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Statistical Analysis for Economics of the Energy Development in North Zone of Cairo

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Abstract

This paper presents the statistical analysis for an ideal official model. The statistical parameters (Mean Value, Limit factors of Maximum and Minimum) of the energy consumption during the last 26 years are determined and analysed. The standard deviation is inserted to be a vital factor for the discussion and analysis. The results are studied and then, recommendations as well as conclusion are stated. The original data are treated within two scales as multi-month reading and the occupied houses conditions. The correlation of energy parameters for the Capital City of Egypt are used for evaluation the statistical factors and evaluation has been done. An official sample for the domestic customers at north Cairo (the Capital of Egypt) over 26 years (Jan 1992-Jan 2018) has been included in the investigation and analysed for the statistical parameters. A sample for the total Energy curves in Cairo City is inserted and investigated. The statistical performance for the readings of the considered Energy curves is deduced and the results are discussed. The given investigation correlates the automatic random characteristics in the domestic loads of customers and the important parameters for Cairo is deduced according to the statistical results. The rate of rise of energy consumption is calculated for the model and the transients of the variation oscillation is investigated. The static rate of rise of energy consumption is estimated for different cases of the model. Both linear growth and exponential are inserted. The results, as a micro scale base, approved the importance of the statistical parameters for the planning problems. Both steady state transients and unstable transients are investigated for the energy consumption readings in the model. Prediction of Energy growth has been studied according to linear, exponential, static and dynamic estimation and the concluded results are given. The fluctuation in recorded methods has been determined and the automation of recording data processes with new technologies is recommended.

Keywords

Energy Consumption, Average Value, Dispersion Factors, Domestic Load, Economics of Pricing, Micro Scale, Transients, Statistical Analysis

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1. Introduction

Recently, the energy consumption floats on the surface because the power generation becomes a complex problem. The strategy of nations is directed nowadays toward the renewable energy since Petroleum is needed to cover future requirements. Therefore, the rationalization comes to minimize the energy consumption and to create new energy sources. Nowadays, this subject is a vital although the traditional fuel is still enough. Either new or renewable energy has analysed in most recent researches, but the solutions are expensive. The improvement of energy consumption comes from the modification of domestic appliances specification where the rating as a power consumption is decreased. Contrary, the number of domestic

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appliances is increasing every day and exceeds the previously energy consumption. This indicates the importance of rationalization strategy in the process of energy utilization and consequentially its consumption not only in a country but also around the world. The per capita data for many countries may be slightly inaccurate as population data may not be for the same year that the consumption data are. Additionally, population data were obtained for years other than the list of countries by population in 2016, in which case they were obtained from the Wikipedia pages for the corresponding countries/territories [1].

Nowadays, energy is the lifeblood of modern societies (as Egypt) because the world's energy consumption and associated emissions increased rapidly due to the increases in population and comfort demands of people. Building energy consumption prediction is essential for energy planning, management, and conservation [2]. Physical modelling (engineering or white-box models) and data-driven approaches have been taken for building energy consumption prediction. Physical models rely on thermodynamic rules for detailed energy modelling and analysis where building energy consumption is calculated based on detailed building and environmental parameters such as building construction details; operation schedules; network design; climate, sky, and solar/shading information. However, some of such detailed data may not be available to the users at the time of simulation and so, failure to provide accurate input can result in poor prediction performance [2]. Contrary, data-driven building energy consumption prediction modelling does not perform such energy analysis or detailed data about the simulated building, and instead learns from historical/available data for prediction due to difficulty to get. In response, a few review studies on the analysis has been published and mostly focused on the machine learning methods/algorithms (artificial neural networks, decision trees, and other statistical) used. Despite the importance of these efforts, there is still a lack of review studies that analyze existing data-driven approaches from a more multivariate perspective, including data aspects such as types, sizes and features for learning [2].

It is known that, residential buildings described as complex social-technological systems expressing component interdependence and chaotic temporal variability. It characterized the dynamics and multiscale relationships of hourly electricity consumption data [3]. However, the approaches of building energy modelling used for high-rise apartment buildings are limited to consider variation in individual apartment units derived from the locations and occupants and therefore, an integrated model. A framework of building energy models established to reflect variation in the location of units and individual heating controls, based on actual energy use. An uncertainty analysis with occupant-related factors was conducted to identify the impact on heating energy use in the building simulation model [4]. Moreover, electricity consumption globally increases at a faster pace than other energy vectors due to electrification of energy uses. Most of the 2017 increase in global electricity consumption occurred in Asia while in 2016, the electricity consumption increased in several developing countries as Iran and Egypt, but it remained stable in Europe [5].

2. Modelling

However, the German industry consumes almost 50% of total electricity produced in Germany. Upon breaking down the industry in terms of electrical energy consumption, more than 70% is required [6]. The potentially broad impacts of human dimensions on energy use are given to meet 2050 energy and greenhouse, gas reduction goals, new data, guidelines, and models are needed to leverage human dimensions towards substantial building energy use reductions and improvements in occupant comfort that can be sustained across an entire building life cycle [7]. Fortuitously, modern utility and property-level smart meters allow for the capture of short-interval building electricity, natural gas, and water consumption patterns. These new data streams fraction down from the coarser-grained annual and monthly-interval consumption summaries to the finer-grained daily, hourly, or even 15-min-interval summaries [3].

The analysis in this work will account the input data of 15 samples, which sorted in two groups as presented in Figure A1 in the Appendix. So, the analysis becomes real and actual although many other consumptions can be expressed in different cities or even in various countries. The mathematical formulation for the statistical investigation would be necessary so that some initial factors could be inserted to be calculated. The domestic energy consumption appears to be one of the vital today items because the rationalization of energy consumption became the principal target for humans on the Globe.

3. Statistical Considerations

The energy management of office buildings has been a rising concern for owners and energy suppliers. The volatility of power load in office buildings threatens energy consumption and risks device security where the load fluctuation patterns in an office building based on user data, using recurrence interval analysis for different thresholds were investigated [8].

Furthermore, various energy models can be used for determining regional or national energy supply requirements (macro-scale) as well as for measuring the efficiency in energy consumption of specific housing with refurbishment strategies (micro-scale). For the specific purposes of macro-scale, building energy consumption models, which can also be called housing stock energy models, can help a decision maker of refurbishment policy and regulations with the cost-benefit analysis. With micro-scale applications, models provide impacts and energy saving because of specific materials and technologies [4].

The common methods of existing housing stock models are either statistical or engineering-based models. However, the limitations of common methods due to accuracy, data collection, computational time, decision-making and flexibility. Statistical models are less flexible although more accurate than engineering-based methods, whereas engineering-based methods are more extensive with computational simulations than statistical models. The limitations are often derived from inherent uncertainties in building factors affecting energy consumption in real situations [4].

