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Comparing Iranian and Spanish Electricity Markets with Nonlinear Time Series[#]

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ABSTRACT

Electricity market analysis is useful for accessing strategic market information in order to set energy policy. According to recent interpretations of the Article 44 of the Iranian Laws, the Iranian electricity market is to become a free market. Mechanisms that were implemented in the Spanish electricity market - a free market - provide a versatile benchmark to employ time series modeling approach to compare Iran and Spain's electricity markets via price and load time series as two main indices. Here, we develop linear (autoregressive integrated moving average [MA]), heteroskedastic (autoregressive MA model [ARMA]-generalized autoregressive conditional heteroskedastic [GARCH]), and nonlinear time series models to model the Iranian/Spanish electricity market for price and load time series indices. We further utilize the conditional variance to propose the ARMA-TGARCH model as the best suited model for the Iranian electricity market price. We employ our models and time series analysis to forecast and question the status of the Iranian market structure as a free market.

Keywords: Time Series, Forecasting, Electricity Market, Spain, Iran
JEL Classifications: C31, Q41, Q47

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1. INTRODUCTION

The competitive electricity market has led to a lot of opportunities in worldwide and to advantages such as cheaper electricity for end consumers as well as higher efficiency in generation, transmission and distribution services (Asgari and Monsef, 2010; Corchero, 2011; Weron, 2007). Another advantage is the development of decision support system models in energy market management (Finn, 2000; Sioshansi, 2008; Ventosa et al., 2005). Since the late 1980s, policy makers and regulators in a number of countries have liberalized and deregulated their electric power sectors (Sioshansi, 2008). The Iranian government is also trying to privatize their electricity market (Khalili and Mehri, 2007). In general, the rate of market growth and restructuring can usually be affected by various economic factors (Aggarwal et al., 2009; Le and Vinh, 2011). Some of these factors are inflation (Le and Vinh, 2011), energy prices (such as oil/gas price) (Boqiang and Dunguo 2008; Farzanegan and Markwardt 2009; Moutinho et al., 2011), the exchange rate (Yu and Mallory, 2013; Cong et al., 2008; Sameti et al., 2004), etc.

In addition, other factors such as "International sanctions" and the "Iranian nuclear crisis" are redefining the Iranian economic market, e.g., the energy sector (BBC News [Middle East], 2015; Monshipouri and Dorraj, 2013; Peterson, 2012). Furthermore, the Iranian government (Ministry of Energy) takes an undeniable role as the primary owner of the giant energy industries, which tremendously influences the market dynamics as well as policy-making (Cavendish, 2007; Enerdata, 2014; Usa, 2009).

The Iranian electricity market took over 100 years to grow, since first being established in Mashhad, Iran in 1901 (Tavanir, 2012) until it was launched on 23 October 2003 (Asgari and Monsef, 2010; Tavanir, 2012). One of the main concerns about the Iranian electricity market is that there is a "market power" similar to the mandatory pool (Asgari and Monsef, 2010). The pool is named as an e-commerce marketplace (Bigdeli and Afshar, 2009; Bigdeli et al., 2009). According to the definition of the pool, two mechanisms determine the price: Uniform pricing, in which the market-clearing price is paid to every winning block; and pay-as-bid (PAB), in which every winning block receives its bid price as its income (Bigdeli and Afshar, 2009; Bigdeli et al., 2009). The Iranian electricity market follows a PAB payment mechanism with an unilateral auction (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009; Bigdeli et al., 2009). It is a hybrid market model, in which the supplier and the consumer both have direct access to the market information, except for the prices. Bilateral contracts are allowed in Iran's energy market (Asgari and Monsef, 2010). However, the consumers and the producers – Similar to the mandatory pool state – have to send their bids to the Market Operator before the market is shaped by the beneficiaries (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009). Also, the Regional Electric Companies are entitled to forecast only their hourly demand, which means that the demand curve has a vertical line at a certain hour (Asgari and Monsef, 2010). On the other hand, the companies have power over pricing to some extent, depending on their size and access to market information (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009).

The annual reports of the performance of the Iranian electricity industry of 2010-2011 also indicate considerable improvements in different sectors of this industry (Tavanir, 2011a). The Iranian government took fundamental technological steps to have a competitive market, and they published some laws (Article 44) facilitating privatization and deregulation of this market, see e.g., Asgari and Monsef (2010), Tavanir (2011a) and Tavanir (2011b). Despite these regulations, the growth in the market seems to be slow, which can be due the political atmosphere related to the Iranian economy (Mazarei, 1996; Khalili and Mehri, 2007; Behboudi et al., 2014).

Power market liberalization was pioneered by Chile. Such reforms were followed by the reorganization of the British electricity sector in 1990, and later in Sweden, Denmark and North America (Weron, 2007). Due to the advantages of a liberalized electricity market, the United States and European countries also applied developed management systems, such as preparing the appropriate states for financial contracts to hedge against the risk of price volatility (Corchero, 2011; Weron, 2007). Such a management system has improved the market in these countries, making them good benchmarks for other countries seeking strategies to improve their electricity market (Weron, 2007).

One of these benchmarks is the Spanish electricity market, the "Iberian Electricity Market (MIBEL)." After establishing MIBEL in 2007, some published rules for the day-ahead, intraday market and for renewable electricity were introduced (Ciarreta et al., 2014; Corchero, 2011; Omel website, 2010; Weron, 2007). These rules encourage joining the Spanish market with the Portuguese electricity system. This is useful for improving the previous mechanisms of the Spanish electricity market in order to extend it into a competition market (Corchero, 2011; Ciarreta et al., 2014).

In contrast to the Iranian electricity market, the operator of the Spanish electricity market considers "the bids for accepting generator companies in the spot markets," and he/she investigates if these agents can pass some sessions in the day-ahead market (Corchero, 2011). The Spanish electricity market is a bilateral market (Gonzalez and Basagoiti, 1999; Corchero, 2011; Muñoz et al., 2013; Weron, 2007), and the price is determined by the spot price; namely, the aggregated demand at a certain hour and the price elasticity of demand is not zero (Weron, 2007; Corchero, 2011). In this market, companies have the ability to present their price to the market, clearly indicating it as a benchmark (Corchero, 2011; Ofgem, 2013; Weron, 2007).

In contrast to the Spanish electricity market price, there is not any publicly published information of the Iranian electricity market indices, as was noted by Asgari and Monsef (2010). Therefore, the producers and consumers rely on price forecasting to prepare their corresponding bidding strategies in order to maximize their profits (Asgari and Monsef, 2010; Amjady et al., 2010; Bigdeli et al., 2009). These situations suggest a non-competitive, oligopolistic (or monopolistic) nature of competition in the Iranian electricity market (Nazemi and Farsaee, 2014; Van Alfen, 2014).

Therefore, the question arises over whether it is possible to describe the Iranian electricity market as a competitive market that is similar to the Spanish electricity market, even when considering its conditions of conflict.

According to contemporary market management principles, in order to understand the patterns of market behavior (or to sell our products/services in international markets), it is essential to plan a market analysis along with information on elements that impact the market, as a marketing approach from Kotler and Armstrong (2010; 2013) and Tanner and Raymond (2011). In other words, the electricity market analysis will be an ideal guide for market analysts and planners in this sector, as noted by Stevens et al. (1993).

To address the topic of energy market analysis, Garcia and Arbeláez (2002) evaluate "the impacts of possible mergers in the Colombian electricity market." Woo et al. (2003) further examine the market reforms in the UK and other countries. Ventosa et al. (2005) focus on electricity generation market modeling. Conejo et al. (2005) and Mazengia and Le (2008) represent electricity price forecasting through time series analysis. Rodriguez and Anders (2004) investigate the competitive Ontario power system market. Ghadrei and Nokhandan (2009), Pao (2007) and Amjady and Keynia (2010) propose a neural network model for forecasting prices. Lora et al. (2007) present the weighted nearest neighbors technique for forecasting electricity prices. Weron (2014) review the state of the art of electricity price forecasting with a look into the future.

Some few studies focus on the Iranian electricity market in terms of: Electricity-price behavior and load, market power and its characterization (Asgari and Monsef, 2010; Bigdeli and Afshar, 2009) and forecasting electricity price by employing autoregressive integrated MA (ARIMA) and generalized autoregressive conditional heteroskedastic (GARCH) models (Safakish and Manzur, 2009). However, these studies do not provide any explanation for the level of competition in the Iranian electricity market.

Electricity price forecasting is also extremely important for all market players in the short, medium and long term (Benini et al., 2002). Some market researches do not consider other factors (such as load) that have a possible impact on the electricity price, especially those studies related to the Iranian electricity market. So, it is critical for market managers to suppose other elements such as load (or demand of the market), which modifies the pricing strategies in the (competitive) market (Bunn, 2004; Kotler and Armstrong, 2010; Nicholson and Snyder, 2011; Weron, 2007). In addition, the basic economic theories explain that the pattern of price via demand is predictable in competitive markets (Nicholson and Snyder, 2011). This suggests the existence of a relationship between price and load in the liberalized markets (Weron, 2007; Nicholson and Snyder, 2011). The variety of the load changes the price in a competitive electricity market (Weron, 2007). The importance of this index has been investigated. Vilar et al. (2012) represent the forecasting of electricity demand and price in the competitive Spanish electric power market. Ahmari et al. (2005) improve on the importance of load amount in the Iranian electricity market. Barforoushi et al. (2006) focus on a market plan based on the load in Iran. Afshar and Bigdeli (2011) consider short-term load forecasting. Several of these studies do not include price as another factor in the Iranian electricity market.

The current research focuses on a time series analysis approach to inspecting the existing relationship between the two indices (price and load) in both markets. The time series approach has been utilized in modeling efforts in diverse applications (e.g., Box et al., 1994; Hu, 2011; Jianqing and Qiwei, 2005 and West et al., 1994). The main objectives of time series analysis modeling are: Data collection methods (such as hourly, daily and so on), the dynamics of the time series behavior, forecasting future events, and controlling future events via intervention (Hu, 2011). The original ideas of proposing theory and applying the time series analysis were formed by Box and Jenkins in 1970 (Box and Jenkins, 1994; Brockwell and Davis, 2006 and Jianqing and Qiwie, 2005). They also generated and popularized the use of "autoregressive–MA." as was pointed out by Box and Jenkins (1994) and Makridakis and Hibon (1997). The "ARIMA" models are generalized based on the autoregressive MA model (ARMA) model theory (Box and Jenkins, 1994 and Makridakis and Hibon (1997). The ARIMA model is a particular type of mathematical regression model and it is used to approximate the behavior of observations in scenarios where data exhibits non-stationary movement (e.g., Armstrong, 2001; Box and Jenkins, 1994; Box et al., 2008; Cryer and Chan, 2008; Makridakis and Hibon, 1997; Wang and Jain, 2003; Wurtz et al., 2006). ARIMA forecasting models were further developed in the theme of economic and financial variables. They are computed and applied for ex-ante and ex-post forecast models as noted by Armstrong (2001). In contrast to regression-form models, ARIMA models (also known as parameter-based models) are utilized to analyze the observations in complicated stochastic processes (e.g., Cryer and Chan, 2008 and Wurtz et al., 2006). Conditional variance and mean in time series lead us to introduce the "GARCH model" (Bollerslev, 1986; Wurtz et al., 2006). Studies considering a "conditional heteroskedastic model" are useful for improving other models (e.g., asymmetric power autoregressive conditional heteroskedastic [ARCH], and ARCH/GARCH models) and their related theorems (Bollerslev, 1986; Tsay, 2005; Wurtz et al., 2006). The GARCH models are applied as both parametric and non-parametric models (Aiube et al., 2011; Hu, 2011; Rohan and Ramanathan, 2013; Taylor, 2006; Tsay, 2005. p. 102-109, 113-136). The ARMA-TGARCH model is further introduced to develop time series estimates exhibiting structural changes in trends and break points (Muñoz et al., 2007; Tsay, 1989; Tsay, 2005). The aggregation of several ARMA-GARCH models formed this model in order to estimate the nonlinear behavior in a time series (Di Narzo, 2008; Muñoz et al., 2007; Tsay, 2005; Wurtz et al., 2006; Zhang, 2009).

This study attempts to address whether or not the Iranian electricity market can be categorized as a liberalized and competitive market. Toward this goal, we compare the market in Iran to that of Spain. Such a comparison sheds light on how Iranian electricity market behavior can be compared to a developed market. So, we further present a time series approach to employing linear and non-linear models with price and load as the main factors in these markets. We also investigate the role of load determination in these markets. Here, the load and price relationship is discovered.

The second section of this research represents data description via time series statistical methods. It surveys four time series, which are named: Iranian electricity price (IEP), Spanish electricity price (SEP), Iranian electricity load (IEL), Spanish electricity load (SEL). In this section, we also investigate the relationship between two indices in these two markets: Price and load. Then, in the third section we focus on two well-known time series models for each time series ARIMA and ARMA-GARCH model for both price and load indices. In addition, IEP and load are also modeled by ARMA-TGARCH and seasonal ARIMA (SARIMA) respectively. The models are selected based on behavioral properties of each of our time series. Then, the fourth section compares these models. This is done in order to find the best and most valid model for each time series. Our next section in this research presents forecasting for IEP and IEL in order to make accurate estimates about the future price and load for the next 14 days. The last section indicates the conclusions of this paper according to our main question. Therefore, the findings of the current research provide strategic knowledge and better estimates regarding this energy market, so that future planning can take into account rapid changes.

2. METHODS

2.1. Data Description: Iranian and SEP and Load

According to "Statistical reports of the Iranian Electric Power Industry" (Tavanir, 2011b), the pricing of electricity sales to various consuming sectors was based upon a constant rate in the last few years (such as 2004). Although there is increasing annual investment in the Iranian electric power industry, there is significant variation in the average pricing rate. This was still the case during the 3 years from 2007 and 2010, as noted in Tavanir (2011b). Inherently, however, it supplies the cost of three significant parts of the electric power industry: Generation, transmission and distribution (Tavanir, 2011a). Here, the important issue is that 85% of power generation is still controlled and managed by the Iranian Ministry of Energy (Mirsaeedi, 2012). The importance of electricity pricing and the matter of variations in the market motivate us to follow Iran's daily electricity price time series over the course of three 3 years so that we can follow the corresponding market responses. Figure 1a displays the IEP time series during this period. We present the reported daily data starting on the 21st of March, 2007 and ending on the 20th of March, 2010. The daily electricity price time series is calculated via the "hourly accepted weighted average price," a quantity based on Rials/kWh, and it is reported by the Iranian Ministry of Energy (Bigdeli and Afshar, 2009; Ministry of Energy [Islamic Republic of Iran], 2010).

