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Modeling Electricity Expenditures using BSOM based on Techno-Socio Economic: A Case Study of Urban Households of Iran's Provinces

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Abstract

Electricity has particular importance in the national economy and provides socio-economic welfare. It is considered an essential infrastructure of countries' development. This is why implementing electricity consumption and formulating appropriate policies is crucial for policy-makers. To do this successfully, it is necessary to identify energy consumption patterns and relevant influential factors. This study aims to identify the qualitative and quantitative significant factors of energy consumption using batch self-organizing maps (BSOM). Electricity consumption in the residential sector accounts for one-third of total electricity consumption. Therefore, this study evaluated the consumption of urban households in Iran's provinces. According to the results, electricity price, household income, and NG gas piping costs, as quantitative factors, number of adolescents, number of rooms, employment status of the household responsible person (HRP), number of children, education level of HRP, house area, house material and use of the stationary gas cooler, as qualitative factors, are the most critical factors affecting electricity consumption. Electricity price, the number of teenagers, rooms, and status of household head activity are identified as the most important quantitative and qualitative factors in all provinces of the country.

Keywords: Electricity Energy Consumption, Residential Sectors, Self-organizing Maps, Socioeconomic Factors, Categorical Data.

JEL Classification: R2, Q47, L94, C45.

1. Introduction

Energy has always played an undeniable role in human life and its importance and effectiveness have been increased over time. Today,

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energy underpins a majority of activities and advancements of societies so that the human lifestyle is dependent on it to the extent that it can be argued that supplying the primary needs of human life is strongly dependent on energy. This dependence becomes stronger by the development of city-dwelling (Zare Shahabadi et al., 2013). Among other types of energy, electricity plays a key and infrastructural role in the national economy so that it can be argued that the development of other economic sectors is dependent on the flourish and appropriate performance of electricity (Ziaei and Parsa Moghaddam, 2010). Currently, the total number of electricity subscribers in Iran exceeds 25 million and almost 1 million subscribers are being added to it on an annual basis. According to statistics, the mean growth rate of residential subscribers has exceeded 5% in recent years, and the mean annual sales rate of electricity to houses is almost 5.5%. In Iran, the electricity consumption of the residential sector accounted for one-third of total energy consumption and preceded only by the industry sector (Aboonoori and Lajavardi, 2016). Also, Iran ranks first in electricity consumption intensity. In most developed and industrial countries, the contribution of the production sector to electricity consumption is several times higher than in other sectors while in Iran, non-productive sectors use almost 40% of total generated electricity (Talebzade and Nasiripour, 2016). The considerable portion of residential subscribers on the one hand and the contribution of this sector to total electricity sales, on the other hand, have made it inevitable to analyze the behavior of the residential sector and to identify relevant influential factors. This problem is highlighted due to climate change and the spread of aridity whereas mean precipitation and dam reservoir level decreases, electricity demand-supply gap increases in warm seasons- a phenomenon that has been frequently observed in recent years in many geographical areas of Iran. This is why the identification of the behavioral pattern of electricity consumers, and its influential factors, are of high importance. This study aims to identify social-economic factors affecting electricity expenditure function among urban households of Iran’s Provinces using the BSOM method. This paper has been structured as follows. The next section explains the theoretical foundations of socio-economic factors and energy consumption modeling and the background of the study. Section 4 describes the data and estimation models, and the last two sections explain the simulation results and conclude the paper, respectively.

2. Theoretical Foundations

Most of the consumption of electric energy by residential sectors in households is used to provide facilities such as lighting, heating, comforting, and entertainment. However, a significant part of the energy consumption in these sectors is affected by a complex series of related factors, such as socio-economic factors, household characteristics, including household size, age, gender and education, and so on (Jones et al., 2017). Therefore, this paper aims at determining the socio-economic factors affecting households' expenditure on electricity. In the following, first, the theoretical foundations of some of these factors are explained, and then the techniques for modeling the energy in the residential sectors are described.

2.1 Socioeconomic Variables

Because of the variations in the household's features and attributes, knowing the effect of these attributes on the household's behavior is very important. Many empirical studies have been focused on the effects of household features on their consumption patterns, however, in general, the impact of some features including household dimension as well as age, gender, and education level of households' head on the pattern of household consumption are originated from theoretical viewpoints. In the following, we investigate some of these factors.

Household dimension: Due to differences in household size, estimating patterns of household consumption without taking into account this difference will be less accurate. Several studies argued that a better empirical model for analyzing household consumption patterns is a model that includes household size (Barnes and Gillingham, 1984; Pollak and Wales, 1981; Ray, 1982). The results of most studies in this context have indicated with the increase in the number of people in a family, the per capita consumption of electricity decreases. This argument demonstrates the economies of scale that are achieved by increasing the family size. Because with the increase in the number of family members, many energy uses are performed jointly (Bhattacharjee and Reichard, 2011).

Age of the household's head: The studies have indicated that the total expenditure is based on the age structure of the population. A household, during its life cycle, adapts its consumption patterns to the habits and real needs and existing conditions. As a result, changes in consumption follow demographic changes (Stover, 2012). Many social theories (Duvall, 1977; Hill and Mattechisch, 1979) and psychology (Levinson, 1978) and economics (Ando and Modigliani, 1963) have stated that individual behavior and developments are different throughout life. According to these theories, the patterns of household consumption change throughout their lives proportional to the age of the head of the household. Younger households' heads are probably spending much of their time at work. It is expected that this pattern will continue until the retirement of the head. For this reason, the younger heads are expected to allocate fewer contributions to energy than the older heads (Ritonga, 1994). This process continues until the children grow older and leave home. Then the electricity consumption increases by increasing the age of the members and retiring because they spend much time at home (Tonn and Eisenberg, 2007).

The education level of the household's head: Schultz by studying human capital showed that increasing incomes and expenditures are some direct economic advantages of education (Schultz, 1963). Moreover, some studies have argued that education can lead to increase productivity in household budget management and better resource allocation (Kaestner & Grossman, 2009) The results of the research indicate the higher the level of education, the greater the efficiency of consumption. In fact, due to increasing knowledge of people about energy costs, their uses, and benefits, their energy-saving behaviors are higher and, ultimately, their energy consumption will decrease (Raaij and Verhallen, 1983).

Household income: This factor can affect household electricity consumption in at least two directions; rising household income (*i*) increases the demand of appliances, and so the consumption of electricity increases, (*ii*) the share of electricity costs will decrease compared with the income, so they will pay less attention to electricity pricing policies, and consequently, power consumption increases (Olaleye and Akinbode, 2012).

Type of building: Energy consumption is directly related to the area of the house. With an increasing number of rooms, area, and home space, the amount of energy needed for lighting, heating, and cooling is increased as well (Kavousian et al., 2013). The more houses are modernized and the more modern equipment and materials used to make them, the lower the amount of energy consumed, e.g., double glazed windows reduce energy consumption (Linden et al., 2006).

