicting time series, and claimed that, the combination of artificial neural network model (as a nonlinear model) and ARIMA (as a linear model) may perform better than either of the models alone when it comes to the prediction of time series. Finally, they proved their hypothesis by adopting several experimental datasets.

The method was originally devised for seasonal adjustment of economic time series (i.e., removal of the seasonal signal), and the basic references are Cleveland and Tiao (1976), Box et al. (1978), Burman (1980), Hillmer and Tiao (1982), Bell and Hillmer (1984), Maravall and Pierce (1987). These approaches are closely related to each other, and to the one followed in this program. In fact, as already mentioned, Seats developed from a program built by Burman for seasonal adjustment at the Bank of England (1982 version).

Some researchers have been using neural networks, time series (ARMA models) or a combination of both to forecast electricity prices in electricity market. The following researchers can be mentioned: Areekul et al. (2010), Bowerman and Richard (1987), Nogales et al. (2002), Senjyu (2010), Sun and Meng (2006), Tiao and Tasay (1983), Voronin and Partanen (2013), Zhang (2003). Gómez and Maravall (1994), Gómez (1998), estimated and interpolated nonstationary series with the Kalman filter.

3. THEORETICAL FOUNDATIONS AND PRICING IN COMPETITIVE ELECTRICITY MARKET

There are two distinctive approaches in electricity market: (1) Electricity trading via optional electricity exchanges (e.g. New Zeeland market) and forced electricity exchange (e.g. UK and Australia). The main advantage of the forced market is transparency across the market which is practiced to confine market power of giant producers.

In a governmental monopoly, electricity prices are set upon governmental orders and are functions of supply costs as well as industrial and social policies adopted by governments. For most part, these prices remain either unchanged or change very slightly and predictably in mid and short runs. Following the restructuring of electricity market in many countries, electricity price is determined in competitive market and under the effect of market forces via interaction of complicated electricity supply and demand functions. Producers and purchasers compete for trading the produced and needed electricity in the market, offering their proposed prices for different hours to the market operator. Demand for electricity depends on the level of economic activities and weather conditions.

Trading methods in an electricity market include: Electricity exchange, bilateral deals, and multilateral deals. In an electricity exchange, all of the sellers and buyers are required to participate in the market and present their purchase/sell offerings. This entity matches cumulative supply and demand curves to determine an equilibrium point for the market. Similar to any other exchange, sales can be either one- way or two-way. In a one-way sale, sellers offer their production level and prices (supply curve), while consumers indicate their needed quantities only. In a two-way sale, both sellers and purchasers are sensitive to price, so that they offer not only the production/consumption quantities, but also the desired price.

In bilateral deals, given that consumers opt for the cheapest producers, market efficiency is enhanced.

Depending on the market mechanisms, the market may be either one-way or two-way. In a one-way market, independent system operator (ISO) considers the predicted load as a reference. This load prediction is performed both by consumers (across the area under their control) and operator (for the entire network). With this approach, the load is specified when launching UC Software. For this level of load, the ISO specifies the quantity of reserve and other ancillary services for each hour. Figure 1 shows how the market is closed in this model.

There is another variant of electricity market wherein energy suppliers and consumers provide not only quantities, but also proposed prices. In such markets, competition is promoted both at production and consumption levels. In two-way markets, the subject matter of maximizing social welfare is highlighted, because in such a case, each party has set load supply strategies by means of the price parameter (Figure 2).