As mentioned before, Spain's electricity market has been deregulated since 2007. The new Spanish Electricity Market begins its general operations, and then all generators, distributors, commercialization companies and final consumers negotiate everything in the spot electricity market, as was noted by Corchero (2011), Gonzalez and Basagoiti (1999) and Muñoz and Dickey (2009). However, the current volatile financial markets make pricing very difficult to predict, even in the case of electricity markets (Muñoz and Dickey, 2009), which lack storage capacity. This research also represents a descriptive analysis of the Spanish electricity spot price time series, which is similar to the IEP time series. It covers 3 years of the SEP time series in Figure 1b. The period of the daily data starts on the 1st of July, 2007 and ends on 30th September 2010.

The important role of load in electricity market pricing motivates us to follow Iran's daily electricity load time series and the SEL over the course of three 3 years, so that we can track the corresponding market responses. Data is calculated daily, similarly to the electricity price for both time series. For the IEL time series in Figure 2a, we present the reported observations, which start on the 21st of March, 2007 (this corresponds to the beginning of the Iranian New Year 1386), and they end on the 20th of March, 2010 (the end of the Iranian year 1388). Similarly to the IEL time series; this study also presents a descriptive analysis of the SEL. It covers 3 years of the Spanish electricity market load in Figure 2b. The period of the daily data starts on the 1st July 2007 and ends on 30th September 2010. The quantity of the load is based on the "kWh" measure. Here, these load time series are divided by 1000 to make the scale smaller and simplify the calculations.

For these two electricity markets, the daily electricity data time series is calculated via the "hourly data." These data are represented by the "Ministry of energy (Islamic republic of Iran" (2010) for the Iranian electricity market and the "Spanish market operator" (2010) for Spain. The price and load are reported daily in order to investigate the behavior via a suitable model during this study. Consequently, the valid prices and load exhibit an indication of the total behavior during a 24-h period. The total number of observations is 1095 for each time series, price and load in the Iranian electricity market. The number of observations of the SEP and load that are investigated is 1188. We employ the software "R" as our statistical analysis tool (R Development Core Team, 2011). Overall, the SEP plot shows daily upward drifts. This systematic pattern happens for approximately the first 600 observations of our time series, and then SEP exhibits a downward tendency in the

Figure 1: (a) Daily Iranian electricity price time series (2007-2010) and (b) daily Spanish electricity price time series (2007-2010). Here, time is shown in the order of observation for each of our daily series

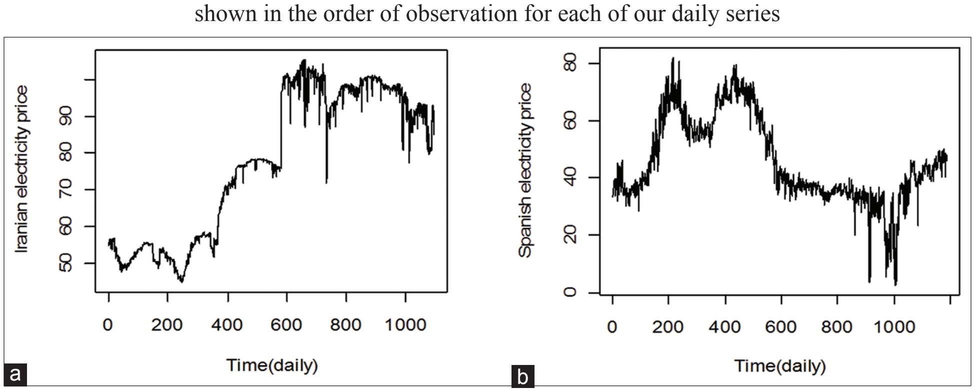
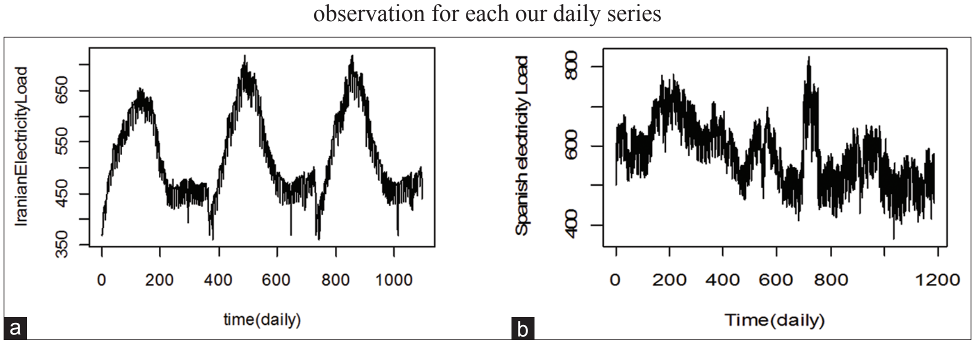


Figure 2: (a) Daily Iranian electricity load (IEL) time series and (b) daily Spanish electricity load time series. Here, time is shown in the order of observation for each our daily series



observations. Again, this behavior pattern happens for the last part of this time series, as is shown by Figure 1b. On the other hand, although this time series has in some parts high spikes and jumps, there is just one span that has noticeably decreasing jumps. They happen at around 2 months, starting in the middle of February and continuing until the middle of March 2010. According to Figure 3, high volatility observed in the price could be due to an increase in electricity generation by wind (Ketterer, 2014).

The oscillations appear close to the upward trend and can be a sign of the seasonal behavior in the SEP. This is shown in Figure 4b and contrasted to the IEP in Figure 4a. The tendency of the observation variance reverts around a mean level. However, in order to get a suitable estimate from the data, the logarithm as a transformation function is not worked out here for both time series. This variety in behavior is more clear and significant for the IEP time series.

The IEP shown in Figure 1a exhibits various behaviors and upward trends in the daily values. Three breakpoints are recognized in the IEP time series using the Breaks for Additive Seasonal and Trend (BFAST) approach (Figure 5). The BFAST methodology is often used as a generic change detection tool in time series (Verbesselt et al., 2010). It involves the detection and characterization of breaks for additive seasonal algorithm and trends. This detection analysis is basically formed according to the decomposition model, which assumes three component behaviors of the time series. "An additive decomposition model is used to iteratively fit a piecewise linear trend and a seasonal model" (Verbesselt et al., 2010). The general model is given by Equation (1), where Y_t is the observed data at time t = 1, 2,.., n = 1095., T_t is the trend component; S_t is the seasonal component; and e_t is the random noise.

$$Y_t = T_t + S_t + e_t \qquad (1)$$

The BFAST integrates the iterative decomposition of time series into two trends: Seasonal and noise components, with methods for detecting change within time series. This method is not specific to a particular data type and can be applied to time series without the need to normalize for land cover types, select a reference period, or change trajectory (or specific thresholds), as noted by Verbesselt et al. (2010). Therefore, three break points are detected at a 95% confidence interval for the IEP time series. These breakpoints happen on the 366th day, 585th day and 846th day of this time series, and they are indicated on the left-hand side of Figure 5 as "Hidden lines." Existence of these breakpoints will indeed influence the choice of the time series model, as they indicate the thresholds in our observations (Verbesselt et al., 2010). Therefore, we notice four separate parts in the treatment of the time series (Figure 6a). These four sections

Figure 3: (a) Daily Spanish electricity price after detecting outliers and (b) daily Spanish electricity generation by wind (scale: Inverse of wind divided by 1000). Time is shown in the order of observation for each of our daily series

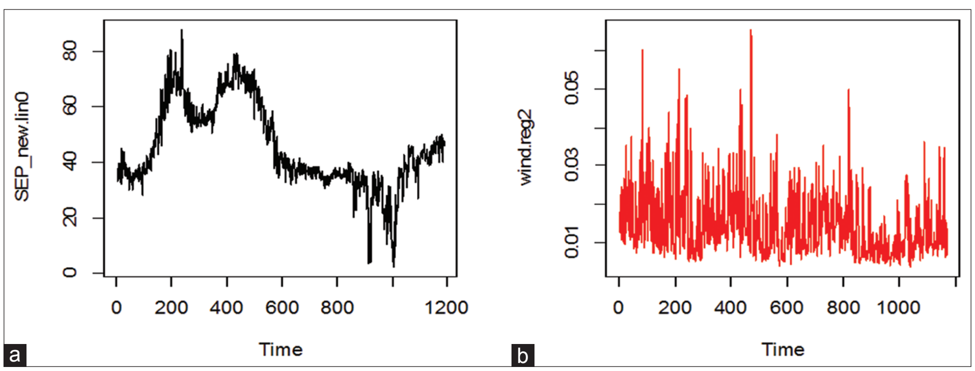
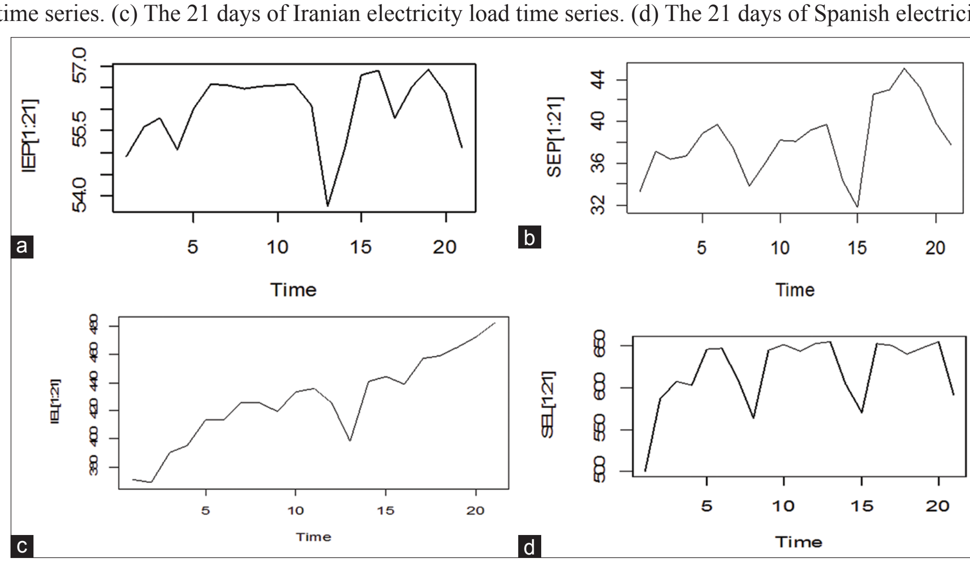


Figure 4: Seasonality behavior shown in four time series. (a) The 21 days of Iranian electricity price time series. (b) The 21 days of Spanish electricity price time series. (c) The 21 days of Iranian electricity load time series. (d) The 21 days of Spanish electricity load time series



are as follows: (a) 21st of March, 2007 until 19th of March, 2008 (approximately a full year); (b) the 20th of March, 2008 until the 25th of November, 2008 (4 months prior to the Iranian new year); (c) 26th of November, 2008 until the 13th of July, 2009; and (d) the 14th of July, 2009 until the 20th of March, 2010.

The IEL time series in Figure 2a and the SEL time series in Figure 2b also demonstrate upward and downward trends in their daily values during the sampled 3 years. Initially, there are some spikes occurring on special dates of the SEL time series, which are not seen in the IEL time series. Figure 4d shows the SEL time series demonstrating seasonality behavior; see also the significant decrease in the variance of this time series in Table 1 after taking a seasonal difference. Although this kind of behavior is not clear for the IEL time series in Figure 4c, a significant decrease in variance of this time series after taking

Figure 5: Plot of BFAST diagram from Iranian electricity price (IEP) time series. (a) Plot of BFAST trend detecting by breakpoints in weekly IEP time series. (b) Plot of BFAST detecting the changes in IEP time series via decomposition model

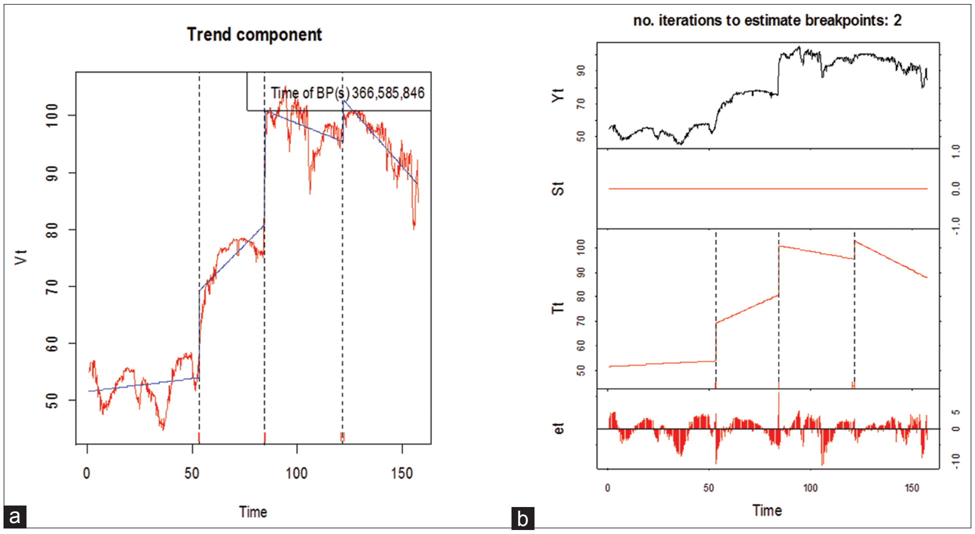
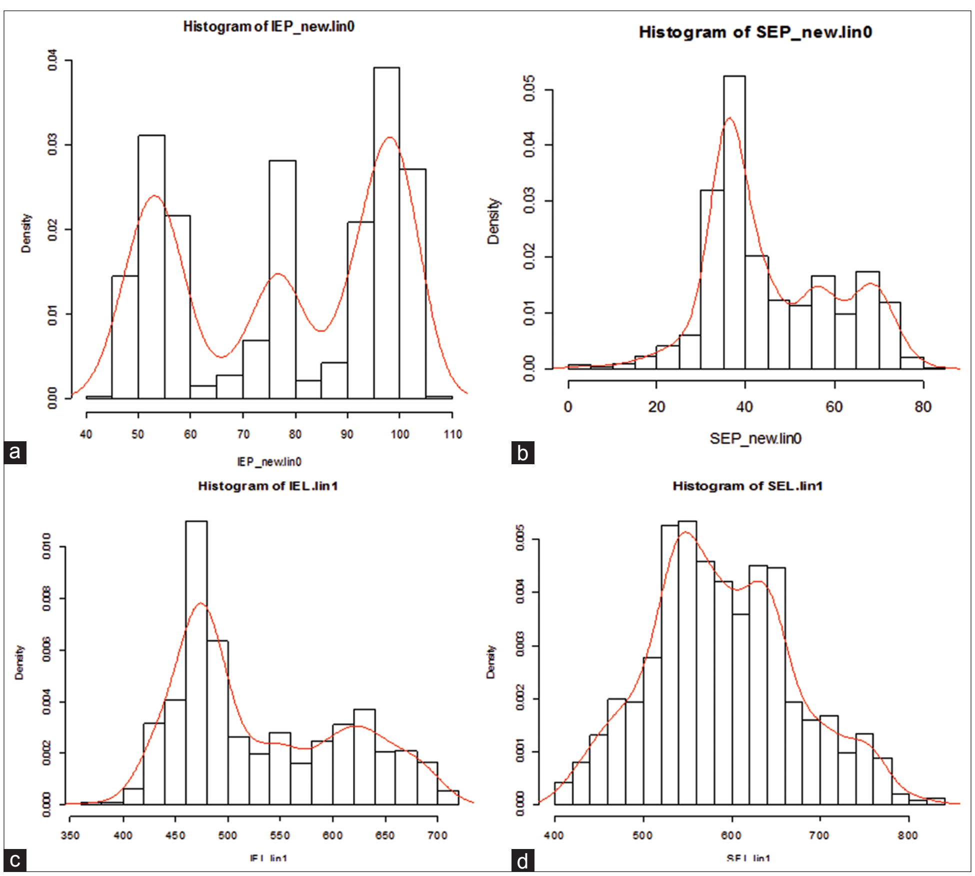


Figure 6: (a) Histogram of daily Iranian electricity price time series. (b) Histogram of daily Spanish electricity price time series. (c) Histogram of daily Iranian electricity load time series. (d) Histogram of daily Spanish electricity load time series



a seasonal difference suggests seasonal behavior in this time series, according to Table 1.