Climate: The temperature of the air, the number of hot and cold days, as indicators of climate conditions affect energy consumption. When the number of hot days and the air temperature increases (e.g., in summer), due to the use of cooling devices such as coolers and fans, the energy consumption increases as well. On the other hand, in cool days (e.g., in winter) electrical heaters appliances consume power (Wilbanks et al., 2008).

Appliances: Electricity demand comes from the demand for services, including lighting, heating, and cooling and cooking. These services are provided through the use of home appliances. Therefore, the higher the number of domestic appliances is used, the power consumption will also increase. The use of depleted and worn appliances will increase consumption. In contrast, the use of up-to-date and modern appliances with new technologies will increase the efficiency of consumption (Jones et al., 2015).

2.2 Techniques for Energy Consumption

According to global statistics, the residential sector accounts for 20% and 35% of total electricity consumption in developed and developing countries, respectively, and the countries face a consumption raise perspective due to the rapid growth of the economy and population and promotion of life standards. Therefore, the identification of electricity consumption patterns in the residential sector is of high importance. Different factors, from the structure of houses and their energy intensity to people’s behavior and from demographic specifications to the type of electric appliances used by families, affect the consumption behavior of families (Yohanis, 2010). Determining the factors affecting energy consumption functions is accompanied by some complexities. In general, however, it can be argued that these factors could be categorized within four main categories namely: technical, economic, social, and behavioral (psycho-social origin).

There are two main approaches to modeling energy consumption function and determining its influential factors: a top-down approach and a bottom-up approach. The former is used to estimate different factors in general and to define the consumption rate of the residential sector at the national level whereas the latter is used in small-scale problems to define influential factors of electricity consumption of families and individuals. Swan and Ugursal (2009) conducted a comprehensive study of techniques used to model the energy consumption of the residential sector. According to their classification, top-down models address technical and econometrics models while bottom-up models include statistical and engineering models. Engineering models are generally used to define thermodynamic relationships, heat transfer, appliance use, and electricity power ranking. Statistical models deal with historical data and statistical analyses and involve in the conditional analysis of demand and artificial neural networks (Roque, 2013). Figure 1 shows the modeling techniques proposed by Swan and Ugursal.

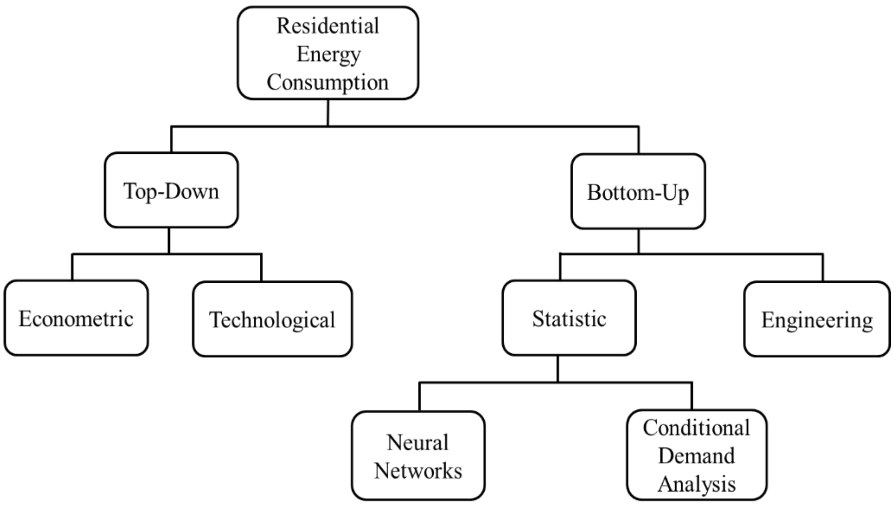

Figure 1: Top-Down and Bottom-up Approached for Modeling Residential Sectors Energy Consumption (Swan and Ugursal, 2009)

Different studies have been conducted across the world using both techniques to estimate the electricity function in the residential sector. However, a majority of them have been focused on developed countries. Therefore, they are not fit models for developing countries because countries possess different socioeconomic, cultural, and climate conditions. Thus, electricity consumption models should be developed based on socio-economic and technical properties that are specific to developing countries to be able to provide rational and practical results (Sena et al., 2018). This argument is valid for small scales such as countries and provinces. To this end, this study uses a bottom-up approach and BSOM technique to identify the influential factors of the electricity cost function in urban households of Iran’s provinces considering their socio-economic and technical factors. All the factors are used as the inputs of our algorithm. The next section explains the study background.

3. Study Background

This section reviews national and international studies on electricity consumption in the residential sector. Different studies have been conducted across the world using different methods. The majority of them, however, have been conducted in developed countries and they have rarely focused on developing countries. There are limited studies on electricity consumption in the residential sector inside Iran. Moreover, none of them has identified socio-economic and technical factors using a bottom-up approach, and there is no study with the BSOM method. It can be argued, therefore, that this is the first study of this type that is conducted inside Iran. The following paragraphs review some national and international studies on electricity consumption in the residential sector.

Ahmadi et al. (2015) evaluated the relationship between the awareness of the consequences of excessive use of electricity and savings using the survey-correlation method. They conducted their study on a group of Yasuj females selected in random. According to their results, there is a positive significant relationship between the awareness of the consequences of excessive use of electricity and savings so that it can justify 43% of changes to electricity consumption. This means that electricity saving can be increased through the promotion of this awareness. Rangriz and Pashoutanizade

(2014) evaluated the effect of the subsidy reform plan on the electricity consumption of Tehran subscribers using a genetic algorithm (GA). They compared the electricity consumption rate before and after this plan, using data of residential subscribers collected from 2000 to 2012. Their results showed that in addition to slowing consumption growth, the subsidy reform plan decreases consumption rate. Moreover, their results showed that the electricity demand is non-elastic to price and income in short-term and price policies fail to control this demand. This means that non-price and encouragement policies should be used to decrease electricity consumption. Aboonoori and Lajavardi (2016) estimated the elasticity of electricity consumption to temperature change in the residential sector. They used the panel data of 31 provinces of Iran from 2011 to 2014 and evaluated the long-term relationship between monthly temperature change and electricity consumption in the residential sector. Their results showed that there is a direct relationship between monthly electricity consumption and air temperature in Iran provinces, so that mean monthly consumption rate increases by 3.7% for a 10-degree increase in air temperature of provinces per month. Zareshahabadi et al. (2013) evaluated the effect of socio-cultural and economic factors on the energy consumption pattern of Yazd citizens using the survey method and questionnaire. They reviewed data of 383 families. According to their results, Yazd families have an acceptable energy consumption pattern with international media, education, high-income level, bachelorhood, poor religious beliefs, and low normality as factors with a negative impact on energy consumption patterns. Their regression analysis results showed that education, international media, birthplace, religious feelings, number of family members, lifestyle, awareness, and years of staying in Yazd justify almost 30% of changes to consumption patterns. Aboonoori and Rahimi Bonekaghi (2007) evaluated the electricity consumption pattern in East Azarbaijan families and proposed a targeted tariff for this province. They studied the theoretical fundamentals of pricing and tariff determination in the electricity industry. They estimated the income of electricity office (in Rials) concerning current tariffs and subscribers' subsidies by deciles. Their results showed that based on current tariffs, higher decile consumers receive considerable subsidies.