4. Pricing

However, the price of energy must be updated, sequentially, according to the modification in the economic system so that the tariff of electric energy in Egypt (for example) is considered for the technology of economic evaluation. The principle of tariff for energy consumption has been widely investigated for a long time according to the social dependency with the official support based on the social content of the society [9]. The load aggregator responds to indicative energy price information succumbing a flexibility bid to a high-resolution real-time balancing market. This bid represents the possibility of the cluster of deferrable loads to deviate from the scheduled consumption, if the bid is accepted. It considers the discretized power profiles of the individual loads, but scalability can be an issue [10].

Yet, the energy pricing depends on two sections (fixed and variable) as a micro term of economics. This means that, the costing of energy must depend on, firstly, the capital cost of stations (power stations and substations) and the connection between them (transmission systems) with the ends of utilization containing transformers, boards and cables (distribution system). The capital cost is expensive because it includes the price of lands for the electric networks (stations and lines). Secondly, the total cost depends also on the running cost, including both generated and consumed powers where the presented research is concentrated to investigate the part of consumption energy with respect to both sides (customers and electricity company). The average monthly price P_{av} in the units of L. E. For the total energy (E_t) may be formulated as a function of the total energy used in the units (kwh) by:

$$\mathrm{Pav} = \left(\frac{1}{\mathrm{Et}}\right) \times \sum_{=1}^{\mathrm{mc}} (\mathrm{P} \times \mathrm{kW}h_{\mathrm{i}}) \tag{1}$$

Then, the average price should be equivalent to the deduced according to the stripes of customers where they have (m) classes for each sector and the price in each can be remarked as P_m for the m^{th} stripe (It varies between 1 and 9) [11]. Thus, the average price will obey the expression in equation (1). All values are based on the P. T. units. This reflects the interaction between the energy consumption and the operating cost (Running Cost) so that the energy investigation may be a major factor for the determination of the energy price. Additionally, the evaluation of the price could be energy utilization dependent where the consumers may be classified into strips.

5. Mean Value

Whatever, a study intended to compare the unit-specific heating controls with the generalized heating control for the building with the same thermal conditions in the district scale, but it took the average heating energy consumption value in existing apartment buildings constructed before 1980, 123.2kWh/m^2/year. It demonstrates the unit-specific energy consumption applied where vertical unit locations from the ground to top floors showed a significant difference in heating energy consumption than the one among horizontal locations among the west, middle and east sides of the floors [4].

One of the difficulties in refurbishing existing buildings is the lack of interaction with occupants. This disparity has been an obstacle to using model estimations for practical application where disparity, various building controls in households and actual consumption data must be essentially reduced. An empirical study, measuring the heating energy consumption in apartment units, showed significant variation depending on location and occupants living in the same building [4, 12].

Since a price stripe inside total consumption depends on the actual period for measurement, the recording date of consumed energy individually must be a constant cycle of time (T). This process is very difficult due to the manual system for recording so that a deflection may occur in the determined consumed energy. This can be treated according to the automation system for recording the energy consumption for each individual consumer to ensure the time of 30 days. Otherwise, the economic style based on the statistical mean value could be implemented to correlate the variation in the time cycle of recorded reading. The cheaper method is preferable while the mathematical formulation for meaning of the mean value is utilized to explain a difficult subject for understanding through its original data. So, the mean value clarifies a hard subject in simple vision where a lot of data can be transformed into an illuminated picture or a number. Then, decency on the mean value leads to understanding in an abbreviated time, unclouded although some items of works in various fields may be treated, too.

Since the initial data are a lot and must be treated for the micro scale, the statistical mean value could be implanted in the computational analysis of the present work. It means generally that; all values of a subject cannot represent a problem for study so that only one value may summaries all of them. Consequently, the input data for the Energy curves are summarized as a Population Mean which may be taken as a mean value (average) X in the form [13]:

$$X = \{(\sum X_i)/N\}, (i = 1, \dots, N) \quad (2)$$

The average value of either a load curve or an energy curve [14] means the mean for the statistical studies, but here this average is tailored in separate ways such as the *Instantaneous Mean* for the two different groups inside the same overall readings of the energy curves in Cairo City [15]. Otherwise, the Weight Loads Mean is required for the analysis of energy curves as given in initial or treated data. The effect of peak on an Energy curve appears to be the most important item for Economists and so, the statistical study of either peak or light loads may be applied for the micro scale according to [13]:

$$X_w = (\sum X_i W_i) / (\sum W_i) \quad (3)$$

Thus, the load curve for a specified place cannot be the same everyday due to the performance of its variation, and so, the speech about all populations of loads may be impracticable. Hence, the concept of simulation (sampling) would be a way to investigate the overall characteristics of loads, however, it will be a step to cost the energy consumption. The sample must reflect the overall view of consumers in the studied field since it may be for only domestic sector of customers. There are two directions for the variation in a random way [13]. The first is the change in the number of customers connected at the ends of the distribution network while the second will be the continuous addition for due to consumers or all together [14]. There are two axes for the possible mistakes in the process of accounting to find the total cost for the consumed energy in a certain reading or the sequence of measurements. The average (mean value) concept can simply solve such problems.

Also, there are two types of distortions in the original readings of the present research since the target is the overall characteristics of the energy consumption in big Capitals around the world such as Cairo. The first distortion is the single reading for the multi-month consumption while the second appears as the starting moment (Energy Utilization Stop) for the consumption of energy either at the beginning of utilization or the stopping for a long time inside the model period (1992-2017). The 15 ideal consumers have been classified in two groups where the first and the second groups contain 8 and 7 consumers, respectively. This may be tailored into two patterns as Multi-Month Readings (Recoding Suitability) and Zero-Start Readings (Occupied Houses) [1, 16].

On the other side, the computed mean values with the modification of multi-reading only for the 8 consumers in the first group are drawn in Figure A2 of the Appendix and similar values for the 7 consumers of the second group are shown in Figure A3 (See Appendix). The Mean Value of the Annual Readings for all consumers in both groups together as a total annual reading may be shown in Figure 1 where yearly energy varied from 72829kWh for 1st consumer to 237734.8kwh for the 14th.

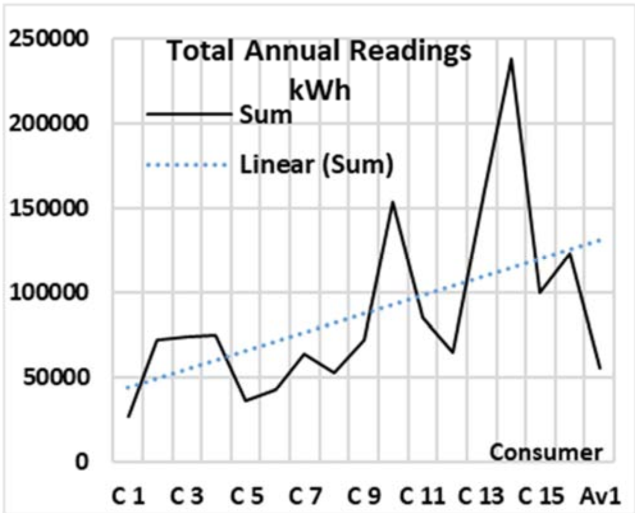

Figure 1. Mean Value for summation of groups.