In addition, the IEL time series has yearly cycling behavior in Figure 2b. The periodogram of the IEL time series in Figure 7a is used to recognize the dominant cyclical behavior (periodic or frequency) in this time series (PennState, 2014; Shumway and Stoffer, 2010).

The dominant peak occurs close to 0.0027 in this diagram. Investigation of the periodogram value indicates that the peak occurs at nearly exactly this frequency. This corresponds to about 1/0.0027≈365 time periods. Thus, this suggests the annual cycling pattern in this time series (for more information, refer to PennState, 2014 and Shumway and Stoffer, 2010). By subtracting the seasonal difference from the yearly time series, the histogram diagrams exhibit a Gaussian-type distribution in Figure 7b.

According to Table 2, the Jarque-Bera test of these four time series demonstrates that there is not any normal distribution in the observations (Bai and Ng, 2005). The Null hypothesis of the Jarque-Bera test is rejected, since the $P < 0.05$. This means that the skewness is not equal to zero and (or) the kurtosis is not equal to three (Pfaff, 2008).

Table 1: Variance of Spanish electricity market time series and Iranian electricity market time series and their seasonal difference and non-seasonal difference time series

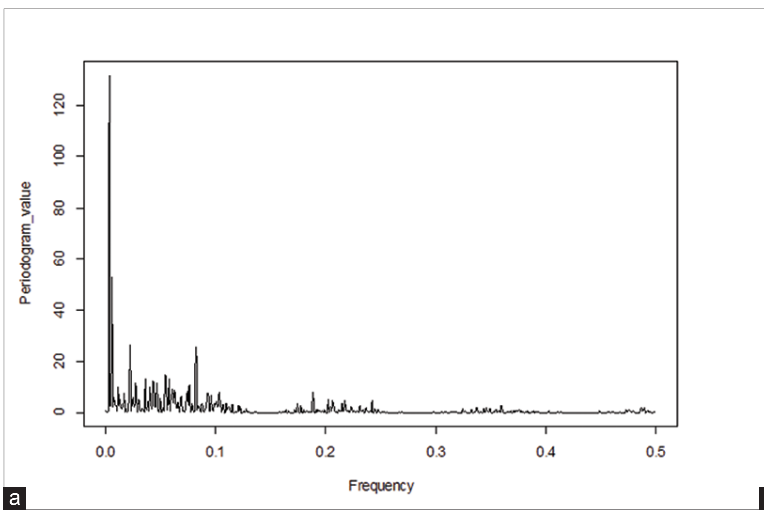
Time series	Variance from four time series after detecting outliers	Variance from four time series after taking seasonal difference	Variance of four time series after taking first order difference
SEP	212.189	23.585	8.959
SEL	6650.003	1769.004	2215.375
IEP - total time series	397.161	-	0.977
First part of IEP	10.844	-	0.621
Second part of IEP	20.519	-	0.872
Third part of IEP	12.850	-	1.217
Four part of IEP	24.366	-	1.224
IEL	6522.622	375.348	452.885

SEP: Spanish electricity price, SEL: Spanish electricity load, IEP: Iranian electricity price, IEL: Iranian electricity load

Furthermore, considering the IEP time series plot in Figures 1a and 5b, we identify four sections that have particularly distinct motions. For each section of the IEP time series, the P value of the "Jarque–Bera normality test" is also <0.05. It shows that skewness and kurtosis do not match a Gaussian distribution (Table 2). In addition, after detecting the outliers, the histograms of the four time series in Figure 6 prove that there is no normal distribution. The IEP time series distribution histogram in particular is not unique, and this is made clear for the IEP in the upper left part of Figure 6, which suggests "trimodality" in the data (Di Narzo, 2008). This proves that the time series exhibits three separate distributions and bimodality of data. These results also indicate that there is symmetry in the SEP and SEL time series as well as in the four parts of the IEP series and IEL; and there are tails on the left (or right) side of their distributions (Figure 6 b-d).

Furthermore, the "augmented Dickey Fuller" (ADF) test is an extension to the Dickey and Fuller test of 1979. It examines whether or not time series are stationary (Di Narzo et al., 2008; Tsay, 2005). Here, the ADF test cannot be utilized, since the IEP exhibits structural changes in its trends, including three break points (Figure 2a). The SEP and SEL (as shown in Figure 4b and d) demonstrate seasonality as well as cycling behavior over time. Also, the IEL has the seasonality component according to Table 1, as the variance of this time series decreases significantly after taking seasonal differences (Box and Jenkins, 1994; Cryer and Chan, 2008; Tsay, 2005). The Zivot and Andrews test was proposed by Zivot and Andrews in 1992. We use this unit root test in order to take into account any possible structural breaks. The null hypotheses is defined such that there exists a unit root with drift and/or break at an unknown point against the alternative hypothesis, which is a stationary trend with a break in intercept or trend at an unknown point (Pfaff, 2008). For four time series, the null hypothesis here is rejected, because the test statistics value is

Figure 7: (a) Periodogram of the Iranian electricity load (IEL) time series after taking the seasonal difference to show its yearly cycling behavior. (b) Histogram of daily IEL time series after taking seasonal difference and seasonal yearly difference



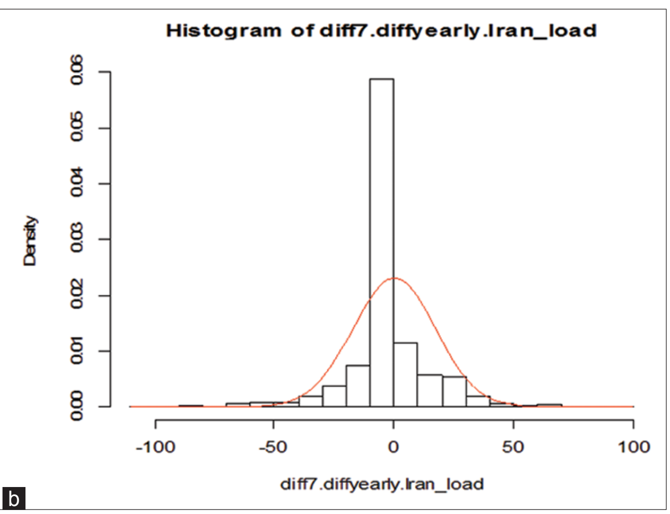


Table 2: Results of Jarque–Bera test performed for Spanish electricity market time series and Iranian electricity market time series (for their price and load)

For	First part - Spanish electricity market time series		
	Number observations	Time span	Jarque–Bera test*
SEP time series	1182	July 2007, 01-September 30, 2010	30.710 P: 2.145e-07
SEL time series	1188	July 2007, 01-September 30, 2010	13.4229 P: 0.001
IEP time series	**Second part - Iranian electricity market time series**		
1st section of time series	365 (1-365)	March 21, 2007-March 19, 2008	14.349 P: 0.0001
2nd section of time series	210 (366-584)	March 20, 2008-October 25, 2008	122.5985 P: <2.2e-16
3rd section of time series	260 (585-845)	October 26, 2008-July 13, 2009	25.4266 P: 3.011e-06
4th section of time series	249 (846-1095)	July 14, 2009-March 20, 2010	45.9925 P: 1.03e-10
IEL time series	1095 (1:1095)	March 21, 2007-March 20, 2010	14.349 P: 0.0001

SEP: Spanish electricity price, SEL: Spanish electricity load, IEP: Iranian electricity price

less than the critical values at each significant confidence interval level (95%, 90% and 99%) (Pfaff, 2008) (Table 3). In conclusion, there is a trend in our four time series. In order to have a better understanding of the SEP, its load and IEP behaviors, the seasonal difference and non-seasonal difference for these time series have been taken. The results of this test are presented in Table 3.

The autocorrelation function (ACF) and partial correlation function (PACF) (Tsay, 2005) are employed to analyze these four time series: The IEP time series, the IEL, the SEP and the SEL time series. They show the correlation between one variable at different times (Cryer and Chan, 2008; Tsay, 2005). The ACFs and PACFs do not display any stationary behavior, even after taking a first-order difference for each of the three time series: The IEL time series (Figure 8c and d), the SEP time series (Figure 8b) and the SEL time series (Figure 8a).

There is weak stationary behavior in each time series. The same pattern is observed in the first part of the IEP in Figure 9a: After its first-order difference, the lags in plots have a slow decay (Figure 10b), as is pointed out by Tsay (2005). This result leads us to use the ARIMA model in order to develop suitable models for these time series (Cryer and Chan, 2008 and Tsay, 2005).

In contrast to the weak stationary behavior in the first section of the IEP time series, we can observe in Figure 10b that, for the last three parts of the IEP time series, the ACF and PACF imply that there is a very weak serial correlation pattern among our observations. It seems that the behavior of the time series is random and the stochasticity component of the IEP time series is white noise. Most of the ACFs and PACFs are equal to almost zero for each section (Cryer and Chan, 2008; Tsay, 2005). The white noise is introduced as a stationary process; this means that the time series behavior is defined as a sequence of independent, identically distributed random variables "e_t" (Cryer and Chan, 2008).

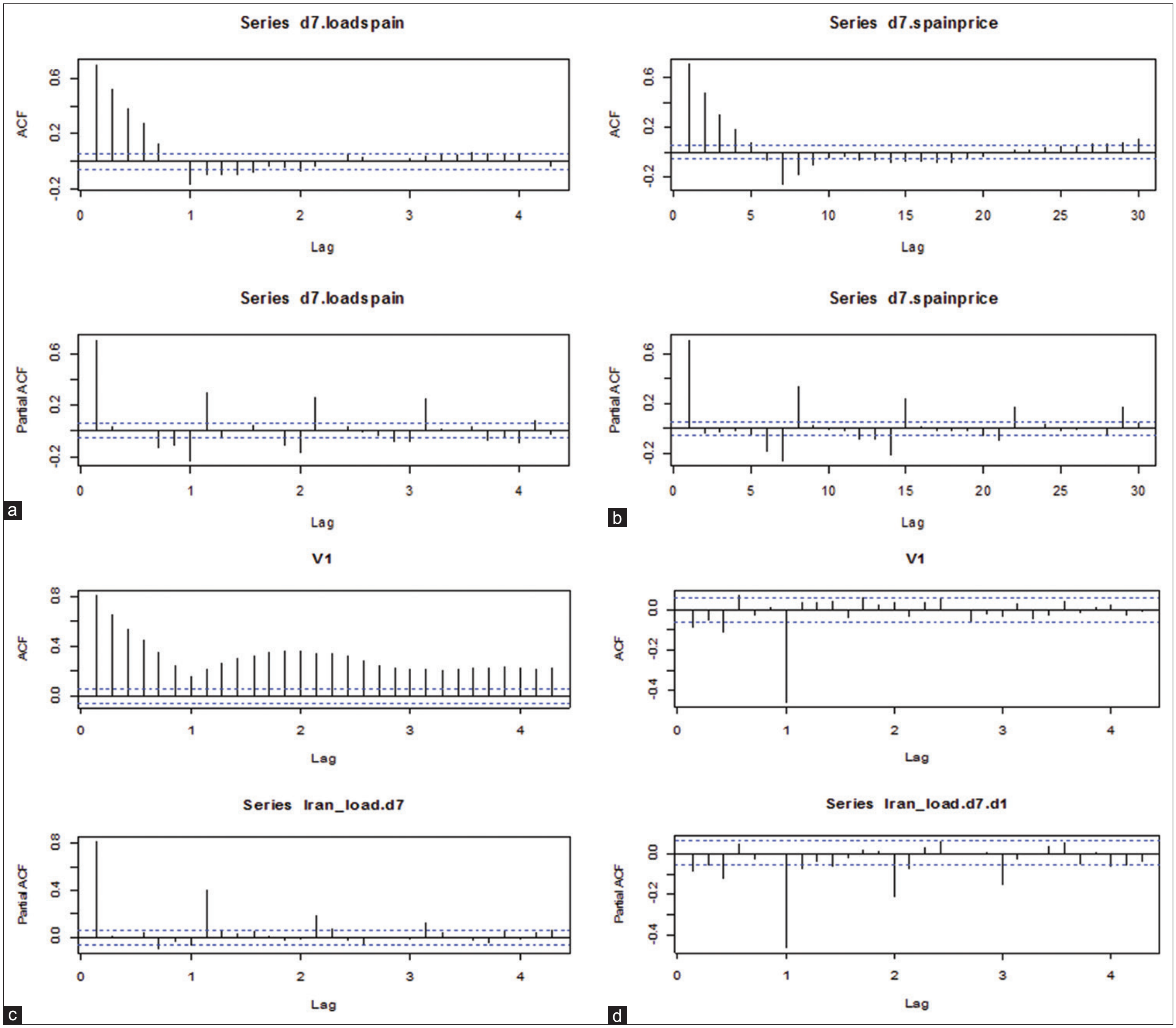
However, we note that the ACFs and PACFs obtained from the set of the squared observations (after taking the first difference) indicate that the magnitude of change in observations may show correlation. In other words, serial dependence exists within the variance of data (Hossain et al., 2011) (Figures 9b-d and 10 – right part [c, f, i, l]; Table 1). On the other hand, as shown in Figure 6, the IEP does not show an independent and identical distribution; the BDS test verifies this claim. The BDS test developed by Brock et al. in 1987 (and later published as Brock et al., 1996) is arguably the most popular test for evaluating nonlinearity (Wuertz, 2013; Zivot and Wang, 2006). It was originally designed to test for the null hypothesis of independent and identical distribution in order to detect non-random chaotic dynamics. The main concept behind the BDS test is to calculate the correlation integral at embedding dimension m. The null hypothesis is defined such that the time series is independently and identically distributed (Zivot and Wang, 2006). According to Table 4, since the P value for five combinations of the IEP time series is <0.05, the null hypothesis is rejected and, therefore, the time series is not a unique distribution series. It means that our alternative hypothesis is accepted (Zivot and Wang, 2006).