LotfaliPoor and Lotfi (2004) designed a single-equation and logarithmic model to estimate the electricity demand of Khorasan province in the country. For this purpose, they used the time series from 1355 to 1380. The results of fitting the model showed that electricity prices and household costs did not have a significant effect on electricity consumption, as well as the price elasticity of oil and natural gas, indicating that electricity and other alternative fuels cannot easily substitute for each other. Also, the consumption variable of the previous period shows that domestic consumers act following their habits.

Bartiaux and Kristen (2005) evaluated the electricity consumption of Belgian families and compared it with that of Danish families. They used 50000 Danish and 500 Belgian families' data. They aimed to determine the effect of socio-economic and house-related factors on the electricity consumption of the families. Their results showed that dwelling type, house area, and the number of residents in a house could justify almost 30% to 40% of electricity consumption of Danish families whereas these factors are less influential in Belgian families and justify only 10% to 30% of electricity consumption. Another important result was that the number of electrical appliances used by families is more important than the electrical productivity of the appliances. Santamouris et al. (2006) evaluated financial, social, and electrical data of 110 families in Athena, Greece. The collected samples were grouped and studied in seven income groups. The obtained results indicated that the quality and level of life are the determinants of the studied families' consumption rate so that low-income families live in old houses with low-productive heating devices. This, in turn, increases thermal and heating energy costs per capita in low-income groups compared to other groups. According to studies, Athena suffers from fuel poverty, especially when the actual price of electricity is taken into account. Baker and Rylatt (2008) evaluated the electricity consumption pattern in England. They tried to obtain the determinants of electricity consumption for both high-consumer and low-consumer groups using questionnaire data, annual consumption data, house area, and the number of house stories. Their results showed that house area and the number of rooms have a significant effect on electricity consumption. Also, they found a strong relationship between house cleaning interval and electricity consumption.

Emphasizing house and house residents' specifications, Mc Loughlin et al. (2012) studied the electricity consumption pattern of 4200 Irish families. They used multivariable linear regression models to obtain the influential factors of total consumption rate, maximum demand, load factor, and duration of electricity use for families with different economic conditions. Amongst others, dwelling type, number of rooms, the age of family head, family composition and social class, and type of cooking fuel were recognized as the most important factors. The maximum demand was under the significant influence of family composition and the type of cooking fuel. Also, the number of electric appliances, especially electric dryers, dishwashers, and electric ovens has a strong relationship with the maximum demand. Furthermore, the age of the family head affects peak hours because younger members use more electricity during the late-night compared to mid-aged and older members. Besides, the use of dishwasher affects peak hours.

Bedir et al. (2013) reviewed data of 323 families and determined the influential factors of electricity consumption patterns in the Netherlands. They used a regression model to determine the direct and indirect influential factors. The number of lights and electric appliances in a house and their activity duration, number of rooms, and house area are examples of direct factors while economic conditions, dwelling type, and demographic specifications are examples of indirect factors. Their results showed that the activity duration of electric appliances and the number of rooms justify 37% and 14% of changes to electricity consumption, respectively. Of the indirect factors, family size, dwelling type, use of the electric dryer, washing machine, dishwasher, and the number of showers are important determinants. Kavousian et al. (2013) evaluated the behavioral and structural factors affecting the electricity consumption of families. They used two separate models for peak hours and off-peak hours. They used 1628 families' data and showed that climate conditions, location, and the number of stories and house areas are among the most important determinants of electricity consumption. In off-peak hours, the number of refrigerators and electric game devices has the maximum contribution to electricity consumption while in peak hours, the number of family members and the number of high electricity consuming appliances, such as electric heaters, has the maximum contribution.

Yi-Tui Che (2017) evaluated the influential factors of electricity consumption and concluded that macroeconomic factors such as GDP, jobless rate, house area, and use of energy labels have a significant effect on electricity consumption. In contrast, electricity prices and energy efficiency standards have no significant relationship with electricity consumption. Among factors with a direct effect on electricity consumption, air conditioners have a significant contribution to the electricity consumption of all families (lights excluded) with a rate of 26.81% followed by the refrigerator and electric ovens with a contribution of 6.27%. GDP has a significant relationship with the number of electric appliances and, therefore, has a significant effect on electricity consumption. Besagni and Borgarello (2018) evaluated socio-economic factors, building specifications, and the number of electric appliances on electricity costs in Italy. They used regression models to estimate the electricity consumption rate. Their results showed that socioeconomic factors have the most potent effect on electricity consumption compared to building specifications and electric appliances. Jones et al. (2014) conducted a comprehensive review of domestic electricity demand studies and, according to a previous study, concluded that as many as 62 factors have been identified as potentially affecting household electricity consumption. Among these factors, 13 related to socio-economic factors, 12 cases related to household profile and type of residence, and the impact of household appliances on household consumption were also affected. Also, among the thirteen economic and social factors, 4 factors, among the variables related to residence, 7 factors, and among the variables related to electrical appliances, 9 factors were widely introduced in most studies and had a greater impact on electricity consumption. Ding et al. (2016) investigated the demand function of domestic electricity in different parts of China by concentrating on different urbanization between 1997 and 2013 and concluded that income and weather conditions, especially air temperatures, had the greatest impact on electricity consumption. They are the level of urbanization and the use of efficient and low-power electrical equipment also had a significant relationship with the amount of electricity consumed.

4. Data and Research Methodology

The data are collected on an annual basis using large or detailed questionnaire-based field data collected from different families across Iran with economic, social (cost and income) items. The questionnaires include 1000 items to be responded to by families. To give better answers to the items, families are compensated for their responses to the items. At present, urban households cost and income statistics are collected by both the Iranian Statistics Center and Iranian Central Bank while those of rural households are collected only by the Iranian Statistics Center. Both plans are implemented by UN recommendations based on NHSCP1 and SNA 2 publications via sample census method and by referring to sample families in urban and rural areas. Regarding the plan coverage, the statistic population consists of all urban and rural households' cost and income data. In addition to processing questionnaire data and publishing relevant results in typical tables of the annual journal of "rural and urban families' cost and income census", Iranian Statistics Center, as the main authority of this census plan, uploads large size information (crude data of questionnaire) on its website in the form of database files. A large portion of this data is not usable by those who are not familiar with database systems. The first part of the questionnaire includes demographic information including the number of family members, age, sex, education, university degree, activity status, and marital status. The second part includes items about dwelling type, facilities, and general appliances used by families. The third part, which is the most comprehensive part used to collect families' budget data, includes items about families' expenditures in 14 groups[1]. The fourth part discusses the families' income. However, it is not

1. 1- eating costs, 2- beverage and smoking costs, 3- clothes and shoe costs, 4- house, water and wastewater, fuel and light costs, 5- appliances, furniture and relevant maintenance costs, 6- health and therapy costs, 7- transportation costs, 8- communication costs, 9- cultural services and entertainment costs, 10- education costs, 11- ready food, hotel and restaurant costs, 12- miscellaneous service and product costs, 13- procurement and sales of durable appliances and other costs of families, 14- investment costs

practically useable because families rarely respond to these items. Therefore, most studies on families' budgets use total expenditures data as the closest index to total income. This study acts similarly and considers the total expenditures of families as an index of total income. Amongst others, this study evaluates 24 items as the influential factor of the electricity consumption of families. These items are electricity price, the total income of the family, number of children, number of adolescents, number of adults, age of family head, education of family head, the activity status of the family head, activity status of spouse, marital status, house material, house area, number of rooms, property status (dwelling type), the existence of stationary gas air conditioner, the existence of stationary water air conditioner, the existence of portable gas air conditioner, the existence of stationary water air conditioner, the existence of washing machine, the existence of fan, the existence of computer, cooking fuel type, heating fuel type, and NG gas piping expenditures.