Figure 1: Balance in a one-way market with predetermined demand

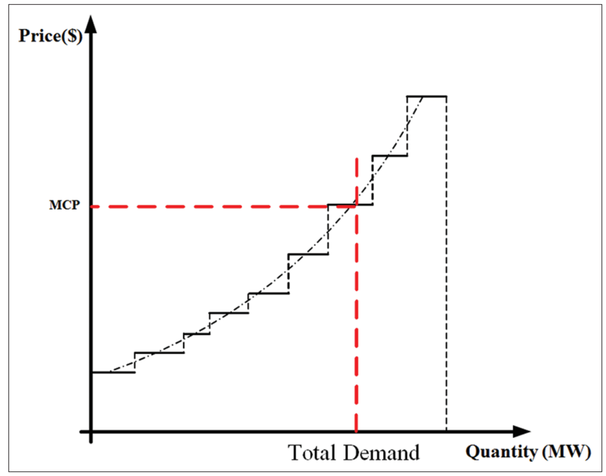
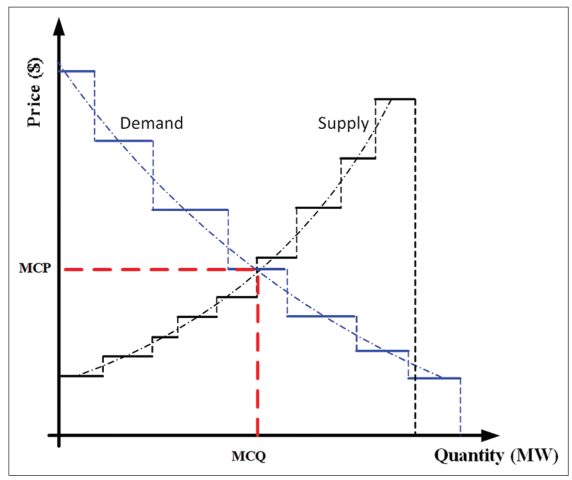


Figure 2: Balance in a two-way market



Pricing is performed via any of the following three methods either in electricity exchange market or by ISO. In a pre-pricing method, price of the commodity is set before delivering the good, with the players agreeing on a quantity of electricity to be delivered at a predetermined price at a given time in future. In post-pricing method, price of the commodity is determined upon delivery; producers and consumers can alter their proposals up to a given time, and the market is settled in the course of offering processes.

The third method is a combination of the two above-mentioned methods. In instantaneous (cash) market, electricity price is determined at the last day before delivery, with any change between predicted and actual values of consumption which may end up with a difference between the predetermined and instantaneous prices being compensated via the second mechanism. In a combined market, system price is set before the delivery, and any imbalance is purchased by ISO in a market known as adjustment market in real-time.

In this case, market closing point is where social welfare is maximal. Producers who can offer their products at lower prices than the competitors will be selected sooner and with a larger deal of chance. In a case where consumers also propose prices for fulfilling their needs, naturally, those who are ready to pay the largest cost for the same commodity will enjoy priority. In such a case, both producers and consumers are well satisfied with the deal.

Electricity supply and demand shall be balanced continuously. Electricity production and consumption are performed at exactly the same time, and no storage facility for this commodity exists across the grid. Given that supply and demand fluctuations cannot be smoothed using inventory, electricity prices in cash market are highly unstable. Moreover, electricity prices are set locally, with no possibility for arbitrage deals on electricity. Electricity is a non-storable commodity, so that demand fluctuations may abruptly fluctuate its price.

4. TIME-SERIES MODELING APPROACH

One of the well-known models for the purpose of this research is autoregressive (AR) integrated moving average (ARIMA) model. In a general case, this method was expressed as ARIMA (p, d, q) by Box-Jenkins, where p is AR order of the model, q is the order of MA, and d is differential order of the model (to make the model stationary). In case one element is equal to zero, the model is denoted as either AR or MA. For instance, MA(1) is the same as ARIMA (0, 0, 1). In this method, once finished with determining the differential order and orders of AR and MA processes, model parameters are found.

Given highly subjective nature of the Box-Jenkins methodology, time-series analyzers have introduced and adopted other criteria for identification and recognition of orders in ARIMA models. Penalty function statistics (e.g. Akaike Information Criterion (AIC), Bayesian Information Criterion, and Hannan Quinn Criterion) have been used in the literature on the analysis of time series for presenting an accurate yet economic model in terms of the count of parameters. All of these functions possess a residual sum of squares (RSS) minimization component along with a penalty element which is a combination of the number of estimated coefficients along with the number of observations[1].

The criteria used to determine lag length in non-seasonal modeling are solely dependent on the parameters q and p. In different configurations of ARIMA model, there are only rare cases where the values of q, d, and p exceed 1, and even this small domain covers many feasible cases in the prediction. Autocorrelation function (ACF) and partial ACF (PACF) are used to determine the values of p and q.

4.1. Seasonal Time Series Modeling – Seasonal AR Integrated MA (SARIMA)

In seasonal time series econometrics literature, there are two approaches to the modeling of seasonal time series. Commonly known as conventional method, the first approach is based on the assumption that, seasonal component of a time series is assumed to be non-stochastic and independent of non-seasonal components. In contrast, the second approach assumes that the seasonal component is random and independent of non-seasonal components. Such that, for example, price of a product in the current period not only is a function of the product price in the preceding month, but also of that in the same month in the past year. Therefore, in order to predict a variable (price or any other variable of interest), not only the prices in the neighboring months (seasons) shall be incorporated into the model, but also the prices at the same month(s) in the previous years(s) shall be further examined. The most well-known seasonal ARIMA model is the multiplicative model known as Box-Jenkins (1976) model.