Table 3: Zivot and Andrews test, unit root test, after detecting outliers for all of our time series

Result of unit root test	Critical values at 99% confidence interval level	Critical values at 95% confidence interval level	Critical values at 90% confidence interval level
Test statistics value for each time series	**Critical values**		
IEP time series Test value: −5.6576	−5.57	−5.08	−4.82
IEL time series Test value: −5.7438	−5.57	−5.08	−4.82
SEP time series Test value: −10.3691	−5.57	−5.08	−4.82
SEL time series Test value: −8.3939	−5.57	−5.08	−4.82

SEP: Spanish electricity price, SEL: Spanish electricity load, IEP: Iranian electricity price, IEL: Iranian electricity load

Figure 8: (a) The autocorrelation function (ACF) and partial correlation function (PACF) from the seasonal order difference of Spanish electricity load time series, (b) ACF and PACF from Spanish electricity price time series after taking seasonal order difference. (c) The ACF and PACF from the seasonal order difference of Iranian electricity load (IEL) time series and (d) the ACF and PACF from the seasonal difference of first order differencing of IEL time series



The BDS test result suggests that the time series has a nonlinear pattern. Therefore, it is necessary to employ a model which is applicable to both "serial dependence in the variance of data" and also to a "nonlinear behavior pattern" in the time series. All of the results lead us to employ the ARMA-TGARCH model, which is explained in the next part (Di Narzo, 2008; Hossain et al., 2011; Muñoz et al., 2007; Tsay, 1989; Wurtz et al., 2006; Zhang, 2009; Tsay, 2005). As shown in Figures 8 and 10 - middle part (b, e, h, k) due to the existence of weak stationary behavior in three of our time series (i.e., IEL, SEP, SEL) and the first section of the IEP time series, the first estimated model that can be applied is the ARIMA model (Cryer and Chan, 2008; Tsay, 2005). Hence, for each of these time series, the third section of our study presents estimated ARIMA models in order to distinguish the behavior of these time series.

2.2. Relationship between the Price and Load

As explained above, the load (as demand) is introduced into the competitive and developed electricity market as the significant index that normally has an impact on the market price (e.g., Kotler and Armstrong, 2010; Nicholson and Snyder, 2011 and Weron, 2007). In accordance with the scatter plot, which is a quick-view method for revealing obvious relationships between two variables (Sharma, 2008), we investigate the pattern of correlation between our pairs of time series indices. Here, we assume the daily IEL time series as the independent variable and the daily electricity price time series as the dependent variable. As we observe in the scatter plot of these two time series, there is no line; and there is also no slope which is positive or negative in Figure 11a (Friendly and Denis, 2005; Sharma, 2008). This suggests that there is no

Figure 9: Four part of daily Iranian electricity price time series (2007-2010), after taking first order difference. (a) First section of time series-after taking first order difference. (b) Second section of time series-after taking first order difference. (c) Third section of time series-after taking first order difference. (d) Fourth section of time series-after taking first order difference

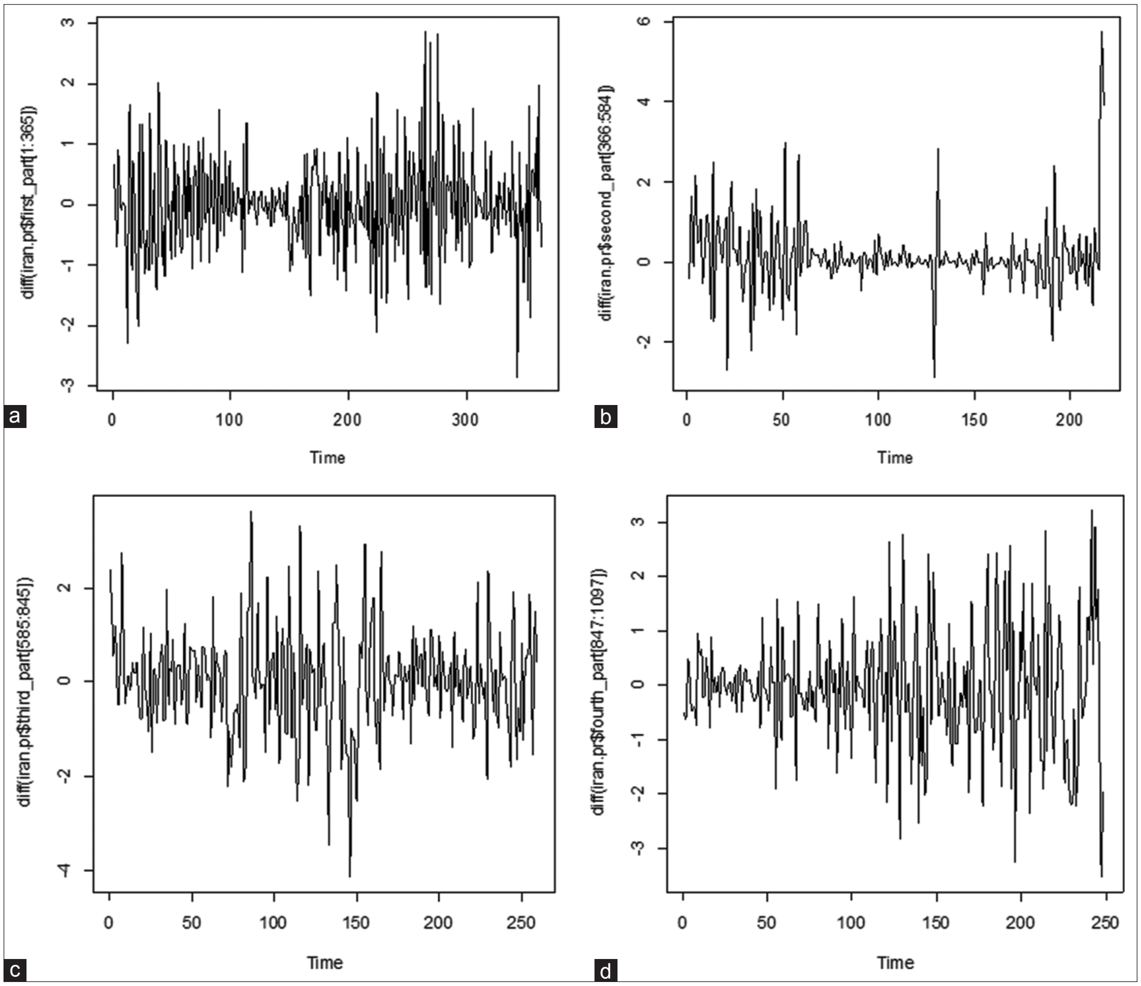


Table 4: BDS test for daily IEP (2007-2010), after detecting outliers

Statistical test	Daily IEP – bds. test (IEP_new.lin0)
BDS test	BDS test data: IEP_new.lin0, embedding dimension m=23 P value = [9.964] [19.928] [29.893] [39.857] [2] 0 0 0 0 [3] 0 0 0 0

IEP: Iranian electricity price

(linear) relationship between the IEP and the IEL time series. In contrast to the Iranian electricity market and the Spanish electricity market, there is a positive correlation between these two time series in some part of the SEP time series and the SEL time series (Figure 11b). This result leads us to consider how Spanish electricity generated by wind impacts the behavior of the price in this market (Ketterer, 2014).

2.3. Modeling Iranian and Spanish Electricity Market Time Series

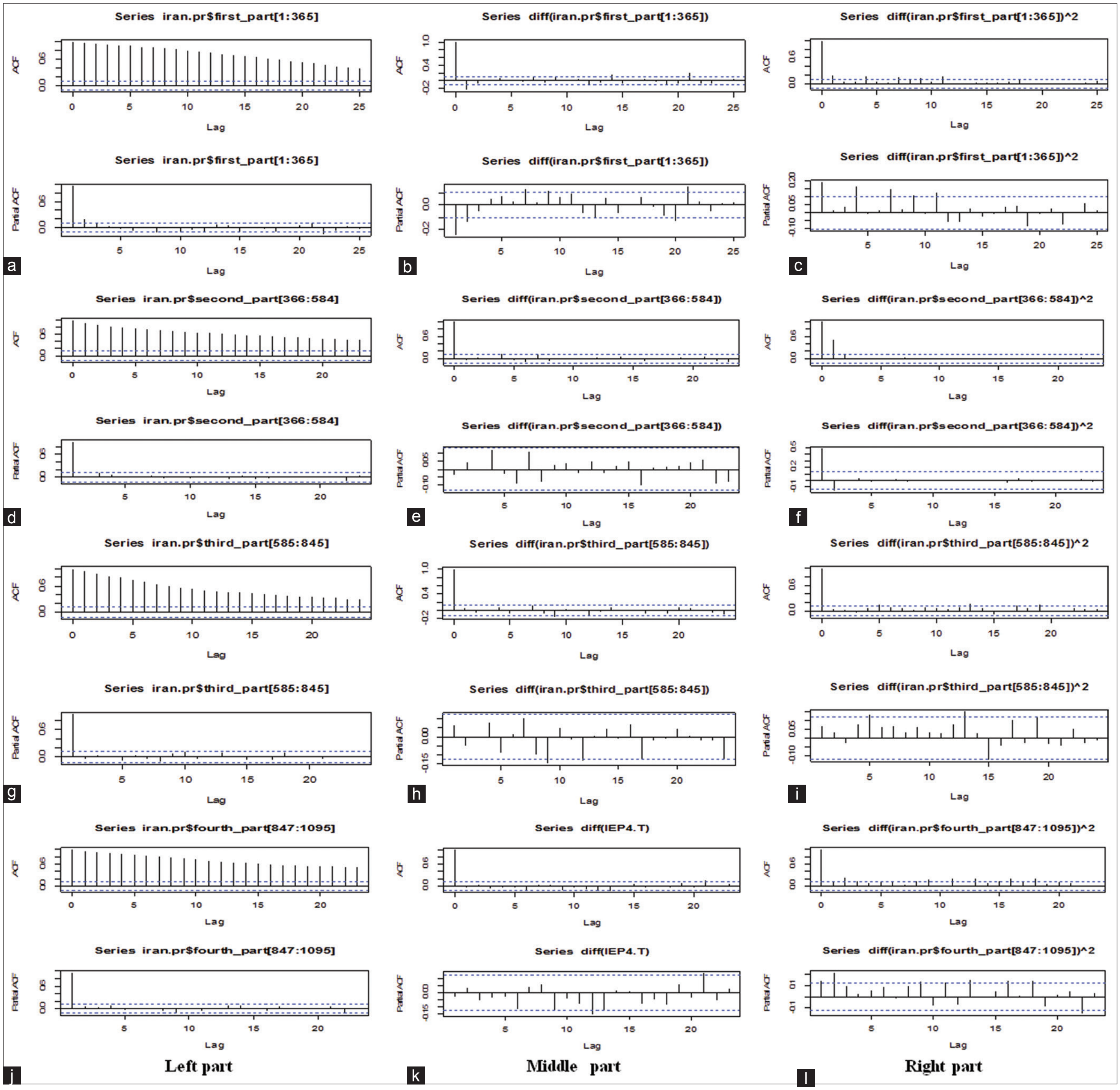
Here, we present the time series modeling analysis in order to obtain the best fitting model for each of the time series.

2.3.1. ARIMA models for Spanish and Iranian price and load time series

As we explained in above, we try to improve on the stationary conditions in the Spanish and Iranian price and load time series by taking the seasonal differences, as shown in Figure 8. However, after taking this seasonal order difference, these time series show a weak stationary behavior pattern during those periods. For the SEP time series and its load, the IEL time series and the first part of the IEP time series, we apply the ARIMA model to estimate the behavior of these time series. The ARIMA model parameters obtained for each time series are presented in Table 5. The inverse of the Spanish electricity generated by the wind coefficient is significant for the SEP. This result leads us to investigate the role of Spanish electricity generated by wind as an exogenous factor (here, it is introduced as the Xreg variable in the ARIMA model) for SEP time series (refer to Chan et al., 2012; Cryer and Chan, 2008 and Eriksrud, 2014).

The general ARIMA (p, 1,q) (P,D,Q) model is introduced in detail by Cryer and Chan (2008), Dahyot (2012), Tsay (2005). Y_t is introduced as a dependent variable in Equation (2). It is defined as electricity price (or load) for both markets at time t, which depends on the price (or load) at the final time.

Figure 10: The autocorrelation function (ACF) and partial correlation function (PACF) from: (Left part) - Four sections of the Iranian electricity price (IEP) time series (a) ACF and PACF from the first section, (d) ACF and PACF from the second section, (g) ACF and PACF from the third section and (j) ACF and PACF from fourth section. (Middle part) Four sections of first order difference of IEP series (b) - ACF and PACF from the first section, (e) - ACF and PACF from the second section, (h) ACF and PACF from the third section and (k) ACF and PACF from fourth section). (Right part) - The ACF and PACF from squared (four sections) IEP time series, after taking the first order difference (c) ACF and PACF from square of first section, (f) ACF and PACF from square of second section, (i) ACF and PACF from square of the third section and (l) ACF and PACF from square of fourth section



$$\varnothing(B)\Phi(B^S)(1-B)(1-B^D)Y_t = \Theta(B^S)\theta(B)e_t \quad (2)$$

The "ϕ" coefficients associated with the autoregressive part of the model and the "p" value determines the order of the AR estimate. The "θ" coefficients related to the MA part of the ARIMA model and the "q" value indicate the order of MA. Here, operator B and B^S are introduced as the backshift and seasonal operator parameters, respectively. In Equation (2), the period of seasonality in the ARIMA models is indicated by the symbol "s." The "Φ" parameter is related to the seasonal part of the AR model. The parameter "Θ"is also related to the seasonal MA part of the model. Variables "P" and "Q" represent the order of the seasonal AR and MA part, respectively. The "D" (the seasonal part) shows the order of the seasonal difference.