4-1 Self-organizing Maps and Batch Self-organizing Maps

In recent years, several kinds of artificial neural networks have been proposed and used to variable selection and feature extraction problems as well as learning and estimating the behavior of real-world functions (Yegnanarayana, 2009). Self-Organized Maps, denoted by *SOMs*, as a competitive artificial neural network have been extensively used on different real word problems such as classification and estimation (Kohenen, 1997). SOMs project higher dimensional data onto a two-dimensional grid containing some cells. This mapping preserves neighborhood property among the data. It helps to visually investigate unknown relation between the data such that the similar data are mapped onto the same or neighbors' cells in the grid. These cells are connected and called **Competitive Units** (CUs). Each CU has some neighborhoods. Figure2 shows an example of a 4-neighborhoods network. A CU is a vector with the same dimension as the training data. In the training phase, the data are presented to CUs, and they try to learn the patterns in the data. At the end of this phase, the network will be able to estimate new data. Such a power, causes SOMs to have broad applications such as clustering, curve fitting, dimension reduction, and prediction (Villmann, 1999).

Formally, a SOM is a network; $G = \{w_1, w_2, w_3, \dots, w_n\}$, where w_i, for $i = 1,2, \dots, n$, is a competitive unit connecting to some of its neighbors. The dimension of w_i is the same as the dimension of the training data, e.g., $w_i = \langle w_i^1, w_i^2, w_i^3, \dots, w_i^m \rangle$, where m is the number of variables in each datum and w_i^j shows the weight of the j^{th} dimension in the i^{th} unit. At the initialization, a random weight is assigned to each unit. When a training datum —called *sample*— is presented to the network, these weights are updated. More precisely, when a sample $X_t = \langle x_t^1, x_t^2, \dots, x_t^m \rangle$ is presented to the network, the similarity between each CU and X_t is computed by considering the distance between them. Let b be the winner of this competition, called the **best matching unit.** So, it is obtained by the following relation:

$$\|X_t - w_b\| = \min_{1 \le i \le n} \{\|X_t - w_i\|\}, \tag{1}$$

where $\|X_t - w_i\|$ shows the distance between two vectors X_t and w_i. The Euclidean distance or inner product of them can be tacking into account, e.g., $\|X_t - w_i\| = \sqrt{\sum_{j=1}^{m} \left(x_t^j - w_i^j\right)^2}$. So, the most similar CU to X_t is close to X_t and has a minimum distance among all CUs. Therefore, it is the winner of the competition. After, determining the winner, the weights of CUs are updated as follows:

$$w_i^j(t+1) = w_i^j(t) + \gamma(t) h_{ib}(t) \left(x_t^j - w_i^j(t)\right), \tag{2}$$

where $\gamma(t) \in (0,1)$ is the learning coefficient and decreases according to the parameter t, $h_{ib}(t)$ is the excitation of the i^{th} competitive unit when the best matching unit is b. Indeed, it is related to the distance between the i^{th} unit and unit b on the network, and similar to $\gamma(t)$ it also decreases according to the parameter t. Equations (3) and (4) are used to update these coefficients.

$$\gamma(t) = \gamma_0 \, exp\left(-\frac{t}{T}\right), \tag{3}$$

$$\gamma(t) = (\gamma_{max} - \gamma_{min}) \frac{T - t}{T - 1} + \gamma_{min}, \tag{4}$$

where T is the number of training samples, γ_0 is the base of the learning rate, and γ_{min} and γ_{max} are the lower and upper learning rates. These equations can be applied for updating $h_{ib}(t)$ as well.

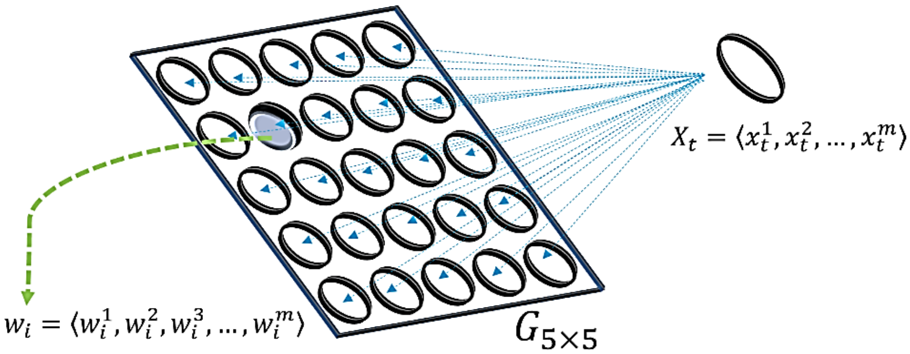

Figure 2: An Example of a SOM. A 5 × 5 Grid contains 25 four-Neighborhoods Competitive Units. After Presenting each Sample X_t, the Unites are Updated Based on their Distance from the Best Matching Unit.

All the samples are presented in the training phase to the network, for $t = 1,2, \dots, T$, and the weights of the CUs are updated. By each updating, a CU tries to get similar to the presented sample. Usually, the training phase is performed for several times or *epochs*. After completing the training, it is possible to judge a new sample by presenting it to the network and determining the best matching unit. For example, during the training phase, the samples with the same competitive winner are almost similar to each other and can be partitioned into the same category. In the context of estimation, this means that the result or output of the samples in the same category must be more or less similar. So, SOMs are useful for clustering, regressing, and estimating unknown functions. Another advantage of SOM is the low sensitivity of this network to noisy data. In fact, in the procedure of finding the best matching unit, see Equation (1), the similarity level of each unit is measured for each sample. Since in this equation, all m variables are considered simultaneously, it is robust and insensitive to the noisy samples and outliers. Note that, since there are different scalers in the data, usually the samples are normalized. Thus, all the dimensions have equal shares $(\frac{1}{m})$ in determining the best matching unit. Also, as stated in Equation (2), after finding the winner, the weights of each competitive unit are updated according to the distance from the winning unit. The units lie near to the winner get to impact more than the ones are farther. Thus, they are not so sensitive to the noise. Moreover, SOMs able to work with and apply on missing data. That is, if x_t^j is not available for some sample t and dimension j, it is possible to determine the winner without regarding dimension j.