If the occupied consumer is considered and the original modified data are accounted, the Annual Mean Value for energy consumption will be different as illustrated in Figure 2. The monthly variation here starts from 2192.89kWh for 1st while the maximum average appears as 19811.23kWh the 14th, too.

Whatsoever, the group consideration may be determined because the detail for the energy growth as concluded from Figure 1 and Figure 2 is found. So, the results of calculation for the Mean Value for the summation of all consumers of the first group are given in Figure 3 where both cases of treatment (multi-reading and actual occupied consumer) are considered. It should be indicated that, the results of calculations are given for all 26 years period where the rise shown in Figure pointed the energy growth always.

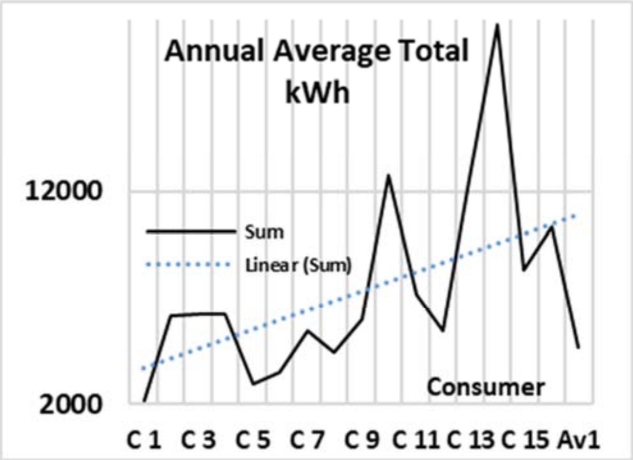

Figure 2. Mean Value at occupation for model.

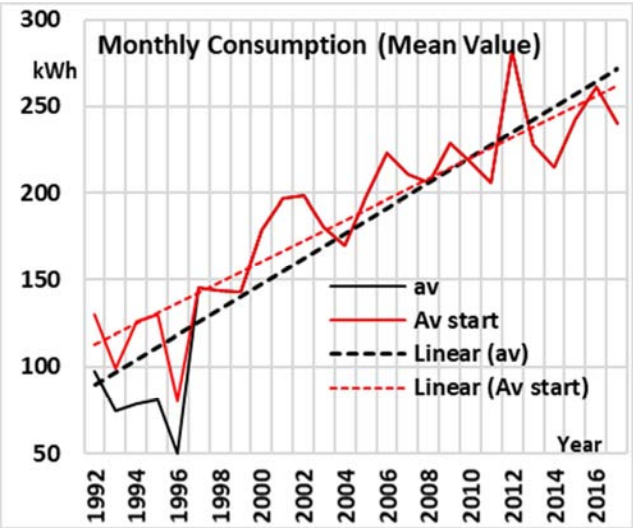

Figure 3. Mean Values for 1st group.

Otherwise, Figure A4 in the Appendix shows the estimated mean values for all 8 consumers (1st group) with the consideration of the multi-month reading treatment in addition to the starting actual occupation correction with their mean value (Av_{start}). Whatever, Figure 1 and Figure 2 say that there are a general sequential of levels for energy consumption between consumers in the first collection so that there are small consumers and others have higher energy consumption etc. this is not a vital remark because electric companies classify consumers according to the level of energy use. The levels of energy consumption have a valuable meaning when it is appeared with time.

Therefore, a sample of official readings is registered for a time range of (1992-2018) years as given in Figure A1 for the energy consumption with an oscillated character. The axes of deflection will be induced as in the period T_i for a sequence of readings (R_i) with their energy (P_i) as a function of the exact month time T (usually T = 30 days). An excess time t_i may control the required aim where the index i means the 12 months (i = 1, 2, …, 12). The annual average energy can be expressed as the sum of monthly readings within the year divided by the number of months despite the number of readings may be different. This case represents the first axis of mistake that needs not only a correlation as proved by the extracted points of mistakes, but also to estimate the actual mean value based on the statistical principle.

Whatever, the load varied not only by time but also with the place or person because the end users are continuously increased day by day, and consequently, the load may be changed. The original data may illustrate that performance while the skewness factor is approached to be a normal distribution. This means that the characteristics of a certain day are stable while the overall performance is widely changing. The statistical study leads to a new correlation due to the unused energy in the network despite the company reserve it for them. So, the unused energy must be shared with customers in the process of accounting. Thus, the allowable energy to be generated will be included through the energy too inside the term of running cost while its installed value is computed with the capital cost. This can balance the process of costing for the energy consumption.

Similarly, the second group is inserted for the calculations of the Mean Value for the second group as a summation for all 7 consumers and the deduced values are drawn in Figure 4. The couple of cases are given together on the same graph while the Mean Value is given per month (not yearly).

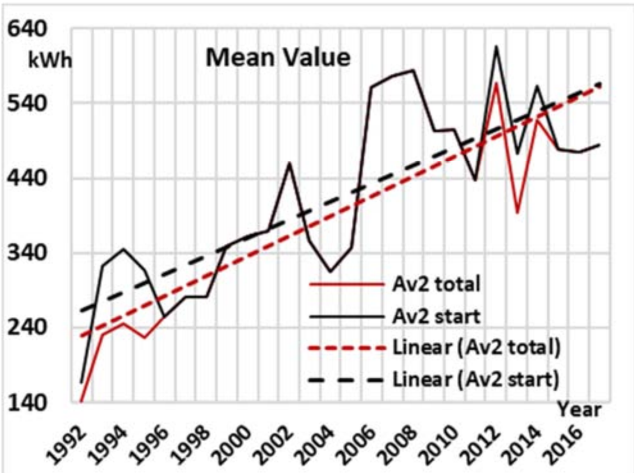

Figure 4. The Mean Value for the 2nd group.

The present model represents the north part of Cairo (Capital of Egypt) because the original data are real. The reason for reality is based on the Electric Distribution Company of North Cairo since the company gave the data officially for 15 consumers, representing the consumers of the company, as a model for all the area. The data had the variety in loading, or in other words, the energy consumption where all data are monthly readings continuously without any break or stop. The selected sample for consumers can be considered as perfect and ready for analysis where the original data may be given as shown in Figure A1 in the Appendix. These data of Electric Distribution North Cairo Co. Readings for the ideal 15 Samples (Jan 1992–Jan 2018) are transformed from the Table style into a Figure because the Table will be impractical vision [17].

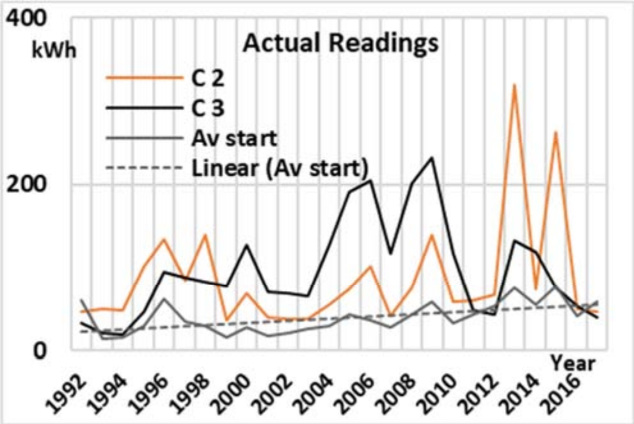

Figure 5. Occupied Houses Readings.