Figure 11: (a) Scatter plot of the daily Iranian electricity price and daily Iranian electricity load time series. (b) Scatter plot of the daily Spanish electricity price and daily Spanish electricity load time series

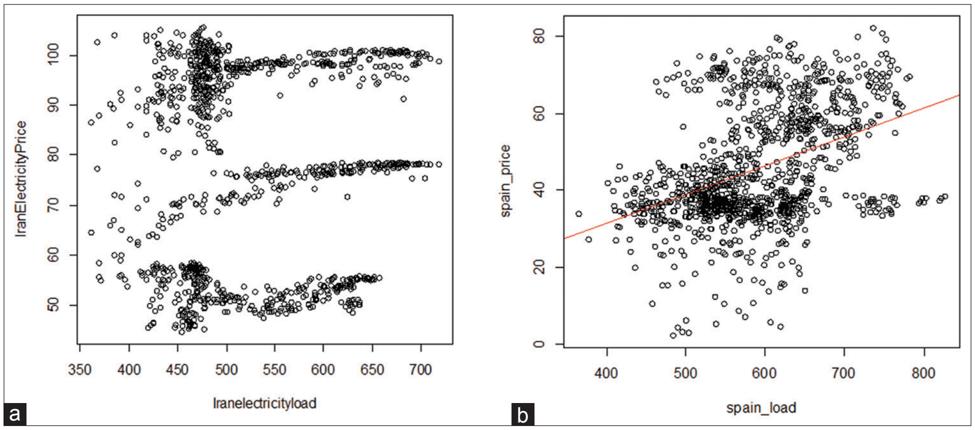


Table 5: Estimated ARIMA models for SEP, IEL and SEL

Time series	Estimated ARIMA models of daily electricity price-load time series in both market											
Daily SEP time series	First ARIMA model for SEP time series											
	ARIMA (NA,0,0,0, NA,0, NA, NA, NA, NA)$(1,1,0)_7$	Coefficients:										
			ar1	**ar2**	**ar3**	**ar4**	**ar5**	**ar6**	**ar7**	**ar8**	**sar1**	**xreg**
			0.717	0	0	0	0.078	0	−0.261	0.170	−.1702	26.150
		SE	0.022	0	0	0	0.025	0	0.042	0.036	0.042	12.983
		σ^2 estimated as 12.59: Log likelihood=−3121.41										
	Second ARIMA model for first section of IEP time series											
First section of daily IEP time series	ARIMA $(2,1,0)(1,0,1)_7$	Coefficients:										
			ar1	**ar2**	**sar1**	**sma1**						
			−0.263	−0.140	0.758	−0.636						
		SE	0.052	0.052	0.129	0.152						
		σ^2 estimated as 0.5525, log likelihood=−408.74, AIC=827.49										
	Third ARIMA model and SARIMA model for IEL time series											
Daily IEL time series	ARIMA $(2,0,0)(1,1,0)_7$	Coefficients:										
			ar1	**ar2**	**sar1**							
			0.843	0.065	−0.456							
		SE	0.030	0.030	0.027							
		σ^2 estimated as 976788: Log likelihood=−8923.38										
	SARIMA (3,1,0,1,1,0,52) or ARIMA $(3,1,0)(1,1,0)_{52}$	Coefficients:										
			ar1	**ar2**	**ar3**	**sar1**						
			−0.090	−0.066	−0.107	−0.507						
		SE	0.031	0.031	0.031	0.027						
		σ^2 estimated as 197.6: Log likelihood=−4212.03										
	Fourth ARIMA model for SEL time series											
Daily SEL time series	ARIMA $(1,0,2)(1,1,0)_7$	Coefficients:										
			ar1	**ma1**	**ma2**	**sar1**						
			0.833	−0.109	−0.069	−0.410						
			0.833	−0.109	−0.069	−0.410						
		SE	0.025	0.039	0.033	0.027						
		σ^2 estimated as 96.79: Log likelihood=−3958.65, AIC=7927.3										

AIC: Akaike information criterion, SEL: Spanish electricity load, ARIMA: Autoregressive integrated moving average, IEL: Iranian electricity load, IEP: Iranian electricity price, SE: Standard error, SEP: Spanish electricity price

The t-value is "calculated as coefficient/standard error" of the estimated parameter in order to gain more information about the ARIMA models (refer to Cryer and Chan, 2008; Dahyot, 2012; Tsay, 2005). The residual analysis of these estimated ARIMA models show that they are not fitted models. The ACF and PACF of square residuals for each time series are shown in Figures 12a-d and 13a, and they prove this claim.

We observe serial correlations in the residuals. For example, first part of the Iranian electricity time series is the Q-Q plot of this model, and it also shows a large, heavy tail in Figure 13b. This suggests the existence of volatility clustering in the residuals of these series (Tsay, 2005; Hu, 2011) (see Fig.12-all parts and Figures14a, d and e). The same analysis is applied to the IEL time series. Despite fitting the seasonal ARIMA model (or SARIMA [p, d, q, P, D, Q, S] model) to the time series, a similar result is obtained, i.e., volatility clustering in the residuals (Figures 13b and d; Figure 14b and c).

The SARIMA model has the same definition as the ARIMA model. Here, the (yearly) cycling behavior is added into this model (Shumway and Stoffer, 2010). Here, the seasonal period is equal

Figure 12: The autocorrelation function (ACF) and partial correlation function (PACF) from (squared) residuals of estimated autoregressive integrated moving average (ARIMA) models, for Spanish electricity price and Iranian (and Spanish) electricity load time series. The ACF and PACF from the residuals of seasonal ARIMA (SARIMA) model for the Iranian electricity load time series (a) Residuals analysis of Spanish ARIMA electricity price model, (b) residuals analysis of Iranian ARIMA electricity load model, (c) residuals analysis of Spanish ARIMA electricity load model and (d) residuals analysis of Iranian SARIMA electricity load model

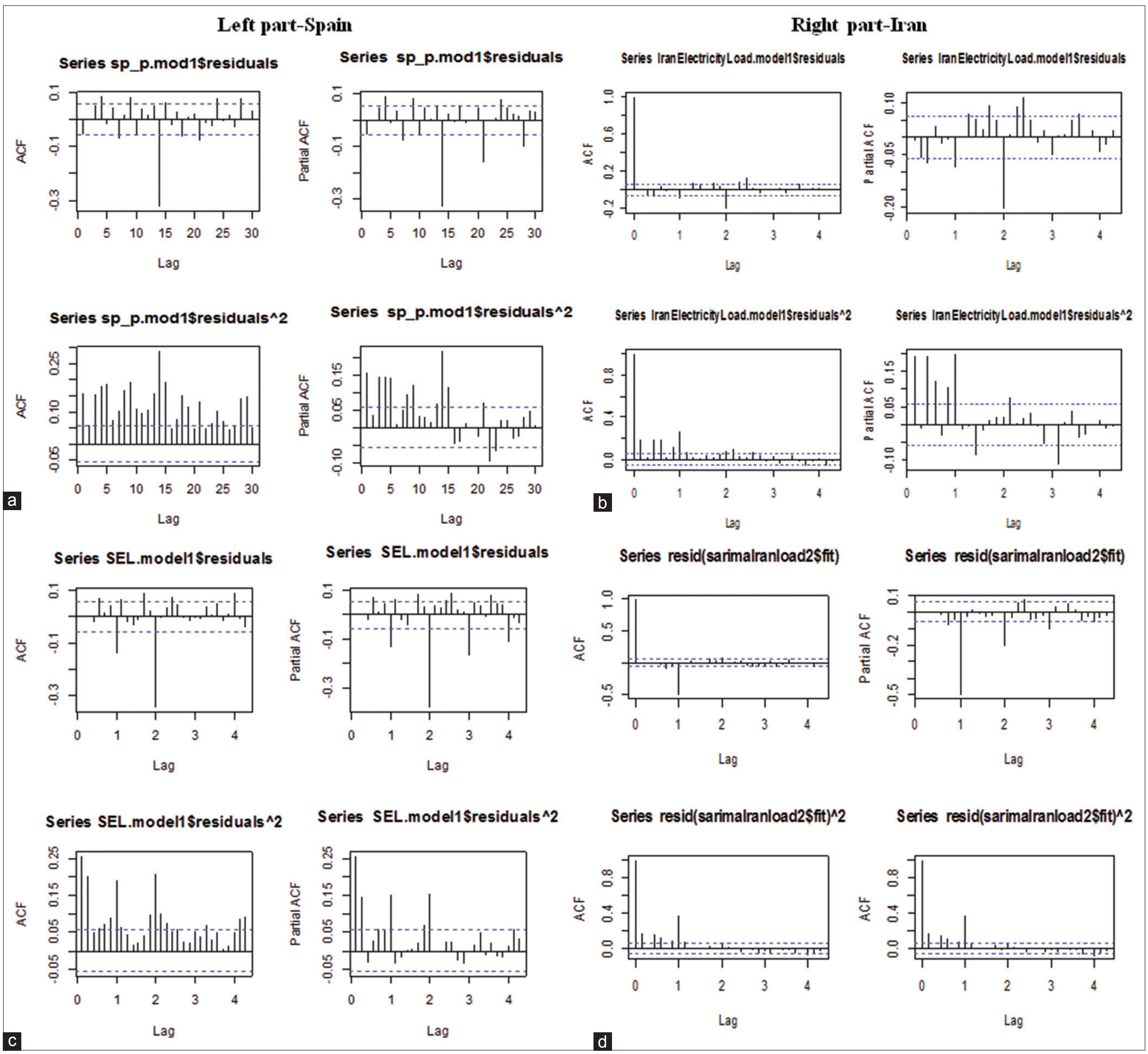
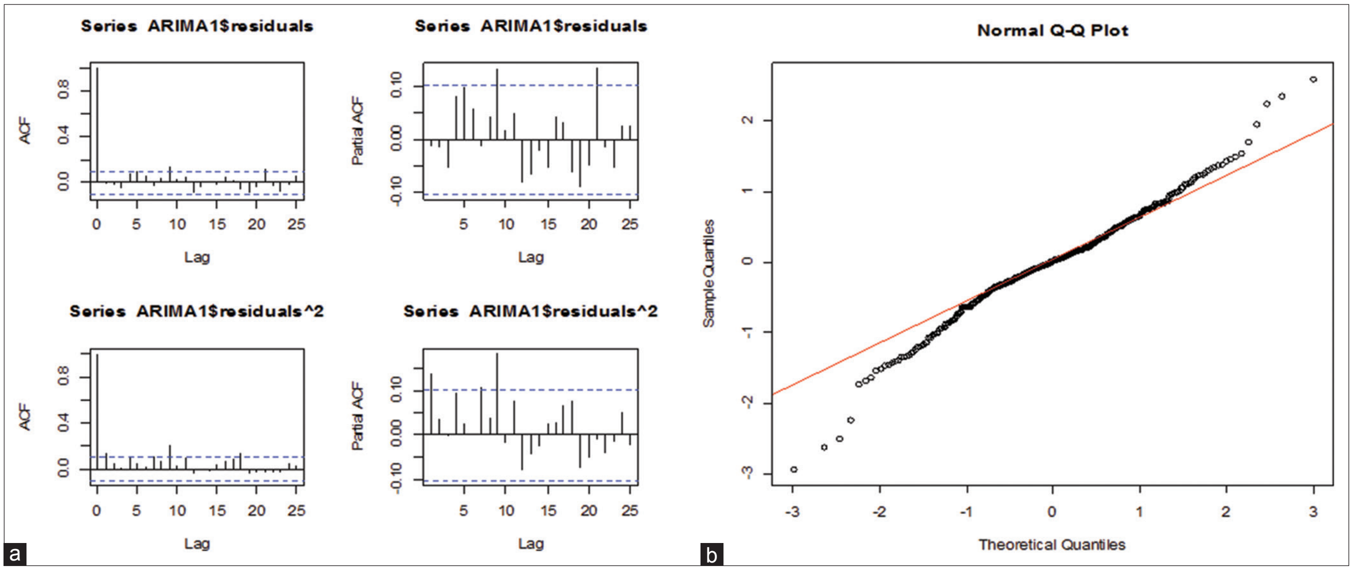


Figure 13: (a) The autocorrelation function and partial correlation of (squared) residuals from the estimated autoregressive integrated moving average (ARIMA) model for the first section of the daily Iranian electricity price time series. (b) Q-Q plot of the first section of the Iranian ARIMA electricity price model



to 52 weeks per year. We then take into account the yearly cycling behavior in our estimated SARIMA model. However, the ACF and PACF functions derived from the residual analysis of this model exhibit the serial correlation in the residuals (Figure 12d). Thus, due to conditional forecasting and temporal fluctuations in the data-variance, no ARIMA model is capable of accurately modeling such a time series.

To model these time series more accurately by investigating their residual patterns, we now employ the ARMA-GARCH model (Cryer and Chan, 2008; Wurtz et al., 2006).

2.3.2. ARMA–GARCH model for Spanish and Iranian price and load time series

Volatility is an important factor in electricity market time series analysis (Tsay 2005. p. 1, 20, 97; Benini et al., 2002). In general, it depends on a large number of parameters and factors, such as fuel prices, currency exchange rates, availability of generating units, etc. (Benini et al., 2002).

Due to the existence of uncertainty (heteroscedasticity), temporal fluctuations and conditional predictions of the data-variance in time series, ARIMA models are not suited to accurately analyzing the Iranian and SEPs and load time series (Cryer and Chan, 2008; Tsay, 2005; Wurtz et al., 2006). As we explained, the residual analysis of ARIMA models display (serial) correlations between the residuals in the first part of the IEP, the IEL, the SEP and the SEL time series. In addition, there is a non-constant volatility condition among them (Cryer and Chan, 2008; Tsay, 2005; Wurtz et al., 2006). As discussed in the previous section, the three parts of the IEP exhibit serial dependence within the variance of observations.