In SOMs, after presenting each sample and determining the best matching unit, the weights of the CUs are updated based on Equation (2). Thus SOMs are sensitive to the order of presenting the training samples. Updating the weights in step t can impact on determining the winner in step $t+1$. In the following, a new variation of SOM, which is used in this paper and called *Batch SOM* (BSOM) is introduced (Kohonen, 1997). The difference between BSOM and SOM is how they provide training samples and update CUs. In BSOM, the samples are presented as a batch to the network, and updating the weights of the units is performed at the end of each batch. Precisely, the winner is determined without regarding the weight's changes but the corresponding calculations in Equation (2) are done after presenting each sample. Finally, the updating of the weights is performed at the end of each batch. It is possible to consider a batch as the all samples. That means the weight's updating is performed at the end of each epoch. Such an updating approach in BSOM would make it insensitive to the order of training samples as well as the possibility of parallel implementation of it (Boulet et al. 2008). So, the updating rule of BSOM is changed as follows:

$$w_i^j(t+1) = \frac{\sum_{t=1}^{n} h_{ib}(t) x_t^j}{\sum_{t=1}^{n} h_{ib}(t)}. \tag{5}$$

Both the algorithms SOM and BSOM can only be applied to numerical data. Generally, the most significant issue of these algorithms in dealing with such non-numerical or *categorical* data is the determination of a metric to calculate the distance or difference between two data (Huang, 1997). In the following, the presented BSOM algorithm is modified to aim this goal. Finally, it is used to determine the variables that are effective in electricity costs.

Assume $p(\leq m)$ variables of a sample $X_t = \langle x_t^1, x_t^2, \dots, x_t^m \rangle$ are categorical and $m-p$ of them are numerical. The distance or dissimilarity between X_t and the competitive unit $w_i = \langle w_i^1, w_i^2, w_i^3, \dots, w_i^m \rangle$ is defined as follows (Huang, 1997):

$$dis(X_t, w_i) = \sum_{j=1}^{p} \delta\left(x_t^j, w_i^j\right) + \sum_{j=p+1}^{m} \left(x_t^j - w_i^j\right)^2, \tag{6}$$

where if $x_t^j = w_i^j$, $\delta\left(x_t^j, w_i^j\right) = 0$, otherwise $\delta\left(x_t^j, w_i^j\right) = 1$ shows the dissimilarity of two categorical variables. So, in BSOM, Equation (6) is used to find the best matching unit.

Finally, after presenting all the training samples of a batch, the weights of numerical variables of the network are updated using Equation (5). However, the method of updating the categorical variables is different. Let $\left\{c_1^j, c_2^j, \dots, c_J^j\right\}$ be the *J* possible symbols of the *j^th^* categorical variable. The frequency of each symbol c_l^j is defined as follows:

$$F\left(c_l^j, w_i^j(t)\right) = \frac{\sum_{t=1}^{n}\left(h_{ib}(t) \middle| x_t^j = c_l^j\right)}{\sum_{t=1}^{n} h_{ib}(t)}, \quad j = 1,2, \dots, J. \tag{7}$$

$F\left(c_l^j, w_i^j(t)\right)$ is a value between 0 and 1 and denotes the frequency of presence of a symbol c_l^j as the value of the *j^th^* variable. After computing all the frequencies, w_i^j can be updated by selecting the maximum frequency symbol or by *Roulette wheel* rule (Epstein, 2009) based on the frequency values.

4.2 Batch Self-organizing Maps for Determining Electricity Cost and Effective Variables

Suppose $X_1, X_2, X_3, \dots, X_T$ are the *T* observed data (or samples) from *T* households. Each sample X_t is an *m*-vector $\langle x_t^1, x_t^2, \dots, x_t^m \rangle$ containing independent numerical and categorical variables. Also, each sample X_t has a specific electricity cost value y_t as the dependent value or function. So, one can be written as follows:

$$y_t = f(x_t^1, x_t^2, \dots, x_t^m). \tag{8}$$

If there is a known definition for the function *f*, computing values of y_t and the effective variables in determining y_t will be straightforward. However, in the issue under discussion in this paper, since most of the variables involved in the amount of electricity consumption are categorical, it is impossible to provide a precise mathematical definition for such a function. So, by applying the presented BSOM algorithm, a training model is provided to learn the patterns in the samples as well as the behavior of the function. After that, by using this model, it can be estimated the cost value y_t using a set of independent variables X_t. Let denote such estimated value by $\widehat{y_t}$. Finally, with the help of such a model, the effective variables in the determination of the function will be extracted. A pseudo-code of the algorithm is proposed in the following.

BSOM algorithm for Estimating Electricity Cost

Input: $(X_t = \langle x_t^1, x_t^2, \dots, x_t^m \rangle, y_t)$ for $t = 1,2, \dots, T$.

Output: A training model for electricity cost estimation.

- **Step 0**: Normalize all numerical data in [0, +1]. Set maximum epoch to Ep and set $epoch$ value to 0.
- **Step 1**: Construct a regular 4-neighborhood network with $m+1$ dimensional weights. Initialize the numerical weights randomly in [0, +1] and initialize the categorical variables by using their corresponding symbols uniformly.
- **Step 2**: Repeat the following sub-steps for *t=1, 2,…,T.*
  - **Step 2(*a*)**: Present $m+1$ dimensional sample $(X_t = \langle x_t^1, x_t^2, \dots, x_t^m \rangle, y_t)$ to the network and determine the best matching unit using Equation (6). Note that the variable y_t is not use in determining it.
  - **Step 2(*b*)**: Compute $h_{ib}(t)$ according to Equations (2)—(4).
- **Step 3**: Update all variable’s weights using Equations (5) and (7) as well as the dimension $m+1$, y_t.
- **Step 4**: Set $epoch = epoch + 1$. If $epoch = Ep$, the training phase terminates, otherwise go to Step 2.

Since the final goal of the training phase is providing a network to estimate the amount of electricity consumption by having its corresponding dependent variables, so y_t as the electricity consumption has been not participated in the determination of the best matching unit in Step 2 (a) and the winner is only determined by first m dimensions as the variables. It should be noted that the values of y_t are updated in separated layers of the network with the same ratio of updating the first m dimensions at the end of each epoch.

After terminating the training phase, the network is ready to compute the estimated electricity consumption $\widehat{y_{t'}}$ by having a new set of variables $X_{t'} = \langle x_{t'}^1, x_{t'}^2, \dots, x_{t'}^m \rangle$. To this end, it is sufficient to present $X_{t'}$ to the network and find the best matching unit. This winning CU is the most similar data to $X_{t'}$ and its $m+1$ dimension is a proper estimation for $y_{t'}$. This method is also used for evaluating the BSOM algorithm in the test phase. To do this, first, the network is trained by 90% of the samples in the training phase. Then in the test phase, the remaining 10% of the samples are presented to the network and their estimation value $\widehat{y_{t'}}$ is compared with the exact value $y_{t'}$. The average value of $|y_{t'} - \widehat{y_{t'}}|$ or any other deviation criteria can be reported as the fitness of the network.