4.2. Monthly Time Series Data Modeling

Box-Jenkins approach can be used as tool for providing reliable predictions for policy-setting. Similar to non-seasonal time series, values of P, Q, p, and q were determined using ACFs and torques of the ARMA (p, q) (P, Q)s process. As an example, autocorrelation behavior of a general seasonal process is expressed as ARMA (0, 1) (0, 1)s with S = 4, 12 where s refers to the type of the time series period. In this seasonal process, the interrupting component is assumed to be white noise, with the absolute values of the two parameters Θ_1 and θ_1 being smaller than 1.

$$x_t = (1-\theta_1 B)(1-\Theta_1 B^S)\varepsilon_t \tag{1}$$

Therefore, ACFs of the time series x_t are as follows:

$$\rho_1 = -\theta_1 / (1+\theta_1^2),\ \rho_s = -\Theta_1 / (1+\Theta_1^2) \tag{2}$$

$$\rho_{s-1} = \rho_{s+1} = \rho_s\rho_1 = \theta_1\Theta_1 / (1+\theta_1^2)(1+\Theta_1^2) \tag{3}$$

For example, in a time series with s = 4, ACFs are non-zero for the lags of 1, 3, 4, and 5 only. Comparing ACFs of the two processes MA (1) and $MA(1)_s$ can be interesting. For the two models, these functions are observed to be $\rho_1 = -\theta_1 / \left(1+\theta_1^2\right)$ and $\rho_s = -\Theta_1 / \left(1+\Theta_1^2\right)$, respectively, which are exactly the two first ACFs of the process SARMA $(0, 1)(0, 1)_s$. Multiplication of these two torques (i.e., $\rho_{s-1}=\rho_{s+1}=\rho_s\rho_1$,) gives mutual effects of these two periods. Parameters of a seasonal model are estimated in a similar way to that followed for an annual time series model. The coefficients can be estimated via either maximum likelihood method (conditional and deterministic) or least squares (linear and nonlinear) method.

4.3. Validation and Model Characterization Criteria

In order to evaluate the estimated model and statistically validate it, one could use white noise test on its residual component. In this hypothetical tests, ACF and PACF shall exhibit no significant difference from zero. Variance (standard deviation) of $\hat{\rho}_k$ can calculated using Bartlett's approximation. For the seasonal time-series model $AIRMA(0,0,1)(0,0,1)_{12}$, Bartlett's approximation of the variance of $\hat{\rho}_k$ is as follows:

$$\mathrm{var}\left(\hat{\rho}_k\right)=(1+2\left(\hat{\rho}_1^2+\hat{\rho}_{11}^2+\hat{\rho}_{12}^2+\hat{\rho}_{13}^2\right)/T;\qquad k>13 \tag{4}$$

1 These sample functions are defined as follows: BCS = log (RSS/T) + [log (t) × K/(T)], BQC = log (RSS/T) + [2 log (log (t))×K/(T)] and AIC = log (RSS/T) + [2 K/(T)]. Where K is the number of estimated coefficients (1+p+q+P+Q), RSS is residual sum of squares, and T is the number of observations. Lag length with optimal minimal is determined by minimizing the above functions. However, finding the solution is somewhat difficult considering the large number of P, Q, p, and q parameters.

For s = 4, the above approximation becomes:

$$\mathrm{var}\left(\hat{\rho}_k\right)=(1+2\left(\hat{\rho}_1^2+\hat{\rho}_3^2+\hat{\rho}_4^2+\hat{\rho}_5^2\right)/T; \qquad k>5 \tag{5}$$

Under null hypothesis (i.e., the studied phenomenon is white noise), all of the autocorrelation factors become zero and standard deviation of $\hat{\rho}_k$ is equal to $1/\sqrt{T}$. In addition, another method for controlling and evaluation of adequacy of a general Box-Jenkins model is to analyze the residuals obtained from the estimated model (7.1). In this approach, partly resembling diagnosis investigations on time-series models with odd periods, ACFs and sample ACFs are used. Also in the seasonal time series data, Box and Pierce's sample function Q and Loung-Box sample function Q* were used, as defined below:

$$Q=T'\sum_{i=1}^{K} r_i^2(\hat{\varepsilon}_t) \qquad \text{(Box and Pierce)} \tag{6}$$

$$Q^*=T'(T'+2)\sum_{i=1}^{K}(T'+1)^{-1} r_i^2(\hat{\varepsilon}_t) \qquad \text{(Loung-Box)} \tag{7}$$