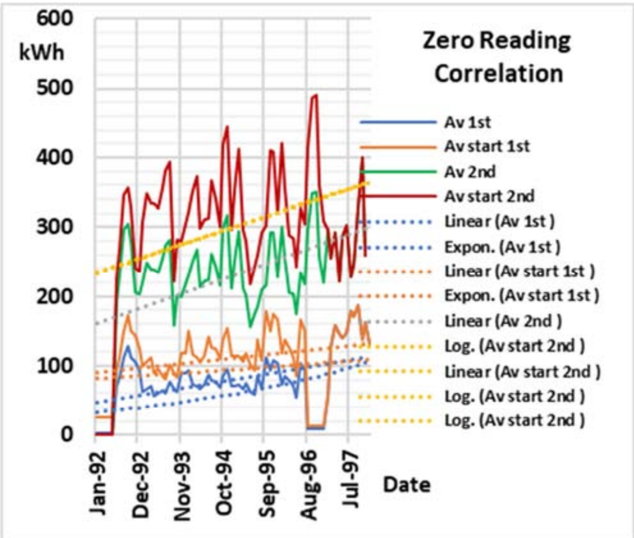

Figure 6. Starting zero Correlation for model.

It is very important to generate and explore *ex-post* distribution-based descriptive statistics and time series analyses for short-interval residential data to compare how they characterize the multiscale dynamics of occupied houses. The social and technological variables driving building dynamics would result in time series data that are distributed non-normally and exhibit complex, nonlinear, fractal signatures [17, 18]. However, the accurate calculations may be required to compensate the variation in readings as a real estate for the characteristics of the load curves or energy curves although the statistical parameters and factors may present accurate vision and very close results. This fact is important for the forecasting determination of the future required for the demand of a network. Then, the details of the computed Mean Value for the groups could be the way to good planning and design for the system under study if the aim is planning for the new power stations.

Figure 5 gives the results of computations for the actual readings for the first group Mean Value, but for clear illustration two of the highest power consumers are added with the curves deduced. The occupied house condition is inserted and the results for consumers 2 and 3 are drawn in Figure 5, too. However, the energy characteristics for the first and second groups are estimated for the case of the multi-reading (av_1 & av_2) for both groups while the second case of actual occupied house ($Av1_{start}$ and $av2_{start}$) is inserted. The results are drawn in Figure 6 where they explain the transients' condition of the model.

6. Energy Limits

It should be mentioned that; discrete empirical interpolation is a domain reduction approach used for reducing the high dimensional ordinary differential equation into lower dimensional. In visual optimization method, the domain reduction is done in two steps, i.e., visualization of optimization problem and search space reduction. Visualization of optimization problem offers a good estimation for getting the optimal results while the search space reduction reduces the complexity of the optimization problem. Adaptive dynamic domain reduction method is used to solve and reduce the dynamic domain problem [18]. Sequentially, residential Buildings divided into two groups depending on several floors: low-rise and high-rise. Low-rise residential buildings mean that the number of floors is less than three while buildings with more than four floors are considered as high-rise, according to standards. So, building energy models of these high-rise residential buildings have been limited to be specialized as a dwelling [4].

Statistical models, despite using actual energy consumption, are inflexible to provide accurate estimation for developing refurbishment policy in macro-scale as well as evaluating refurbishment strategies in micro-scale. It is because the statistical models only consider the selected parameters, not the uncertainties and unselected parameters. The first has been made on the premise that building occupants living in different units have unified building controls (heating and cooling systems). Then, the energy model mostly ascribed variation in energy consumption to the physical conditions of building envelope.

Therefore, it became radically simplified by only considering the physical conditions of building envelope exposed to the outside disregarding internal details. Alternatively, it can build a model with only several representative units that are in adverse physical conditions for efficiency in the building.

Human interaction controlling energy systems mostly took the standardized case although it is difficult to clarify [4].

6.1. Maximum Value

However, the averaged heating energy consumption of whole building has a limited interpretation to represent the wide range of heating energy use in apartment units with different locations from 96 to 171kWh/m^2/year. It was found that apartment units on lower floors need either higher set-point temperatures or longer heating hours than the probable heating control in the building-scale [4].

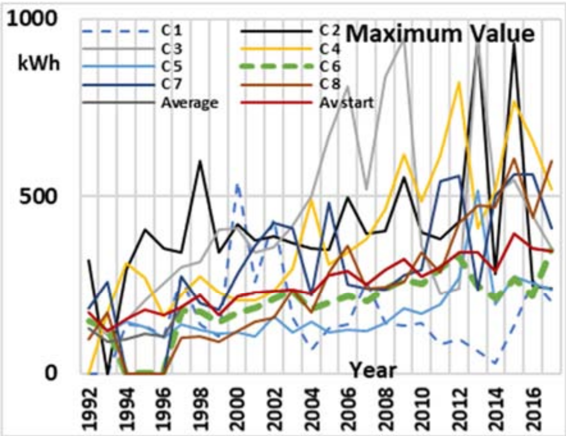

Figure 7. The maximum readings annually.

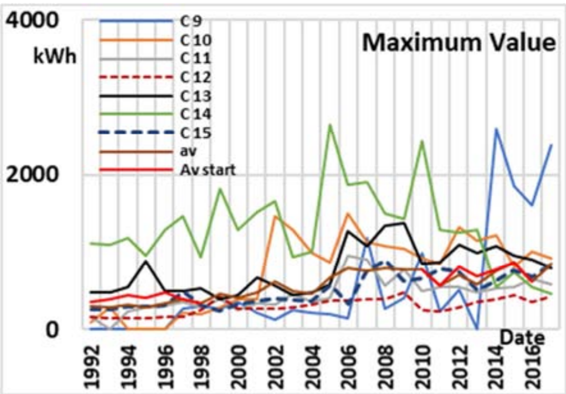

Figure 8. Maximum Value for consumers 2nd group.

The maximum month reading is computed annually, while the results are given in Figure 7 for consumers in the first group. The average (Mean Value) for readings of the group at the two cases (Multi-month reading and the occupied house condition) is evaluated and the results are added to Figure 7, too. Similarly, the second group is subjected to the same calculations of maximum month within each year and the results are shown in Figure 8 for both cases, too. Figure 9 shows the annual Sum Performance for all consumers per year reading in the two groups (first and second) where the maximum reading for each consumer is detected and drawn in Figure 9.