According to time series analysis approaches, we can employ ARMA-GARCH models to investigate and estimate these cluster patterns in each time series (Cryer and Chan, 2008; Tsay, 2005). Therefore, we apply the ARMA-GARCH models referred to as conditional heteroskedastic (or non-constant variance) models (Cryer and Chan, 2008; Tsay, 2005; Wurtz et al., 2006). As demonstrated before, the IEP time series exhibits nonlinear behavior. With three break points in the time series, each segment's behavior has to be modeled separately by using the ARMA-GARCH model. Thus, the aggregation of all ARMA-GARCH models obtained for the four sections of the IEP time series result in an ARMA-TGARCH model (Hu, 2011; Di Narzo, 2008; Hossain et al., 2011; Muñoz et al., 2007; Tsay, 2005; Wurtz et al., 2006; Zhang, 2009). Next, we derive the ARMA-TGARCH model for the IEP time series. Subsequently, we present the estimated ARMA-GARCH model for the three time series of the IEL, the SEP and the SEL.

We define the μ_t and the standard deviation, σ_t, for the time series by:

$$\mu_t = E(r_t \mid F_{t-1}),\ \sigma^2 = Var(r_t|F_{t-1}) = E[(r_t-\mu_t)^2 \mid F_{t-1})] \tag{3}$$

Then, the general ARMA-GARCH models are described in this way:

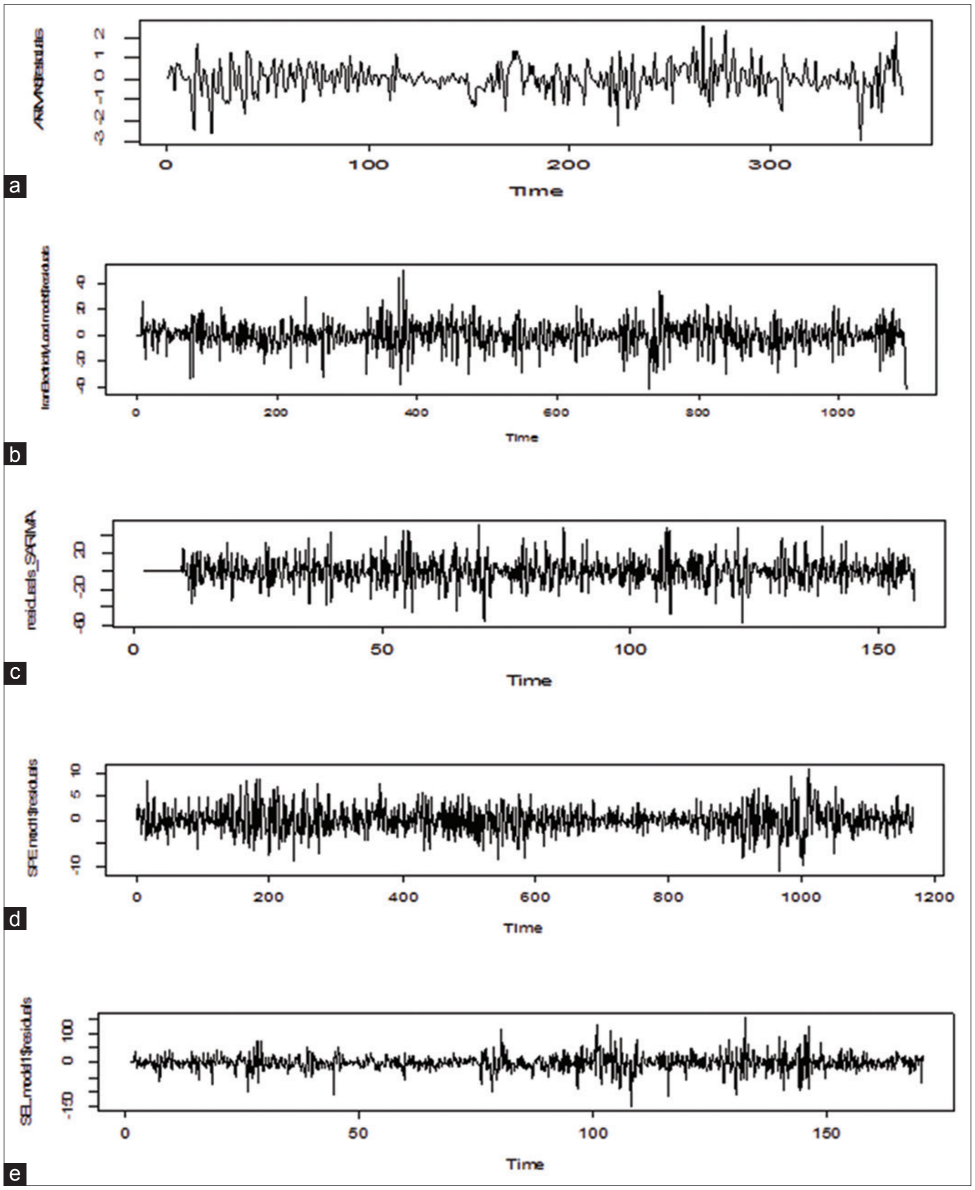
$$r_t = \mu + \sum_{i=1}^{p}\varphi_i r_{t-1} + \sum_{j=1}^{q}\theta_j a_{t-j} + a_t \tag{4}$$

$$a_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m}\alpha_i a_{t-1}^2 + \sum_{j=1}^{s}\beta_j \sigma_{t-1}^2 + a_t \tag{5}$$

The return, "r_t," follows the ARMA (p, q) part of these models and "a_t" is distinguished as the noise term of the ARMA model in Equation (4). It is introduced as one parameter of the GARCH model in Equation (5) (Tsay, 2005; Wurtz et al., 2006; Zhang, 2009). Here, the Gaussian white noise with unit variance is introduced by parameter "ε_t." An aggregation of the α and β is also desirable in Equation (5), which will be <1. These coefficients

Figure 14: Residual behavior of all our autoregressive integrated moving average (ARIMA) models and seasonal ARIMA (SARIMA) model (a) Residuals of autoregressive moving average (ARMA) model related to first section of Iranian electricity price time series, (b) residuals of ARMA model related to Iranian electricity load (IEL) time series, (c) residuals of SARIMA model related to IEL time series, (d) residuals of ARMA model related to Spanish electricity price time series, (e) residuals of ARMA model related to Spanish electricity load time series



α and β should be positive in order to be stationary with a finite variance (Tsay, 2005; Wurtz et al., 2006; Zhang, 2009). The parameters "σ_t^2" are related to the conditional variance and heteroscedasticity (Tsay, 2005; Wurtz et al., 2006; Zhang, 2009). Table 6 presents the ARMA-GARCH model parameters obtained for the IEL time series (after taking the seasonal difference and the first difference) as well as the SEL and price time series (after taking the seasonal difference).

In Table 7, after taking the first difference from each part of the IEP time series, we estimate an ARMA-TGARCH model for four parts of the IEP. Although the Q-Q plots and histogram of the residuals prove that these models for our four time series do not exactly exhibit a Gaussian distribution, the heavy tail decreases significantly (Figures 15 - left part and 16 - left part). In particular, Tables 6 and 7 also demonstrate the results obtained from Shapiro–Wilk, and the standardized residuals suggest that all-time series do not follow a Gaussian distribution (Zhang, 2009). The ARMA-GARCH model estimated for the fourth section of the IEP time series demonstrates a skewed-generalized error distribution for the conditional variance (Zhang, 2009) (for analyses given in Tables 6 and 7, the significance level is 0.05).

According to the ACF and PACF plots shown in Figures 15 - right part and 16 - right part, no volatility and serial correlation among the residuals is observed, and therefore our modeling approach is valid (Cryer and Chan, 2008; Tsay, 2005).

Furthermore, the polyroot test is applied in order to find the zeros of polynomials in the AR part of these developed ARMA-GARCH models Table 8. The results of this test indicate that there are not

Table 6: Estimated ARMA-GARCH models for SEP, IEL and SEL time series

First - ARMA-GARCH model - SEP time series, after taking the seasonal difference				
R Code (1)- garchFit (~arma (1,7) +garch (1,1), data=d7. spainprice, [1:1168], trace=F, cond.dist="std")				
ARMA-GARCH model. Error analysis:				
Coefficient (s)				
	Estimate	**SE**	**t-value**	**Pr(>|t|)**
mu	0.029 (μ)	0.070	0.421	0.674
ar1	0.566 (φ_1)	0.051	11.086	<2e-16***
ma1	0.164 (θ_1)	0.037	4.375	1.21e-05***
ma2	0.152 (θ_1)	0.035	4.247	2.16e-05***
ma3	0.145 (θ_1)	0.034	4.265	2.00e-05***
ma4	0.156 (θ_1)	0.033	4.691	2.72e-06***
ma5	0.145 (θ_1)	0.032	4.484	7.34e-06***
ma6	0.141 (θ_1)	0.031	4.468	7.91e-06***
ma7	−0.748 (θ)	0.032	−23.371	<2e-16***
omega	0.039 (α_0)	0.021	1.838	0.066
alpha1	0.069 (α)	0.013	5.170	2.34e-07***
beta1	0.928 (β)	0.012	75.088	<2e-16***
shape	10.000	2.384	4.194	2.74e-05***
Second - ARMA-GARCH model - SEL time series, after taking seasonal difference				
R Code (2)- garchFit (formula=~arma (1, 7)+garch (1, 1), data=d7.loadspain[1:1168], cond.dist="norm", trace=F)				
ARMA-GARCH model. Error analysis:				
Coefficient (s)				
	Estimate	**SE**	**t-value**	**Pr(>|t|)**
mu	0.979 (μ)	1.265	0.774	0.439
ar1	0.419 (φ_1)	0.090	4.653	3.28e-06***
ma1	0.346 (θ_1)	0.076	4.551	5.33e-06***
ma2	0.333 (θ_2)	0.074	4.474	7.69e-06***
ma3	0.336 (θ_3)	0.073	4.575	4.76e-06***
ma4	0.334 (θ_4)	0.072	4.598	4.26e-06***
ma5	0.324 (θ_5)	0.072	4.484	7.31e-06***
ma6	0.324 (θ_6)	0.071	4.550	5.36e-06***
ma7	−0.618 (θ_7)	0.070	−8.748	<2e-16***
omega	80.264 (α_0)	14.995	5.353	8.67e-08***
alpha1	0.293 (α)	0.046	6.295	3.08e-10***
beta1	0.570 (β)	0.055	10.192	<2e-16***
Third - ARMA-GARCH model-IEL time series, after taking the seasonal and first non-seasonal differences				
R Code (3)-garchFit (formula=~arma (2, 8)+garch (1, 1), data=d7d1.loadiran[1:1073], cond.dist="std", trace=F)				
ARMA-GARCH model. Error analysis:				
Coefficient (s)				
	Estimate	**SE**	**t-value**	**Pr(>|t|)**
mu**	0.014 (μ)	0.019	0.755	0.450
ar1	0.683 (φ_1)	0.058	11.704	<2e-16***
ar2	−0.022 (φ_2)	0.045	−0.488	0.625
ma1	−0.877 (θ_1)	0.049	−17.625	<2e-16***
ma2	0.029 (θ_2)	0.035	0.824	0.409
ma3	0.007 (θ_3)	0.026	0.284	0.776
ma4	0.018 (θ_4)	0.026	0.699	0.484
ma5	−0.005 (θ_5)	0.025	−0.234	0.815
ma6	−0.020 (θ_6)	0.027	−0.740	0.459
ma7	−0.661 (θ_7)	0.027	−23.712	<2e-16***
ma8	0.594 (θ_8)	0.033	17.635	<2e-16***
omega	6.603 (α_0)	3.499	1.887	0.059
alpha1	0.193 (α)	0.053	3.641	0.0002***
beta1	0.768 (β)	0.0695	11.053	<2e-16***
shape	3.977	0.539	7.378	1.61e-13***

The symbols in parenthesis (such as μ, $\varphi1$, $\theta1$) are not related to our R code. They are introduced as related to each parameter in the ARMA-GARCH model. ARMA-GARCH: Autoregressive moving average-generalized autoregressive conditional heteroskedastic, SEL: Spanish electricity load, IEL: Iranian electricity load, SEP: Spanish electricity price

any kinds of roots in our models (Pfaff, 2008; Box et al., 2008). This also verifies the validity of our developed models.

3. RESULTS

3.1. Comparison of Models

In the previous section, we discussed our model estimation approach for each market and their corresponding time series. Here, we compare different models for each market. As presented in Table 9, due to the volatility clustering of the residuals, the classical ARIMA models did not perform well and could not be employed to estimate the time series of the daily SEP, daily SEL, the IEL, and the first part of the IEP. Furthermore, the computed mean square error (MSE) values (Wu and William, 1994) are significantly higher than the average values found for the ARMA-GARCH models (except for the first part of the IEP). Unlike the SEP time series, we cannot find a suitable ARMA-GARCH model to estimate the serial dependence of the variance in the time series, due to the nonlinear behavior of the IEP. Therefore, the ARMA-TGARCH model is suggested for better estimation of the IEP time series. For each part of the IEP time series, the MSE related to the ARMA-GARCH is very low. Moreover, the average values for the ARMA-TGARCH model are also very low. In addition, there is no serial correlation among the residuals computed for this model or for each ARMA-GARCH model related to each section. It is similar to our other estimated ARMA-GARCH models. Therefore, these results suggest that the best model for predicting and describing the behavior of the IEP time series is the ARMA-TGARCH model. Meanwhile, ARMA-GARCH models with specific coefficients are the best suited models for estimating all the other time series.

3.2. Forecasting the IEP and Load

Finding more strategic knowledge about the Iranian electricity market leads us to present a forecasting for the IEP and IEL. This prediction helps us to know the behavior of the price and load as important elements in this market. Because as we know, for example, that electricity price forecasting will be helpful for market players, particularly generating companies who must manage their units and the associated economic risk (Benini et al., 2002). Here, the forecasting is represented for around 14 days. For the IEP, we make a prediction out-of-sample via the fourth part of the ARMA-TGARCH model in Table 10.

We also forecast and predict the IEL out-of-sample via the ARMA-GARCH model (Table 10), as it is the best of our estimated model. These predictions are presented in Figures 17 and 18. In Tables 11 and 12, our forecasting for price and load are also described. We observe our forecasting to be within the confidence intervals at a 95% level. These results indicate that our estimated models for electricity price and load are strongly fitting models for distinguishing the behavior of price and load in this market.