Where T′ = T−(d+s.D) and T is the number of observations in the main time series, s is the number of seasons per year (or the number of months per year, 4 or 12), and d and D are the number of annual and monthly differentiation of the studied time series to arrive at a stationary process z_t (or filtered x_t). The parameter r_i^2 is the squared sample correlation at lag i for the residuals of the estimated model (7.1). It is obvious that, if D = d = 0, then T′ = T; this is the sample function used to identify annual data.

Both of these sample functions can be used for identification studies. However, it can be proved that, Q* exhibits better performance in this respect, so that this statistic is generally recommended for checking adequacy of the model. The larger the value of $r_i^2(\hat{\varepsilon}_t)$ and hence Q*, the further autocorrelation will be the residuals. Then, Q* shows that the estimated model is inadequate and the obtained residual is not white noise. That is, there are still some information in $\hat{\varepsilon}_1$ which are of particular trend and should be considered in the autocorrelation or MA component of previous values of z_t.

Monthly seasonal time series parameters were estimated similar to the quarterly time series using conditional maximum likelihood method. Complexity of modeling this data arises from identifying different types of unit roots that this process may have.

5. GÓMES-MARAVALL MODEL

SEATS stands for Signal Extraction in ARIMA time series; this is the model introduced by Gómes and Maravall for predicating seasonal data with missing data points. In this research, the Gómes model was used to predict electricity price in energy market. This model uses monthly data and SARIMA to predict time series based on actual time series. This model enjoys numerous advantages. Firstly, the data are studied based on monthly seasonal changes, e.g. it compares all Octobers and uses the results for time-series prediction. Secondly, missing data points may not interrupt the estimation flow. One of the most important advantages of this model is to assign larger weights to the most recent data during the period considered for prediction (Gómez and Maravall, 1998). In the present research, monthly data during 2006–2015 periods were used for estimating the models using Gómes model. The program falls into the class of so-called ARIMA-model-based methods for decomposing a time series into its unobserved components (i.e., for extracting from a time series its different signals). The program starts by fitting an ARIMA model to the series. Let x_t denote the original series, (or its log transformation), and let:

$$z_t = \delta(B)x_t \tag{8}$$

Represent the "differenced" series, where B attitudes for the lag operator, and δ(B) stand for the differences taken on x_t in order to achieve stationarity. In seats,

$$\delta(B) = \nabla^d \nabla_s^D \tag{9}$$

Where $\nabla = 1-B$, and $\nabla_s^D = (1-B^s)^D$ represents seasonal differencing of period s. The model for the differenced series z_t can be expressed as

$$\phi(B)(z-\bar{z}) = \theta(B)a_t \tag{10}$$

Where $\bar{z}$ is the mean of z_t, at is a white-noise series of innovations, ordinarily distributed with zero mean and variance σ^2, ϕ(B) and θ(B) are AR and MA polynomials in B, correspondingly, which can be conveyed in multiplicative form as the produce of a regular polynomial in B and a seasonal polynomial in B^s, as in

$$\phi(B) = \phi_r(B)\phi_s(B^s) \tag{11}$$

$$\theta(B) = \theta_r(B)\theta_s(B^s) \tag{12}$$

Putting together 1–5, the complete model can be written in detailed form as

$$\phi_r(B)\phi_s\left(B^s\right)\nabla^d\nabla_s^D x_t = \theta_r(B)\theta_s\left(B^s\right)a_t + c \tag{13}$$

And, in concise form, as

$$\Phi(B)\, x_t = \theta(B)\, a_t + c \tag{14}$$

Where Φ(B) = ϕ(B)δ(B) represents the complete AR polynomial, including all unit roots. Notice that, if p denotes the order of ϕ(B) and q the order of θ(B), then the order of Φ(B) is P = p+d+D×s.