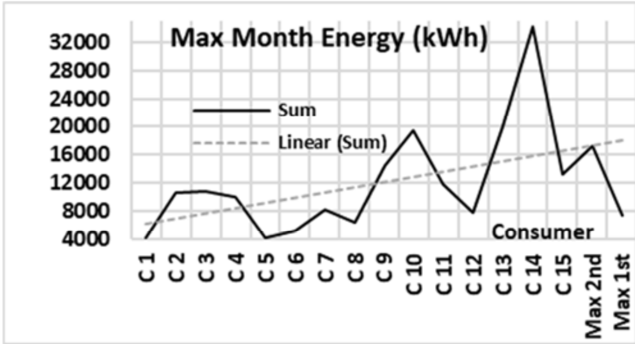

Figure 9. The annual Sum Performance.

Thus, a deep analysis for the maximum value would be implemented in the work if a good conclusion is desired. Then, the maximum value within the 26 year is estimated as given in Figure 10 but two higher consumers are added to clarify the goal of calculations.

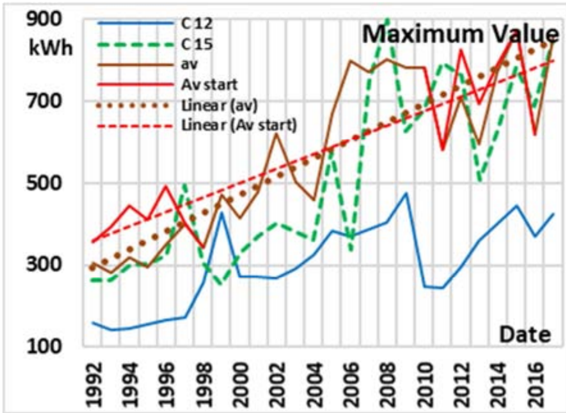

Figure 10. Maximum Value trend.

6.2. Minimum Value

Unlike the regression model, time series analysis considers future power load as a function of previous load. They consist of a multiplicative autoregressive model, an autoregressive integrated moving average, & an autoregressive moving average with exogenous input model. It is effective in short-time load prediction, its requirement for the accuracy of historical data is extremely high, and the algorithm may be complex and unstable in some nonlinear or non-stationary cases. Further, when involving meteorological factors, time series analyses are unable to deal with the inaccuracy problems [8].

The minimum value as a limit value appears to be important for the technical point of view although it is needed for the complete characteristics of the phenomenon studied. Then, the minimum value details for all consumers is determined in both groups but only the results of the second groups (for shortly explanation) have been given in Figure A5 in the Appendix. Figure A5 proves the great variety between consumers due to the different in life as well as the traditional society. Theoretically, the minimum value is one of the limit points in the statistical analysis and it confirm the minimum requirement for the item studied. If the minimum value is very small, the margin of investigation will be wide spread and vice versa. Therefore, the average characteristics for the minimum value is deduced for the consumers in the investigated model while both cases of multi-readings and the actual occupied house are accounted for all consumers in the first group as shown in Figure 11.

Sequentially, the second group is introduced for the minimum value computations and the results are drawn in Figure 12. In recent years, China's national economy has developed rapidly, with a high daily electricity consumption whose peak appears during the daytime, especially in summer. Large companies, shopping malls, office buildings, and other buildings need air-conditioning systems to adjust the temperature [8].

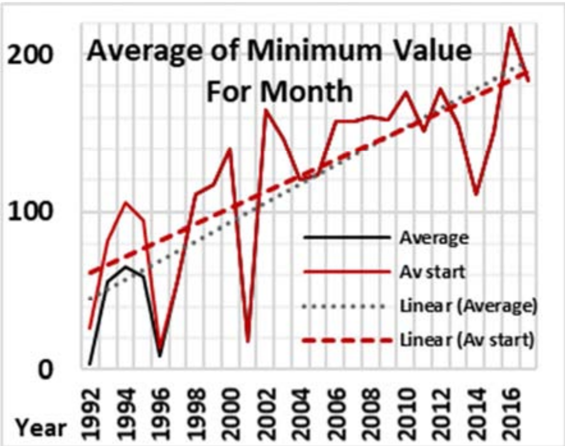

Figure 11. Minimum readings 1st Group.

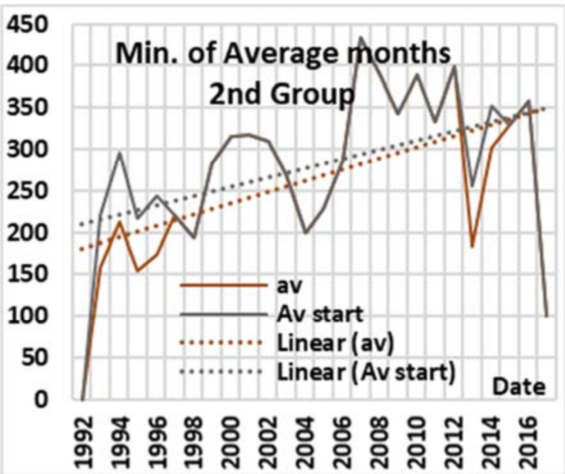

Figure 12. Minimum readings 2nd group.

6.3. Limits Analysis

It is defined that; energy management reflects the quantified data of energy conservation and plays an important role in emission reduction. Meanwhile, it contributes to applying the energy data as a management tool and means for accurate diagnosis and analysis and promotes the utilization of construction energy, resulting in energy savings in office buildings. As one of the indispensable developments in social energy, electricity is considered of great significance to the economy [8].

The overall vision for the limits of the energy consumption in the domestic sector can be deduced easily where both limits for each group may be evaluated, individually. The first group consequences are determined as drawn in Figure 13, which presents the annual reading for the first group totally, but all statistical parameters are shown.

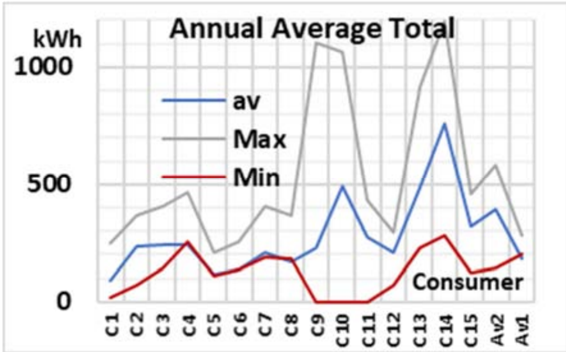

Figure 13. Limits characteristics total Annual.

Both maximum and minimum values as well as the Mean Value of the group are appeared in the right place of distribution while the Mean value is located not in the middle, but it is close to the maximum value. The reason is that the timing of appearance of the maximum value for a month within the year differs from that timing of the minimum although the presence of zero readings are shown in the results. Otherwise, the zero readings should be subjected to the modification as well as to the condition of occupied house pattern. The general performance of the Mean Value takes the same of Maximum value although it differs a little from the minimum value variation.

It should be stated that, the curves of yearly energy consumption in Figure 13 are corresponding to the model as total where each consumer values are pointed on the graph for the three values. Otherwise the cases of total first and second groups are illustrated at the end of Figure 13 while the consumers have a high diversity factor for either minimum or maximum values and consequentially for the average energy. Whoever, the monthly readings can be estimated to go to Figure 14 where the same performance, of Figure 13, as results output is shown in Figure 14.