4. DISCUSSION

This study has attempted to address whether or not the Iranian electricity market can be categorized as a liberalized and competitive market. Nowadays, fundamental progress has

Table 7: ARMA-TGARCH estimated models for IEP time series

First - ARMA-GARCH model for first part

R-cod (4)

garchFit (formula = ~arma (0, 1) + garch (1, 1), data=iran.pr.d1)

ARMA-GARCH model-error analysis:

Coefficient (s)

	Estimate	SE	t-value	Pr(>|t|)
mu	$0.0002(\mu)$*	0.026	0.009	0.992
ma1	$-0.264(\theta_1)$	0.059	−4.463	8.07e-06***
omega	$0.029(\alpha_0)$	0.014	1.983	0.047*
alpha1	$0.120(\alpha)$	0.043	2.767	0.006**
beta1	$0.836(\beta)$	0.050	16.679	<2e-16***

Standardised residuals tests:

			Statistic	P value
Jarque-Bera test	R	Chi-square	114.386	0
Shapiro-Wilk test	R	W	0.972	1.97e-06
Ljung-Box test	R	Q (10)	7.710	0.061
Ljung-Box test	R	Q (15)	24.965	0.051
Ljung-Box test	R	Q (20)	29.436	0.079
Ljung-Box test	R^2	Q (10)	6.335	0.786
Ljung-Box test	R^2	Q (15)	7.738	0.933
Ljung-Box test	R^2	Q (20)	12.019	0.915
LM ARCH test	R	TR^2	8.166	0.771

Second - ARMA-GARCH model for second part

R-code (5)

garchFit (formula = ~arma (0, 1) + garch (1, 1), data=iran.pr.d2)

ARMA-GARCH model-error analysis:

Coefficient (s)

	Estimate	SE	t-value	Pr(>|t|)
mu	$0.012\ (\mu)$	0.028	0.430	0.667
ma1	$-0.287(\theta_1)$	0.083	−3.430	0.000***
omega	$0.088(\alpha_0)$	0.024	3.566	0.000***
alpha1	$0.456(\alpha)$	0.115	3.954	7.68e-05***
beta1	$0.540(\beta)$	0.078	6.901	5.16e-12***

Standardised residuals tests:

			Statistic	P value
Jarque-Bera test	R	Chi-square	1467.688	0
Shapiro-Wilk test	R	W	0.834	1.599e-14
Ljung-Box test	R	Q (10)	6.574	0.764
Ljung-Box test	R	Q (15)	9.454	0.852
Ljung-Box test	R	Q (20)	11.976	0.916
Ljung-Box test	R^2	Q (10)	1.300	0.999
Ljung-Box test	R^2	Q (15)	1.533	0.999
Ljung-Box test	R^2	Q (20)	1.766	1
LM ARCH test	R	TR^2	1.683	0.999

Third-ARMA-GARCH model for third part

Rcod (6)

garchFit (formula=~arma (0,1)+garch (1,1), data=iran.pr.d2)

ARMA-GARCH model-error analysis:

	Estimate	SE	t value	Pr(>|t|)
mu	$0.019\ (\mu)$	0.019	1.010	0.313
ar1	$0.656\ (\varphi_1)$	0.166	3.942	8.07e-05 ***
ma1	$-0.768\ (\theta_1)$	0.161	−4.768	1.86e-06 ***
omega	$0.055\ (\alpha_0)$	0.041	1.320	0.187
alpha1	$0.126\ (\alpha)$	0.061	2.064	0.039 *
beta1	$0.833\ (\beta)$	0.077	10.820	<2e-16 ***
shape	10.000	6.893	1.451	0.147

Standardised Residuals Tests:

			Statistic	P value
Jarque-Bera test	R	Chi-square	4.787	0.091
Shapiro-Wilk Test	R	W	0.988	0.041
Ljung-Box test	R	Q (10)	14.211	0.163
Ljung-Box test	R	Q (15)	24.238	0.061
Ljung-Box test	R	Q (20)	28.201	0.104
Ljung-Box test	R^2	Q (10)	6.524	0.769
Ljung-Box test	R^2	Q (15)	23.599	0.072
Ljung-Box test	R^2	Q (20)	27.454	0.122
LM ARCH test	R	TR^2	8.170	0.771

Fourth-ARMA-GARCH model for fourth part

R-code (7)

garchFit (formula = ~arma (0, 1) + garch (1, 2), data=iran.pr.d4, cond.dist = “norm”)

ARMA-GARCHmodel-Error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)
mu	$-0.056(\mu)$	0.031	−1.816	0.0692
ma1#	$-0.304\ (\varphi_1)$	0.083	−3.63	0.000 ***
omega	$0.014(\alpha_0)$	0.015	0.979	0.327
alpha1	$0.277\ (\alpha_1)$	0.081	3.431	0.000 ***
beta1	$0.107\ (\beta 1)$	0.135	0.791	0.429
beta2	$0.642(\beta 2)$	0.143	4.460	8.19e-06 ***

Standardised residuals tests:

			Statistic	P value
Jarque-Bera test	R	Chi-square	9.963	0.006
Shapiro-Wilk test	R	W	0.987	0.031
Ljung-Box test	R	Q (10)	13.293	0.207
Ljung-Box test	R	Q (15)	30.230	0.011
Ljung-Box test	R	Q (20)	38.084	0.008
Ljung-Box test	R^2	Q (10)	13.853	0.179
Ljung-Box test	R^2	Q (15)	16.474	0.351
Ljung-Box test	R^2	Q (20)	19.848	0.467
LM ARCH test	R	TR^2	13.978	0.302

The symbols in parenthesis (such as μ, $\varphi 1$, $\theta 1$, etc.) are not related to our R code. They are introduced as related to each parameter in the ARMA-GARCH model. ARMA-GARCH: Autoregressive moving average-generalized autoregressive conditional heteroskedastic, IEP: Iranian electricity price, LM: Lagrange multiplier, ARCH: Autoregressive conditional heteroskedastic

been made within the current technical establishments and infrastructure of the Iranian electricity market, given that the government supports the idea of moving towards privatization and a deregulated market status rather than a pure governmentally controlled state. According to the new interpretations obtained from Article 44 of the Iranian Laws, this market is going to be a “free” market. This investigation is useful in understanding how the market mechanism shall be after having fundamentally improved the dimensions of each electricity market. Toward this goal, we have presented a time series approach that employs linear and non-linear models using price and load as the main factors. We further compared the market in Iran with that in Spain. Such a comparison enlightens how Iranian electricity market behavior can be compared to a developed market. With further comparisons to the studies mentioned above, this research has also provided insights into the Iranian electricity market’s level of competition.

We also investigated the role of load determination in the Iranian electricity market and additionally presented a forecasting of the IEP and load, in order to clarify its behavior. We further suggested

Figure 15: Right part: Histogram of autoregressive moving average (ARMA) generalized autoregressive conditional heteroskedastic (GARCH) models from the Iranian electricity load (IEL) and Spanish electricity load (SEL) and price series (First) Histogram - Residuals analysis of Iranian ARMA-GARCH electricity load model, (Second) Histogram - Residuals analysis of Spanish ARMA-GARCH electricity load model and (Third) Histogram - Residuals analysis of Spanish ARMA-GARCH electricity price model. Left part: The autocorrelation function (ACF) and partial correlation function (PACF) from (square of) residuals of the estimated ARMA GARCH models for IEL, SEL and Spanish electricity price (SEP) time series (First - ACF and PACF of ARMA-GARCH model - IEL time series, Second - ACF and PACF of ARMA-GARCH model - SEL time series and Third - ACF and PACF of ARMA-GARCH model - SEP time series

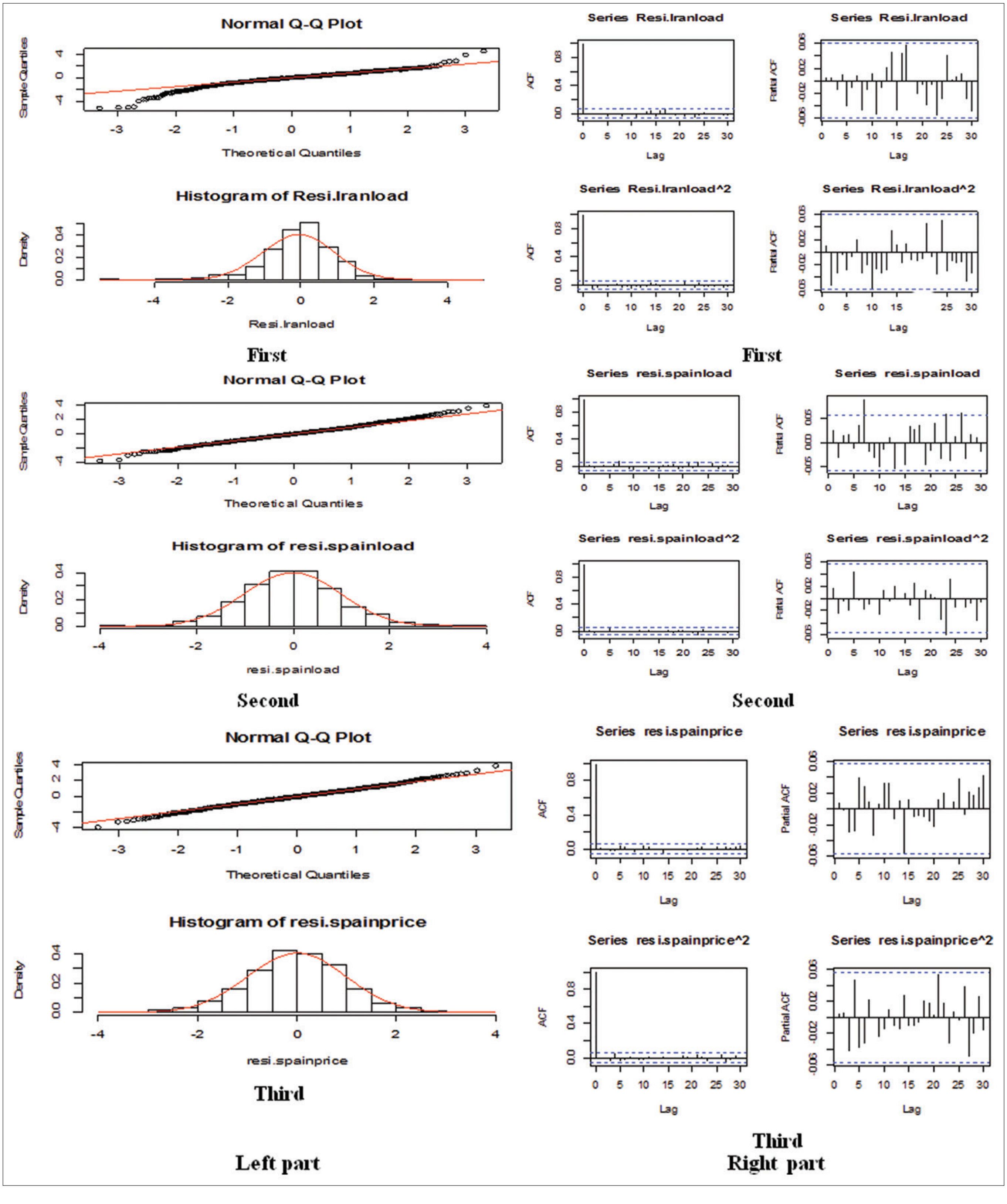


Figure 16: Left part: Residuals analysis (Histogram and Q-Q plots of autoregressive moving average (ARMA)-T generalized autoregressive conditional heteroskedastic (GARCH) model from the Iranian electricity price (IEP) time series (for four sections of time series). Right part: The autocorrelation function and partial correlation function from (squared) residuals of the estimated ARMA-TGARCH models from each section (of IEP time series)

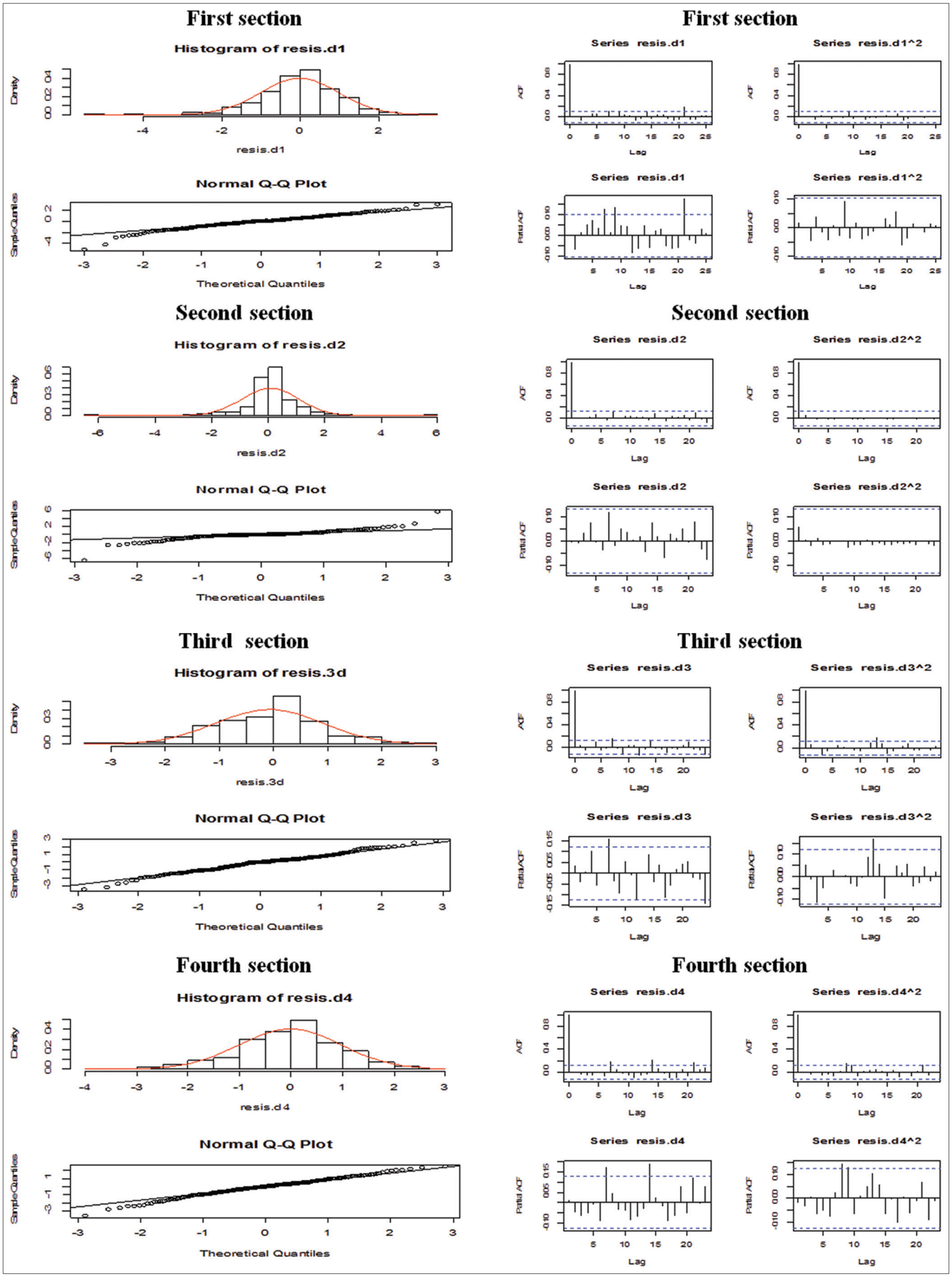


Table 8: Univariate analysis of stationarity for four estimated ARMA-GARCH models