Finally, to determine the most important and influential variables in electricity consumption, it is possible to train the network with all the available samples once again and measure its fitness. If a variable x^j has an important role in electricity consumption, so changing its value results in different estimated electricity consumption in the trained network. On the other hand, if x^j does not have an important role, its value does not significantly change the estimated electricity consumption. So, let $\hat{y}_t$ be the estimated value of the trained network for a sample $X_t = \langle x_t^1, x_t^2, \dots, x_t^m \rangle$, and let $\widehat{y_{tJ}}$ be the estimated value for the sample X_t whose j^{th} variable, x_t^j, is replaced by a random value. If $\left|\hat{y}_t - \widehat{y_{tJ}}\right|$ is small for the samples $t = 1,2,\dots,T$, it can be concluded that the j^{th} variable is not so important in determining electricity consumption. Repeating this process for all the variables $j = 1,2,\dots,m$, and computing the average changes of the estimated electricity consumption will result in an order of variable's importance.

5. Simulation Results

In this section, we implemented the proposed algorithm in MATLAB 2017 and apply for the problem of estimating expenditure electricity and determining influential variables. Table 1 shows the parameter setting to implemented the BSOM algorithm.

Table 1: Parameter Setting of the BSOM Algorithm

Size of the network	A regular 40×40 grid
Distance definition between two units	The Manhattan distance on the grid
Similarity criteria	Equation (6)
$(\gamma_0, \gamma_{max}, \gamma_{min}, \lambda, Ep)$	$(1,2,0,0.6,100)$

In the case study discussed in this paper, the total number of available samples is 14097 household's information derived from the **household budget plan**. Since the geographical conditions of the households may affect electricity consumption, in this study, the data are partitioned according to each province, and the algorithm runs for each of them separately (31 times). We normalize the numerical data into [0,1]. To evaluate the algorithm, we use the criteria **Mean Absolute Deviation** (MeAD), **Root Mean Square Error** (RMSE), **Mean Absolute Percentage Error** (MAPE) and **R- Squared** (R^2) whose relations presented below.

$$MeAD = \frac{1}{T}\sum_{t=1}^{n}|y_t - \hat{y}_t|. \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}{T}}. \tag{10}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|. \tag{11}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{T}(y_t - \bar{y})^2}. \tag{12}$$

In the above criteria, T is the number of samples, y_t and $\hat{y}_t$ are the exact and the estimated electricity consumption for sample t, respectively. $\bar{y}$ is the average of exact electricity consumption. R^2 ranges from zero to one such that $R^2 = 0$ indicates that the proposed model does not improve estimation over the mean model, however $R^2 = 1$ indicates good and customized training of the model which completely fits the samples.

We use 90% of the samples for training the model and the remaining 10% of them for testing it. Table 2 shows the results of estimations for each province separately. As it is clear, except for a few provinces, the mean absolute deviation is near to 938 *Rials* with an average RMSE value of 2404. Moreover, overall MAPE for the provinces is less than 10%. Also the coefficient R^2 is near to 0.85 in most of the provinces. The reported error measures confirm the efficiency and validity of the model.

Finally, to determine the priority and importance of the variables in electricity consumption, the following method is used separately for each province. First, the network is trained for all the samples of each province with the parameters reported in Table (1). Then, focusing on the variable *j*, all the samples are presented to the network with a random replacement of their j^{th} variable's value instead of their accurate observed data. Finally, the electricity consumption is estimated for such constructed random samples, and using Equation (10) the criteria of RMSE are measured. Larger RMSE indicates the importance of variable *j* in determining electricity consumption. The above process repeats for all variables $j = 1,2, \dots ,24$ and priority of them are determined. We categorize the variables in three levels according to their importance. Among of all 24 investigated variables, 11 variables illustrated in Table (3) are extracted as the most important numerical and categorical variables.

Table 2: Evaluation Results; Error Ratio of the BSOM Training Algorithm for the Provinces

Province	**Markazi**	**Gilan**	**Mazandaran**	**East Azr.**	**West Azr.**	**Kermanshah**	**Khuzestan**	**Fars**
# all Samples	504	393	436	386	437	418	503	519
#Training samples	454	354	392	347	393	376	453	467
#Test samples	50	39	44	39	44	42	50	52
MeAD	338.9750	323.8313	417.9805	260.9892	399.6292	457.4004	3460.9290	615.1195
RMSE	783.0870	1077.94	1016.6030	676.2605	1014.3290	1044.9065	7482.150	1540.6655
MAPE	0.0812	0.0703	0.0998	0.0967	0.1017	0.962	0.1109	0.1275
R^2	0.7688	0.8603	0.7731	0.9148	0.7728	0.9353	0.9153	0.8964
Province	Kerman	Khorasan Razavi	Alborz	Esfahan	Sistan	Kordestan	Hamadan	Bakhtiyari
# all Samples	419	550	393	513	367	352	450	386
#Training samples	377	495	354	462	330	317	405	347
#Test samples	42	55	39	51	37	35	45	39
MeAD	659.5590	520.517	380.1216	581.7710	7035.28	141.7203	434.1816	165.9436
RMSE	1774.1730	1972.3495	1054.433	1347.01	10482.9	470.8164	1094.8140	475.8993
MAPE	0.1010	0.1168	0.0905	0.1320	0.0910	0.0876	0.0899	0.0529
R^2	0.8981	0.8622	0.8547	0.8240	0.8240	0.8538	0.8919	0.9156
Province	Lorestan	Ilam	Kohkeloyeh	Boushehr	Zanjan	Semnan	Yazd	Hormozgan
# all Samples	407	362	190	430	476	397	484	455
#Training samples	366	326	171	387	428	357	436	410
#Test samples	41	36	19	43	48	40	48	45
MeAD	230.2389	983.5985	162.8488	4142.3365	387.8978	185.0550	358.6174	3505.12
RMSE	598.9540	7341.930	500.9065	11414.255	1002.7545	536.5895	766.604	12013.25
MAPE	0.0682	0.0694	0.0793	0.1120	0.0919	0.0537	0.1011	0.1034
R^2	0.9049	0.6666	0.9223	0.8808	0.7063	0.9103	0.8862	0.6451
Province	Tehran	Ardabil	Qom	Qazvin	Golestan	South Khorasan	North Khorasan	
# all Samples	1253	349	375	346	499	583	467	
#Training Samples	1128	314	338	311	449	525	420	
#Test Samples	125	35	37	35	50	58	47	
MeAD	993.0035	175.1662	342.2388	138.3986	633.579	388.9655	275.324	
RMSE	1705.1305	564.5875	1079.0575	380.9574	1428.2010	1078.7565	810.863	
MAPE	0.1362	0.0514	0.0585	0.0963	0.1347	0.1243	0.0718	
R^2	0.7523	0.9169	0.8394	0.8926	0.8926	0.7575	0.7463	
Average of metrics	**MeAD**		**RMSE**		**MAPE**		**R^2**	
	938.6563		**2404.1655**		**0.0933**		**0.8411**	