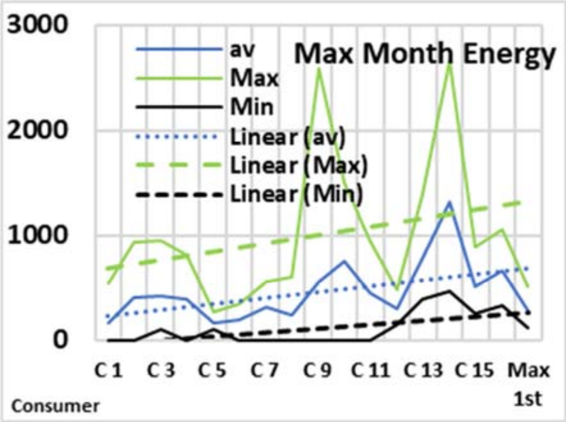

Figure 14. Monthly Limits of Average for the model.

Figure 14 summaries all above details for the limit performance of the studied model where the highest comer of energy is still consumer 14 with a maximum of 2653kWh/month, minimum of 472kWh/month and Mean Value of 1318.9423kWh/month. Contrary, the lowest consumer consumption is the consumer 1 with the maximum of 542kWh/month, minimum of 0kWh/month and Mean Value of 160.4135kWh/month. It is remarked that, the minimum of the consumer 14 is greater than the maximum of consumer 1 while the consumer 1 has the zero energy readings.

Many recent publications present a variety of algorithms for appliance-level demand response. In most studies, appliance power consumption is constant at its rated power without any cycling or variation during its operation. The main reason underlying the flat appliance power consumption assumption is the lack of knowledge about detailed appliance operating characteristics, and most importantly the lack of publicly available measurement data. Variation in appliance power consumption is an intrinsic characteristic of most major household appliances. Using realistic load profile so find individual appliances for such studies will lead to more accurate research findings and analyses. To date, there are only a few comprehensive sources of energy use data at the household level [12].

However, most data available in the library are for low-wattage appliances, such as gas-based clothes dryers, fans, and light bulbs. In addition, the data are of varying time intervals (1-s, 1-min, 5-min, etc.) obtained from different individuals using assorted measuring devices, which may not be calibrated to provide consistent results. This inconsistency prevents the use of this data from analyzing Drop port unities of different appliances [12].

However, the characteristics of the consumers in the model are tested for the limit analysis individually as presented in Figure A6 in the Appendix. Figure A6 indicates a high energy consumption for the consumer 9 with unordinary rise in the performance relative to others so that it may be subjected for more study. Therefore, deep investigation must be developed for the amplification of the meaning of results of calculations where the limit analysis is presented in Figure 15 for highest consumer in the second group. Since consumer 9 is the target (highest Maximum Consumption), Figure 15 gives the results of maximum, minimum and the Mean Values.

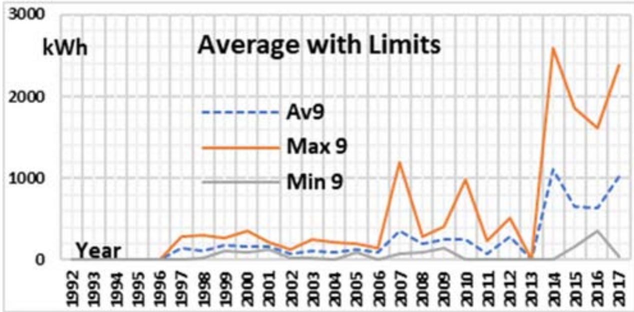

Figure 15. The limits for consumer 9.

Consequentially, the groups characteristics would be introduced, and the corresponding results are drawn in Figure 16. The three limit values are given for the second group for both cases of modification, individually. Then, the model characteristics have been added as shown in Figure 16.

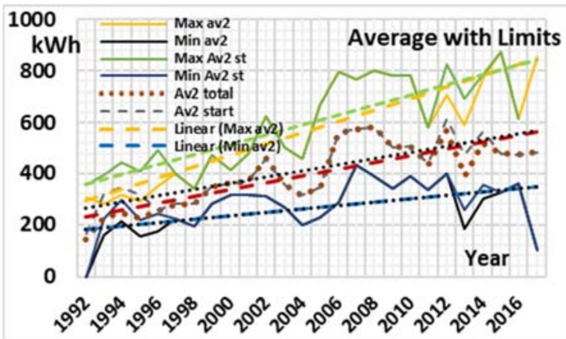

Figure 16. Overall characteristics for second group.

7. Dispersion Factors

Nowadays, the energy consumption of high-rise buildings in the heating-cooling process is much higher than the global average, which makes it urgent to strengthen energy management for office buildings and promote the rational and efficient utilization of energy [8]. At present, one-third of total societal energy consumption goes to buildings in the developed world. Though the amount is less than in these developed countries, the proportion of energy consumption in Chinese buildings has increased in recent years due to the rapid development of the construction market. It is forecasted that the number of large public buildings in China (e.g., offices, apartments, restaurants, convention centers, and others) will rise dramatically in the next few years, and China will add an area of about 1 billion square meters of large public buildings by 2020 [8].

The current research is pointing to the importance of domestic energy in the future and so, the forecasting concept related to the energy consumption in mega cities is an interesting item for investigation. Thus, the domestic energy consumption in Cairo takes the priority for analysis and investigation. The present paper studies the domestic energy consumption in circle of required points to investigate in a micro scale, but for Cairo as a mega city. Other sectors of energy consumption are important too although the work here is concentrated on the domestic [1].

7.1. Standard Deviation

The massive apartment constructions brought about the radical changes in the urban form of the city, Seoul. With these descriptions, building energy models regarding physical characteristics of the many typical buildings can be somewhat useful enough to have rough estimations for these similar-shape residential buildings. However, it would not be accurate enough to be used for actual implementation, especially for existing buildings that necessarily need a calibration process of building energy models [4].

The scattering values around the mean value notify the shape of data distribution along the studied period where the origin of data is expressed as the mean value. Then, a second factor is required to represent the scattering style within the period while it is the key factor for study. This second factor may be defined as the variance S^2 (one of the dispersion factors) while this factor generates the actual needed factor as the standard deviation S. The standard deviation S for populations N would be formulated by:

$$S = \left\{\sqrt{\sum(X_i - X)^2}\right\} / \mathrm{N}, (\mathrm{I} = 1, \dots, \mathrm{N}) \qquad (4)$$

Secondly, the sampling style can be used as an appropriate tool for the statistical evaluation where we can divide the samples into n samples. The standard deviation of samples leads to the principal factor for the sampling method while the mean value of the samples would be known as**.** Also, the formula of standard deviation σ is defined mathematically as:

$$\sigma = \left\{\sqrt{\sum(X_i - \mu)^2}\right\} / \mathrm{n}, (\mathrm{I} = 1, \dots, \mathrm{n}) \qquad (5)$$

Smart grid components as smart home and battery energy management, penetration of renewable energy systems and demand response activities, require accurate electricity demand forecasts for the successful operation of electricity distribution networks. The analyzed stock of 14 households from the state of New South Wales, Australia, with at least a year worth of 5 min. resolution data. Finally, it is shown that the load profile of some households varies significantly across different days; as a result, providing a single model for the entire period may result in limited performance [19].