R Code: Mod (Polyroots $(1,\varphi_i)$) For	The estimation mod of poly roots test for AR parts of each ARMA-GARCH model
ARMA-GARCH models of SEP time series	Estimation of AR (1)-process with φ_1=0.566: 1.766
Second part of IEP	Estimation of AR (1)-process with φ_1=0.656: 1.766
SEL time series	Estimation of AR (1)-process with φ_1=0.419: 2.386
IEL time series	Estimation of AR (2)-process with φ_1=0.683, φ_2=0.022: 1.401, 32.027

ARMA-GARCH: Autoregressive moving average-generalized autoregressive conditional heteroskedastic, SEL: Spanish electricity load, IEL: Iranian electricity load, SEP: Spanish electricity price, IEP: Iranian electricity price, AR: Autoregressive

Table 9: Comparison of our estimated models for each market time series

Estimated models	Model validation	Residual validation	Data	MSE
Models for IEP time series	Make a comparison from all of estimated models for daily Iranian electricity price models			
ARIMA model for first part (1-365)	Not valid	Volatility	First part of Iranian electricity price time series	0.550
ARMA-TGARCH model	Valid-accepted	No volatility	All IEP time series after taking the first difference	0.978
ARMA-GARCH model - for first part (1-365)	Valid	No volatility	First part of time series after taking the first difference	1.001
ARMA-GARCH model - for second part (365-586)	Valid	No volatility	Second part of time series after taking the first difference (366-584)	1.004
ARMA-GARCH model - or third part (585-845)	Valid	No volatility	Third part of time series after taking the first difference	0.992
ARMA-GARCH model - for fourth part (846-1095)	Valid	No volatility	Fourth part of time series after taking the first difference.	0.916
Models for SEP time series	Make a comparison from all of estimated models for daily SEP models			
ARIMA model	Not valid	Volatility	time series	12.579
ARMA-GARCH model	Valid-accepted	No volatility	Daily SEP time series after seasonal difference series	0.980
Models for IEL time series	Make a comparison from all of estimated models for daily IEL models			
ARIMA model	Not valid	Volatility	Total time series	97.847
SARIMA	Not valid	Volatility	IEP time series	187.985
ARMA-GARCH model	Valid-accepted	No volatility	Daily IEL time series after seasonal and non-seasonal difference	0.958
Models for SEL	Make a comparison from all of estimated models for daily SEL models			
ARMA model	Low valid	volatility	Total time series	735.041
ARMA-GARCH model	Valid-accepted	No volatility	daily SEL time series after taking seasonal difference	0.998

ARMA-GARCH: Autoregressive moving average-generalized autoregressive conditional heteroskedastic, SEL: Spanish electricity load, SEP: Spanish electricity price, SARIMA: Seasonal ARIMA: Autoregressive integrated moving average, IEL: Iranian electricity load, IEP: Iranian electricity price

that no significant relationship exists between the price and load in the Iranian electricity market, and we question claims that have been made regarding its liberalization and decentralization.

5. CONCLUSIONS AND POLICY IMPLICATIONS

The current study employed time series analyses to investigate the policies implemented by the Iranian government towards a decentralized and competitive Iranian electricity market. As a benchmark for such a free market and for the sake of comparison, we conducted our analyses for both Iran's and Spain's electricity markets. To carry out our modeling, two important factors (price and load) in time series data from both markets were chosen.

For IEL, SEP and SEL time series, seasonality impacts the process of estimating a valid model for each time series. In addition, analyzing the estimated models (such as ARIMA models) of these two indices proved the significant role of volatility and serial correlation among our observations in each time series, suggesting the influence of other factors in these energy markets. For example, our research into SEP shows that the electricity generation by wind in Spain impacts the electricity market price.

ARMA-GARCH models, also known as heteroskedastic time series models, were employed and further verified using the MSE tests to estimate the behavior of IEL, SEP and SEL.

Unlike the Spanish electricity market, our analysis suggests that the Iranian electricity market price exhibits a fully-nonlinear behavior. This is confirmed by the existence of break points and structural changes in the data trends. Therefore, in contrast to the Spanish market, the Iranian electricity market price time series is estimated by an ARMA-TGARCH model. We further utilized several ARMA-GARCH models to accurately forecast the price/load, taking into account nonlinear behavior in the market. We note that our analysis also demonstrates similar patterns in the SEP and each parts of the IEP time series, since IEP is also fitted

Table 10: Mathematical equation of price and load-estimated models for forecasting in Iranian electricity market

For Iranian electricity price time series	Mathematical equations of price and load-estimated models
ARMA-TGARCH model	For IEP time series
A - For first section ARMA-GARCH model	$r_t = a_t - 0.264a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.029 + 0.121\varepsilon^2_{t-1} + 0.8360\sigma^2_{t-1}$
B - For second section ARMA-GARCH model	$r_t = a_t - 0.287a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.088 + 0.456\varepsilon^2_{t-1} + 0.541\sigma^2_{t-1}$
C - For third section ARMA-GARCH model	$r_t - 0.656\, r_{t-1} = a_t - 0.768\, a_{t-1}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.126\varepsilon^2_{t-1} + 0.833\sigma^2_{t-1}$
D - For fourth section ARMA-GARCH model	$r_t = -0.056 + at - 0.304\ at - 1$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 0.277\varepsilon^2_{t-1} + 0.642\sigma^2_{t-2}$
ARMA-GARCH model	For IEL time series
E - ARMA-GARCH model	$r_t - 0.683r_{t-1} + 0.022r_{t-2} = at - 0.877a_{t-1} - 0.661a_{t-7} - 0.594a_{t-8}$ $a_t = \sigma_t \varepsilon_t$ $\sigma_t^2 = 6.603 + 0.193\varepsilon^2 + 0.768\sigma^2_{t-1}$

ARMA-GARCH: Autoregressive moving average-generalized autoregressive conditional heteroskedastic, IEL: Iranian electricity load, IEP: Iranian electricity price

Figure 17: Forecasting the Iranian electricity price (for 14 days). Red points in our figures show forecasting. Black line shows the real price. The green and blue lines show the confidence intervals

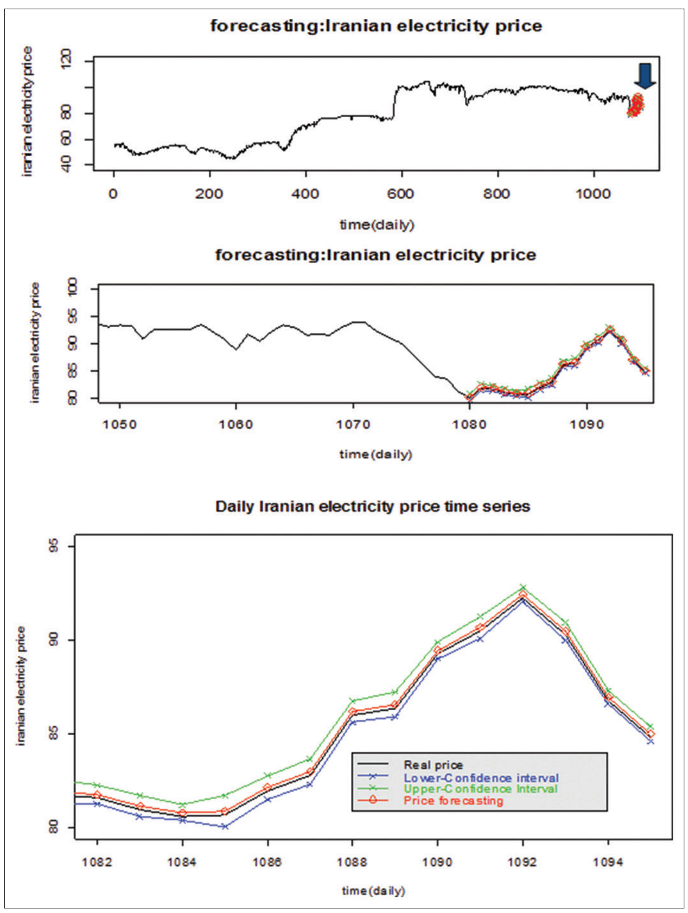
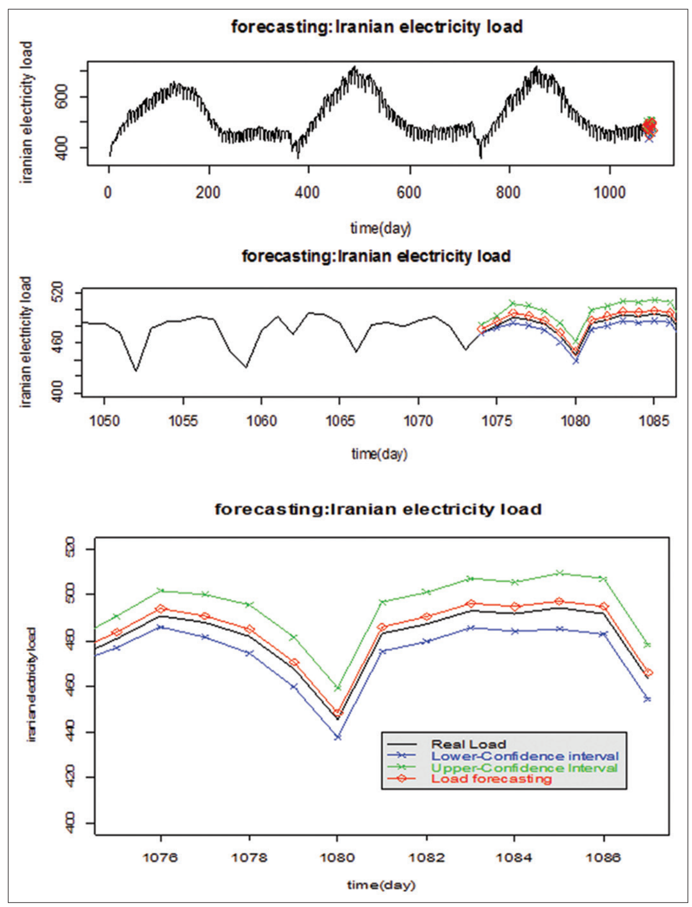


Figure 18: Forecasting the Iranian electricity load (for 14 days). Red points in our figures show forecasting. Black line shows the real load the green and blue lines show the confidence intervals



by means of an ARMA-GARCH model. On the other hands, for the Spanish electricity market, both indices (i.e., price and load) follow a similar pattern and are estimated via ARMA-GARCH models. Our investigation suggests that the Iranian and Spanish electricity markets exhibit a fundamental difference concerning the behavior of load and price time series.

Table 11: Forecasting IEP and comparing it with the real electricity price

No.	The real observations	With 95% confidence intervals		Forecast from Iranian electricity price	Sigma.t
		Lower	Higher		
1	81.567	81.249	82.263	81.756	0.253
2	80.959	80.586	81.709	81.148	0.280
3	80.602	80.375	81.206	80.791	0.207
4	80.680	80.042	81.697	80.869	0.413
5	81.945	81.502	82.767	82.134	0.316
6	82.788	82.296	83.657	82.977	0.340
7	85.995	85.627	86.742	86.184	0.278
8	86.371	85.902	87.218	86.560	0.329
9	89.267	89.004	89.909	89.456	0.226
10	90.479	90.078	91.258	90.668	0.294
11	92.244	92.063	92.804	92.433	0.185
12	90.273	89.980	90.945	90.462	0.241
13	86.759	86.591	87.305	86.948	0.178
14	84.817	84.618	85.394	85.006	0.193

IEP: Iranian electricity price

Table 12: Forecasting the IEL and comparing it with the real electricity load

No.	The observations	With 95% confidence intervals		Forecast from IEL	Sigma.t
		Lower	Higher		
1	471.820	467.685	483.192	475.438	2.584
2	480.732	473.789	494.912	484.350	3.520
3	490.825	482.390	506.497	494.444	4.017
4	487.799	477.529	505.306	491.418	4.629
5	481.953	470.797	500.346	485.571	4.924
6	467.535	456.079	486.228	471.153	5.024
7	445.419	433.725	464.350	449.037	5.104
8	483.004	466.118	507.128	486.623	6.834
9	487.357	468.465	513.486	490.976	7.503
10	493.221	475.627	518.054	496.840	7.071
11	491.768	474.509	516.264	495.387	6.959
12	494.275	477.959	517.829	497.894	6.644
13	491.922	476.342	514.740	495.541	6.399
14	463.136	442.894	490.617	466.755	7.953

IEL: Iranian electricity load

Our study strongly suggests that the rate of load does not influence the Iranian electricity market's price in a meaningful way. In other words, the scatter plots of these time series for each country suggests that, unlike Spain, the Iranian electricity market does not exhibit a clear relationship between load and price indices, which rejects the existence of any meaningful dependency on price volatility and load in the Iranian market. According to the principles of economic theories, our results indicate that the Iranian electricity market cannot be considered a free competitive market (Nicholson and Snyder, 2011).

The importance of forecasting in energy markets policy led us to short-term predictions for each index separately: IEP and IEL. This forecasting employed the best fitting models in this study. Our prediction also clearly shows the different behavior patterns amongst these indices (factors) in the future Iranian electricity market.

Considering the modeling and analysis we performed for both markets, the state of the Iranian electricity market can be recognized as a non-free/centralized market. Furthermore, this calls into question the policies implemented toward a decentralized and private Iranian market.

For any meaningful improvement towards a free market, potential policy reforms need to be implemented by policy makers. These policies may be limited not only to technological improvements but also to the current challenges facing Iran and the Iranian market, i.e., international sanctions, the Iranian political economy, the inflation rate, and law-making policies. In addition, it will be fruitful for future research to investigate the impact on pricing of other micro- and macroeconomic factors, such as gas/oil price, the US dollar/Rial exchange rate, and other political factors (e.g., the Iranian government's strategies regarding international embargos).

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