The AR polynomial ϕ(B) is allowed to have unit roots, which are typically estimated with considerable precision. Unit roots in ϕ(B) would be present if the series were to contain a nonstationary cyclical component, or if the series had been under differenced. They can also perform as nonstationary seasonal harmonics. The program decomposes a series that follows model (10) into several components. The decomposition can be multiplicative or additive. Since the former becomes the second by taking logs, we shall use in the discussion an additive model, such as:

$$x_t = \sum_i x_{it} \quad (15)$$

Where x_{it} represents a component. The components that seats considers are:
x_{pt} = The TREND component,
x_{st} = The SEASONAL component,
x_{ct} = The CYCLICAL component,
x_{ut} = The IRREGULAR component.

Broadly, the trend component represents the long-term evolution of the series and displays a spectral peak at frequency 0; the seasonal component, in turn, captures the spectral peaks at seasonal frequencies. Besides capturing periodic fluctuation with period longer than a year, associated with a spectral peak for a frequency between 0 and (2π/s), the cyclical component also captures short-term variation associated with low-order MA components and AR roots with small moduli. Finally, the irregular component captures erratic, white-noise behavior, and hence has a flat spectrum. The components are determined and fully derived from the structure of the (aggregate) ARIMA model for the observed series, which can be directly identified from the data. The program is mostly aimed at monthly or lower frequency data and the maximum number of observations is 600.

6. RUN THE MODELS AND RESULT

Tramo ("Time Series Regression with ARIMA Noise, Missing Observations, and Outliers") performs estimation, forecasting, and interpolation of regression models with missing observations and ARIMA errors, in the presence of possibly several types of outliers. Seats ("Signal Extraction in ARIMA Time Series") performs an ARIMA-based decomposition of an observed time series into unobserved components. The two programs were developed by Victor Gomez and Agustin Maravall. Used together, Tramo and Seats provide a commonly used as a program for seasonally adjusting a series. Typically, individuals will first "linearize" a series using Tramo and will then decompose the linearized series using Seats. The parameters of the Gomez-Maravall model are estimated in Table 1 that is derived from the implementation of this model.

Refer to Gómez and Maravall (1996) for the interpretation of Table 1. After run the model and specify the parameters of model, the Eviews software provides the price forecast for 24-month period, as shown in Figure 3.

6.1. Electricity Price for Hydropower Plants

To estimate the electricity price of the Karun 1 and 3 dams, we use the forecasted results of the electricity price for MasjedSoliman hydropower plant. The electricity price for these three power plants is close and there is no significant difference. As a result, ordinary least squares method is used to estimate these prices. To do this, we consider electricity prices for the Karun 1 and 3 dam as a function of the price of the MasjedSoliman hydropower plant. First, for the Karun 3 hydroelectric power station we have:

$$P_t^{k3} = \alpha + \beta . P_t^{Msjd} + \varepsilon_t \quad (16)$$

Then for the Karun 1 power plant:

$$P_t^{k1} = \alpha + \beta . P_t^{Msjd} + \varepsilon_t \quad (17)$$

The predicted results are presented in Table 2.

Using the above models, the results of which are reflected in Table 2, the estimated values of electricity purchasing price from Khuzestan hydroelectric power plants (by Iranian electricity market) are presented in the following Table 3.

7. CONCLUSIONS

In most of modeling practices, various possible methods have been used for estimating the models followed by comparing the methods based on statistics indicating the power of predictions. In the present research, however, Gómez and Maravall (1996) model are investigated and compared using seasonal data.

Prices tend to move along an average price determined by the competitive market forces. In electricity market, the production

Figure 3: 2-year forecast of electricity prices using the Gomez Maravall model

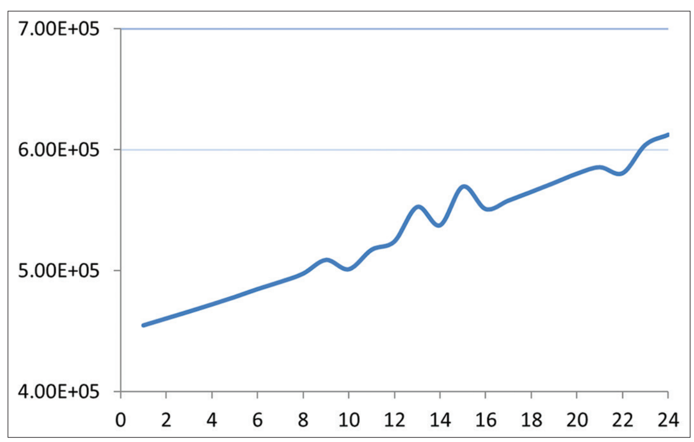


Table 1: The results of the Gomez-Maravall model in predicting electricity prices