The standard deviation of the first group is examined for individual consumers as well as average the group for both cases of modification and the details of estimations are presented in Figure A7 where all characteristics are illustrated in detail. The history of standard deviation for both cases of modification in the model is illustrated as presented in Figure 17.

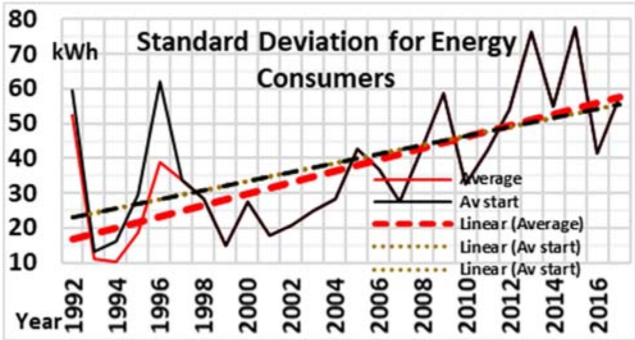

Figure 17. The calculated average readings.

Consequentially, the consumers individually have been studied in the same margin and the standard deviation for all consumers is deduced as shown in Figure 18. The single curve of Figure 18 represents the individual consumers and the two groups of the model where the calculation of standard deviation is corresponding to the mean values of energy for each consumer and the two groups. It is remarked high values can be concerned to the annual readings consideration while the smaller referred to the monthly readings. Thus, Figure 17 presents the standard deviation for average month readings where consumer 9 has elevated level relative to all others. It should be cited that; the occupied houses are considered in the mathematical processing (1992-2018).

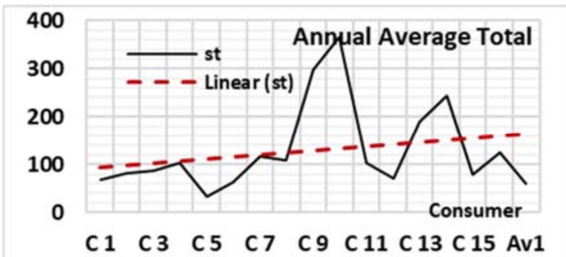

Figure 18. Standard Deviation of Average monthly.

It is important to state generally that, there are readings of zero value so that the total maximum value for the annual reading can be elevated highly. So, the standard deviation goes very high. The maximum values of energy consumption for all consumers, with the consideration of occupied houses, are introduced for the derivation of standard deviation and the deduced results are given in Figure 19.

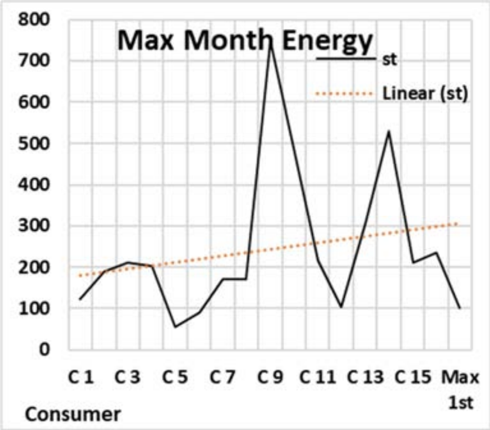

Figure 19. Standard Deviation for maximum month.

Since the second group has the elevated values of energy consumption, the standard deviation for its consumers may be necessary for analysis. So, the calculation results of standard deviation for the consumers of the second group are accounted where the standard deviation for the average of the group is treated for both the modified (Av) and the occupied houses (Av start) is determined as shown in Figure 20.

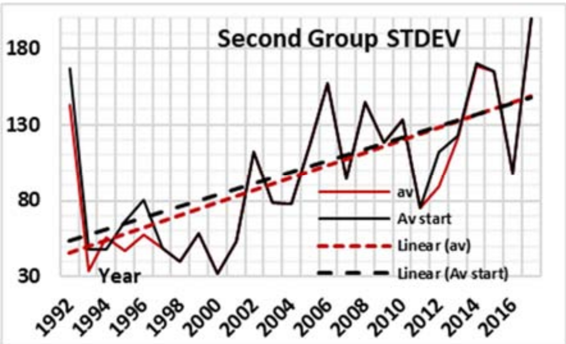

Figure 20. The second group (Standard /deviation).

7.2. Rise Rate of Energy Consumption

Regarding to building utility consumption trends, one might ask what descriptors best characterize the data (e.g., mean, variance, skewness, kurtosis) and aggregate scale (e.g., a year, a month, a week, a day, an hour). A statistical model of building performance which presume (or transform utility data into) distribution normality potentially must be flawed. The dynamics of an occupied house, when viewed as a complex, social-technological system, are such that there are no suitable Gaussian-based statistics and no single characteristic scale to describe the distribution of the energy consumption data over time [3].

Electricity generation requires the development of annual, monthly, daily, and even hourly power system generation planning. Generation ability satisfies most needs for power in cities, but managers are more concerned with fluctuations. In the grid, it is important to design the power capacity of transmission lines, devices, and load fluctuation makes capacity design more complex and equipment more expensive with “redundant” performance, but rate of return on investment is less [8].

In the power market, the load of a single building may have little effect on the power grid but considering the process of Chinese urbanization and its countless buildings in cities, multiple load fluctuations at the same time will threaten the security of the energy supply. Regarding electricity market reform in China, both the amount and the volatility of the power load are essential and of great value to formulate a suitable energy supply strategy and reduce the running cost of buildings [8].

The mathematical analysis for the rate of rise of the energy consumption RREC may be implemented into two parts such as the monthly rise and the yearly rise where the mathematical formula is expressed as:

$$RREC_i = (R_i - R_{i-1}) / R_i \qquad (6)$$

The first part of this equation can be defined as the difference between the two subsequent readings is evaluated and the results of estimation are drawn in Figure 14 because the variation steps may be valuable. The results are illustrated for both groups. Then, the high fluctuation in the oscillation values for the cycle of variation forced to the calculations of summation of difference in each cycle and each half cycle where the characterizing statistical parameters are listed in Table 1.

Table 1. Details of RREC (Difference & Percentage).

Date	Sum Part Difference	Sum Part %
Sum	780	-78
Av	5.693431	-0.56934
Max	371	144
Min	-333	-133.4
STDEV	116.45	37.85

Otherwise, the variation of cycle length is expressed in Figure 21 while the nonconstant semi-cycle is remarked. The direction of variations may be illustrated through Figure 22 although the variation has high response as shown in Figure 22.