Electricity price, total family income, and heating fuel costs, especially costs associated with NG piping operations, were identified as the most important quantitative factors. On the other side, number of adolescents, number of rooms, the activity status of the family head, number of children, education of family head, house area, house material and existence of stationary gas air conditioner were identified as the most important qualitative factors of electricity costs function of urban households of Iran provinces in three influencing levels. Of quantitative factors, price and income have the highest effect on electricity costs function followed by NG gas piping costs. Electricity power ranks first as a quantitative factor in all 31 studied provinces. It should be mentioned that in southern provinces i.e. in Fars, Khuzestan, Sistan and Baluchestan, Kerman, Bushehr, Kohgiluyeh and Boyer-Ahmad and Hormozgan, and Semnan, South Khorasan, North Khorasan, and in Northern Provinces i.e. in Golestan, Mazandaran, and Gilan, electricity costs of urban households are less sensitive to electricity price compared to other provinces. The total income of the family was identified as the second influential quantitative factor. However, it was more influencing in dispossessed provinces of Ilam, Sistan and Baluchestan and Kordestan than other provinces. Heating fuel was identified as the third influential quantitative factor of electricity costs function. NG gas piping cost was more influencing in cold provinces i.e. in East Azarbaijan, West Azarbaijan, Ardebil, Kermanshah, Kordestan, Hamedan, Zanjan, Lorestan, Chaharmahal and Bakhtiari compared to other provinces.

Table 3: Variable Extraction Results, and Priority of Variables in Determining Electric Expenditure

Level Of Importance	Numerical Variables	Categorical Variables
3	1. Electricity Power Price 2. Total household's Expenditure	1. Number of Adults 2. Number of Rooms 3. Status of Employee
2	1. Plumbing Gas Expenditure	1. Number of Children 2. Education Level (HH degree)
1		1. Total Floor Area 2. House Material 3. Gas Cooler

Of qualitative factors, the number of adolescents, number of rooms and activity status of the family head were identified as the most influential factors of electricity consumption function of urban households, respectively where some adolescent ranks the first and has almost the same importance in all provinces followed by a number of rooms. Surprisingly, electricity cost is less sensitive to this factor in Northern Provinces i.e. in Mazandaran, Gilan, and Golestan, compared to other provinces. The reason may be big houses of the cities with more rooms. In Khuzestan, Kerman, Bushehr, Hormozgan, Razavi Khorasan, Tehran and Alborz, the activity status of the family head was more important than other provinces.

The number of children and education of family head are respectively two influential qualitative factors of electricity costs function in all urban households of Iran Provinces where the number of children is less important in Hormozgan, Bushehr, and Qom. Besides, the education level of the family head has almost the same importance in all 31 provinces and ranks fifth. House area, house material, and stationary gas air conditioner are less important than the aforementioned qualitative factors and are placed in the third level of influence. House area ranks the sixth in the influential qualitative factors in urban households of Iran Provinces with lower influence in Alborz, Tehran, Qazvin, Sistan and Baluchestan, Esfahan, Kerman, Fars, Khuzestan, Gilan, Golestan, and Mazandaran. The reason may be traced in almost the same house areas in the provinces. House material and use of air conditioners such as gas air conditioners are the last influential qualitative factors. House material is more important in Golestan, Mazandaran, and Gilan than other provinces. Regarding gas air conditioner, although it ranks the 8^{th}, it was identified as an influential factor only in hot provinces of Iran i.e. in Khuzestan, Fars, Bushehr, Yazd, Hormozghan, Qom, Sistan and Baluchestan and Esfahan with higher importance than house area and house material while it has a negligible effect in other cities.

6. Discussion and Conclusion

Electricity is an important energy carrier in today's modern world with a significant effect on countries' development. Therefore, the management of optimal consumption and formulating appropriate policies for it are of high importance. This is highlighted in some countries, including Iran, which involves widespread aridity and will suffer essential problems due to decreased precipitation and low dam reservoir levels. Such policies demand the identification of the behavioral pattern of electricity consumers. The residential sector accounts for one-third of total electricity consumption in Iran. Therefore, by the identification of families' consumption patterns and implementing optimal policies proportional to their behavioral pattern, energy loss could be avoided in more than one-third of total electricity consumption. To this end, this study tried to identify the influential factors of consumption patterns of urban households across Iran Provinces using BSOM. Of 24 studied factors, selected from the family budget questionnaire, 11 factors i.e., three quantitative factors and 8 qualitative factors were identified in three influence levels. The general order of the factors in the studied provinces was as follows; electricity price, the total income of family and NG gas piping costs, as quantitative factors, and number of adolescents, number of rooms, the activity status of the family head, number of children, education level of the family head, house area, house material, and stationary gas air conditioner, as qualitative factors. The order of these factors differs in some provinces depending on climate condition and social, economic, and cultural factors. Identification of these factors can serve as a beneficial tool for The Ministry of Energy in the way of formulating appropriate policies for different provinces. Also, researchers are recommended to deepen this study considering seasonal changes and different months of a year or concerning climate categories which can provide interesting results. According to the findings of the research, it can be concluded that due to the wide range of qualitative factors affecting household electricity expenditure in the provinces, the energy consumption policy should be focused on these factors. For example, electricity tariffs can be designed based on the combination of households, the number of rooms, and the status of the household's head.

References

Abounoori, E., & Lajevardi. H. (2016). Estimated Elasticities of Household Electricity Consumption to Changes in Weather

Temperature. 31st International Power System Conference, Retrieved from http://psc-ir.com/cd/2016/include/index.html.

Abounoori, E., & Rahimi Bonekaghi, M. (2007). Household Electricity Consumption Model for Proposing a Targeted Tariff. *Daneshvar Raftar*, *5*(23), 33-52.

Ahmadi, S., Salehi, F., & Navaei, S. (2015). Relationship between Awareness to Consequences of Excessive Consumption of Electricity and Power Saving Among Married Women in Yasouj. *Quarterly Journal of Social Development*, *9*(4), 51-66.

Baker, K. J., & Rylatt, R. M. (2008). Improving the Prediction of UK Domestic Energy-Demand Using Annual Consumption-Data. *Applied Energy, 85*(6), 475-482.

Barnes, R., & Gillingham, R. (1984). Demographic Effects in Demand Analysis: Estimation of the Quadratic Expenditure System Using Microdata. *The Review of Economics and Statistics*, *66*(4), 591-601.

Bartiaux, F., & Gram-Hanssen, K. (2005). Socio-political Factors Influencing Household Electricity Consumption: A Comparison between Denmark and Belgium. *ECEEE Summer Study Proceedings, 3*, 1313-1325.

Bhattacharjee, S., & Reichard, G. (2011). Socio-economic Factors Affecting Individual Household Energy Consumption: A Systematic Review (891-901). *ASME; 5th International Conference on Energy Sustainability*, Washington, DC: American Society of Mechanical Engineers.

Bedir, M., Hasselaar, E., & Itard, L. (2013). Determinants of Electricity Consumption in Dutch Dwellings. *Energy and Buildings*, *58*, 194-207.