Index 1	Index 2	Index 3	Index 4	Index 5
MQ=12	IMEAN=1	LAM=-1	D=1	BD=1
P=0	BP= 0	Q=1	BQ=1	IREG=0
ITRAD=0	IEAST=0	IDUR=0	M=36	QM=24
AIO=2	INT1=1	INT2=120	RSA=0	SEATS=2
VA=3.50	PC=0.143	NOADM=1	BIAS=1	MAXBIAS=0.5
SMTR=0	THTR=-0.4	RMOD=0.5		

Source: Research results

Table 2: Results of electricity price estimates for Karun 1 and 3 dams

Depended variables	C	β	t	MA (1)	R^2
Electricity Price of Karun 1	3801	1.006	84	0.57	0.99
Electricity Price of Karun 3	1286	1.019	71	0.71	0.99

Source: Research results

Table 3: Predicted price of electricity purchased from hydropower plants of Khuzestan province

		Hydropower Plants		
	Months	MasjedSoliman	Karun 3	Karun 1
First Year	JANUARY	454,923	466,296	465,386
	FEBRUARY	460,643	472,159	471,238
	MARCH	466,354	478,013	477,080
	APRIL	472,250	484,056	483,112
	MAY	478,367	490,326	489,369
	JUNE	484,911	497,034	496,064
	JULY	490,897	503,169	502,188
	AUGUST	497,698	510,140	509,145
	SEPTEMBER	509,056	521,782	520,764
	OCTOBER	501,328	513,861	512,859
	NOVEMBER	517,456	530,392	529,357
	DECEMBER	524,345	537,454	536,405
Second Year	JANUARY	552,876	566,698	565,592
	FEBRUARY	537,654	551,095	550,020
	MARCH	569,678	583,920	582,781
	APRIL	551,078	564,855	563,753
	MAY	558,156	572,110	570,994
	JUNE	565,309	579,442	578,311
	JULY	572,750	587,069	585,923
	AUGUST	580,343	594,852	593,691
	SEPTEMBER	585,678	600,320	599,149
	OCTOBER	580,760	595,279	594,117
	NOVEMBER	604,223	619,329	618,120
	DECEMBER	612,543	627,857	626,631

Source: Research results

unit with the lowest efficiency will be the last unit to respond to the demand for electricity. Moreover, as an effective factor in determining prices, air temperature follows a periodic pattern which returns to the average price. This pattern is commonly used to explain the autocorrelation of electricity price time series. As such, some sort of mean reversion model is expected for electricity prices.

The solution which makes the model able to predict these data is to include the variable of time scattering variable into the mean reversion model. These models can further take into account intense fluctuations in the values of variables, making them suitable for modeling electricity price data which can be influenced by network interruptions, meteorological factors, sudden rise of demand, and production fluctuations. Fluctuations in electricity prices are commonly not stable, so that the prices reverse to the mean rapidly. ARIMA and seasonal ARIMA models introduce effect of the information received from common and uncommon states into the model. Some of the received information are of the type of normal events and result in smooth changes in prices; these changes are explained by the mean reversion model. Some other received information is uncommon and lead to fluctuations in prices. These models express market prices as a function of preceding prices and previous error terms.

Short-term electricity prices are highly unstable due to inability to store the electricity, inelasticity of demand with respect to prices, and supply limitations, particularly during peak consumption periods. Instantaneous (cash) instability of electricity prices may change due to weather conditions and the forces contribuxting to supply and demand. However, time series of mid-term prices, such as monthly average price, exhibit more stable trend and are seemingly more suitable for predictive models, especially in hydropower plants where loner-term seasonal changes are common.

We used two programs were developed by Victor Gomez and Agustin Maravall. We used a commonly program, Tramo and Seats for seasonally adjusting a series. Typically, individuals will first “linearize” a series using Tramo and will then decompose the linearized series using Seats. We used Gómes-Maravall model, an ARIMA model was estimated for predicating electricity price in Iranian market using energy purchase data from a hydropower plant. The model was run utilizing SEATS (Signal Extraction in ARIMA Time Series) and TARMO (“Time Series Regression with ARIMA Noise, Missing Observations, and Outliers”) programs. For this purpose, energy purchase data from three Karun river hydropower plants (Khuzestan Province, Iran) was used.

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