Besagni, G., & Borgarello, M. (2018). The Determinants of Residential Energy Expenditure in Italy. *Energy*, *165*, 369-386.

Boulet, R., Jouve, B., Rossi, F., & Villa, N. (2008). Batch Kernel SOM and Related Laplacian Methods for Social Network Analysis. *Neurocomputing*, *71*(7-9), 1257-1273.

Chen, Y. T. (2017). The Factors Affecting Electricity Consumption and the Consumption Characteristics in the Residential Sector-A Case Example of Taiwan. *Sustainability,* Retrieved from https://www.mdpi.com/2071-1050/9/8/1484/pdf.

Ding, Y., Qu, W., Niu, S., Liang, M., Qiang, W., & Hong, Z. (2016). Factors Influencing the Spatial Difference in Household Energy Consumption in China. *Sustainability*, *8*(12), 1-20.

Duvall, E. M. (1988). Family Development's First Forty Years. *Family Relations, 37*(2), 127-134.

Epstein, R. A. (2012). *The Theory of Gambling and Statistical Logic*. Oxford: Academic Press.

Huang, Z. (1997). Clustering Large Data Sets with Mixed Numeric and Categorical Values. *Proceedings of the 1st Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD)* (21-34), Retrieved from https://grid.cs.gsu.edu/~wkim/index_files/papers/kprototype.pdf.

Jones, R. V., Fuertes, A., & Lomas, K. J. (2015). The Socio-economic, Dwelling, and Appliance Related Factors Affecting Electricity Consumption in Domestic Buildings. *Renewable and Sustainable Energy Reviews*, *43*, 901-917.

Kaestner, R., & Grossman, M. (2009). Effects of Weight on Children's Educational Achievement. *Economics of Education Review*, *28*(6), 651-661.

Kavousian, A., Rajagopal, R., & Fischer, M. (2013). Determinants of Residential Electricity Consumption: Using Smart Meter Data to Examine the Effect of Climate, Building Characteristics, Appliance Stock, and Occupants' Behavior. *Energy*, *55*, 184-194.

Kohenen, T. (1997). Self-organizing Maps, 30. *Lecture Notes in Information Sciences*, Retrieved from https://www.springer.com/gp/book/9783540679219

---------- (1990). The Self-organizing Map. *Proceedings of the IEEE, 78*(9), 1464-1480.

Levinson, D. J. (1978). Eras: The Anatomy of the Life Cycle. *Psychiatric Opinion, 15*(9), 10–11, 39–48.

Lotfalipour Lotfi, A. (2005). The Survey and the Estimation of Effective Factors on Household Electricity Demand in Khorasan Province. *Knowledge and Development, 7*(15), 47-69.

McLoughlin, F., Duffy, A., & Conlon, M. (2012). Characterizing Domestic Electricity Consumption Patterns by Dwelling and Occupant Socio-economic Variables: An Irish Case Study. *Energy and Buildings*, *48*, 240-248.

Pollak, R. A., & Wales, T. J. (1981). Demographic Variables in Demand Analysis. *Econometrica: Journal of the Econometric Society, 49*(6), 1533-1551.

Rangriz, H., & Pashootanizadeh, H. (2014). Evaluation of the Effects of Targeted Subsidies on Household Subscribers Electricity Consumption in Tehran Using Genetic. *Journal of Economic Modeling*, *5*(17), 123-144.

Ray, R. (1982). The Testing and Estimation of Complete Demand Systems on Household Budget Surveys. *European Economic Review, 17*(3), 349-369.

Ritonga, H. (1994). The Impact of Household Characteristics on Household Consumption Behavior: A Demand System Analysis on the Consumption Behavior of Urban Households in the Province of Central Java, Indonesia. Retrieved from https://lib.dr.iastate.edu/cgi/viewcontent.cgi?article=12311&context=rtd.

Roque, M. (2013). *Survey and Artificial Neural Network Analysis on Occupant's Household Energy Use in a High-Rise Multi-Unit Residential Building in Toronto, Canada* (Doctoral Dissertation and Master Thesis, Ryerson University, Canada). Retrieved from file:///C:/Users/hossein%20zade/Downloads/OBJ%20Datastream.pdf.

Santamouris, M., Kapsis, K., Korres, D., Livada, I., Pavlou, C., & Assimakopoulos, M. N. (2007). On the Relation between the Energy and Social Characteristics of the Residential Sector. *Energy and Buildings*, *39*(8), 893-905.

Schultz, T. W. (1963). *The Economic Value of Education*. Columbia: Columbia University Press.

Sena, B., Zaki, S. A., Yakub, F., Yusoff, N. M., & Ridwan, M. K. (2018). Conceptual Framework of Modelling for Malaysian Household Electrical Energy Consumption using Artificial Neural Network based on Techno-Socio Economic Approach. *International Journal of Electrical and Computer Engineering (IJECE), 8*(3), 1844-1853.

Stover, B. (2012). *The Influence of Age on Consumption (3808).* Retrieved from file:///C:/Users/hossein%20zade/Desktop/Discussion%20Paper_Britta%20Stoever.pdf.

Swan, L. G., & Ugursal, V. I. (2009). Modeling of End-use Energy Consumption in the Residential Sector: A Review of Modeling Techniques. *Renewable and Sustainable Energy Reviews*, *13*(8), 1819-1835.

Talebzadeh, S., & NasiriPour, A. (2016). Electricity Consumption Peak Efficiency. *31st International Power System Conference*, Retrieved from https://www.sid.ir/FileServer/SF/7831395H31313.pdf.

Tonn, B., & Eisenberg, J. (2007). The Aging US Population and Residential Energy Demand. *Energy Policy*, *35*(1), 743-745.

Raaij, W. F., & Verhallen, T. M. (1983). Patterns of Residential Energy Behavior. *Journal of Economic Psychology*, *4*(1-2), 85-106.

Villmann, T. (1999). Benefits and Limits of the Self-Organizing Map and its Variants in the Area of Satellite Remote Sensoring Processing. *Topology*, Retrieved from https://www.researchgate.net/.

Wilbanks, T., Bhatt, V., Bilello, D., Bull, S., Ekmann, J., Horak, W., & Scott, M. J. (2008). Effects of Climate Change on Energy Production and Use in the United States. *US Department of Energy Publications*, Retrieved from https://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1005&context=usdoepub.

Yegnanarayana, B. (2009). *Artificial Neural Networks*. New Delhi: Prentice-Hall of India.

Yohanis, Y. G. (2012). Domestic Energy Use and Householders' Energy Behavior. *Energy Policy*, *41*, 654-665.

Zare Shahabadi, A., Hajizadeh Meymandi, M., & Lotfaliyani, A. Z. (2013). Socio-cultural Factors Affecting Energy Consumption Patterns of Households in Yazd. *Quarterly Journal of Energy Policy and Planning Research*, *1*(3), 17-50.

Ziyaei, O., & Parsamoghadam, M. (2010). Long Term Electricity Consumption Modeling for Iran Using Cointegration. *Modarres Technical and Engineering, 38*, 31-39.