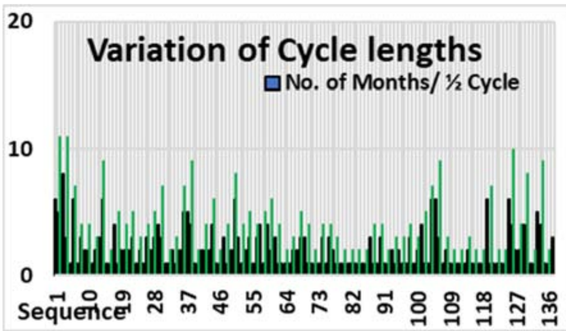

Figure 21. The cycle length per cycle and ½ cycle.

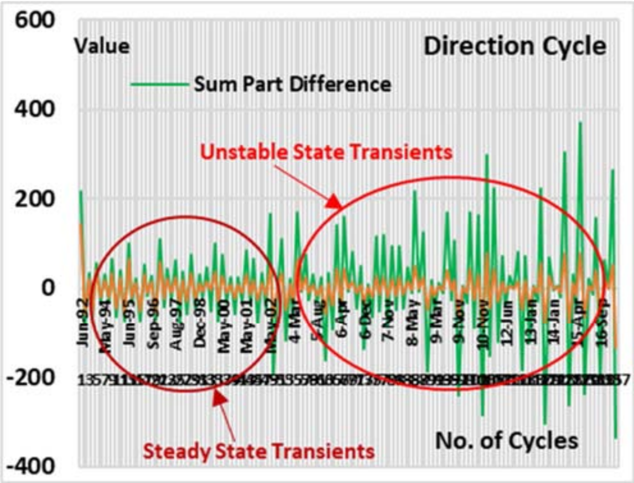

Figure 22. No. of Variations.

7.3. Transients Analysis

Recently, the increment of distributed electricity generation based on renewable energy sources and improvement of communication technologies have caused the development of next-generation power grids known as smart grids. The information on power consumption and load profiles of home appliances is essential to perform load management in the dwelling accurately. Although results do not completely reflect the energy consumption behaviour of people who live in this region, they can reveal the trends in load demands based on a real sample and customer consumption behaviour of typical readings [20].

Referring to Figure 22, the remarked fluctuations in the graph have two types where each of them means a defined performance for the case. So, the first type is that at the beginning of the curve in Figure 22 while the second type is the next time with elevated values of vibrations. Then, the first case is defined as the steady state transients according to the actual results drawn in Figure 22, but the second case is known as the unbalanced state transients. Both types of transients mean the non-steady state studied and so, more explanation may be required. If the system is stable, transients will be referred to the steady state transients. Contrary, if the system is unstable, the deduced position will be the unstable transients.

It is needed to find the reasons for the steeply rate of variation in the use of home appliances if the development and rationalization of energy utilization is aimed. This may include also the wiring, piping, gas installation, decoration, water cycle system and others because the style of life and community base, in most developing countries, deals with these subjects in discrete type of work and the consumption of energy would be sharply varied. These works indicate the unstable energy consumption, but later the family live in a stable system and the energy consumption becomes stable [1]. Whatever, the oscillation at beginning of occupied houses and end of the curves are the transients of energy consumption while the straight line represents the stable time [1]. The first beginning transients is occurred due to the community character in general or sometimes, but that transients at the end of curves may be happened because of the new appeared cost on energy consumption according to the tariff development policy. Otherwise, the average of the total energy consumption lies in a high scale relative to the others two [1].

Thus, both types are occurred within the readings of the investigated model where the first part of the curve in Figure 22 could be titled the steady state transients. Consequentially, the last part with high fluctuation may be named as the unstable transients since this condition is related to the beginning for occupied houses as well as at the end years of readings due to the vibration in the energy cost as a function of the family availability. The human behaviour within the community as well as the local traditions could be an effective factor, too.

Otherwise, the first part should be the steady state of reading although the oscillations are presented too. The reasons may be referred to the non-automatic registration for the monthly energy consumption. Thus, the period T for reading recording can be varied so that the average value is deviated from each next month/months. Additionally, the number of readings (monthly reading system) is computed (Figure 23).

Table 2. The Statistical shape of waveform frequency.

SN	Cycle length	Repeating No.	½ cycle Length	Repeating No.
1	2	19	1	66
2	3	10	2	26
3	4	16	3	21
4	5	7	4	11
5	6	2	5	4
6	7	5	6	8
7	8	2	8	1
8	9	4		
9	10	1		
10	11	2		
Sum	65	68		137

Figure 23 presents the meaning of steady state and unstable types of transients because it illustrates the non-equal oscillation period. This leads to a vital meaning that included in the characteristics of transients' phenomenon in general. Therefore, the sequence of equal values (or semi-equal) in Figure 23 indicates the steady state condition period while the violation in the sequence equality means the unstable transients. Otherwise, the period of steady state transients is illustrated in both Figure 22 and Figure 23 while the two zones for the unstable transients are indicated in Figure 24. One of the unstable transients is clear in Figure 22 but the second in very thin to be illustrated. However, the dummy (not clear) characteristics may appear in Figure 21 totally so that the performance of repeated cycles and semi-cycles are listed in Table 2 for each length.

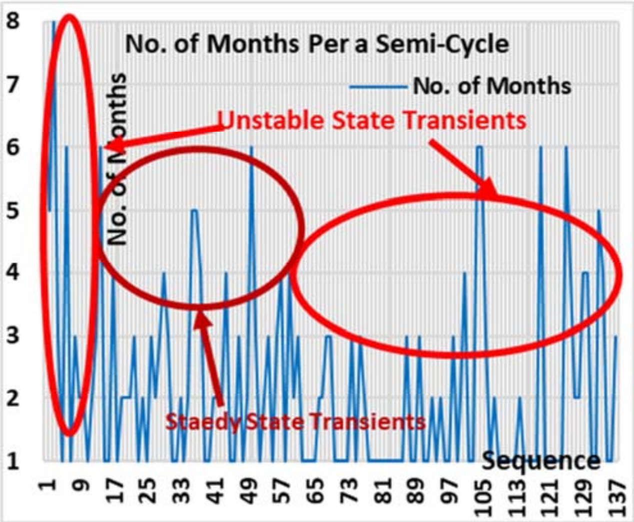

Figure 23. No. of Moths per half cycle.

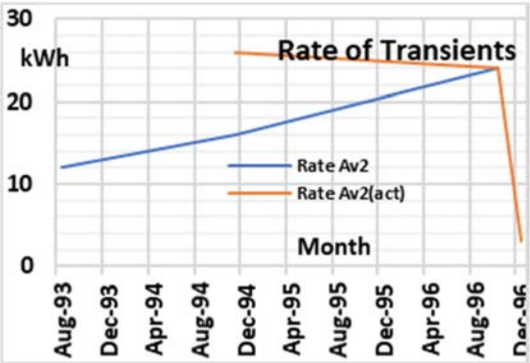

Figure 24. Energy Rate during high fluctuation.

The profit-maximizing demand response of an energy customer in the real-time electricity market would be the major aim for each company. In a real-time electricity market, the market clearing price is determined by the random deviation of actual power supply and demand from the predicted values in the day-ahead market.

An energy customer, which requires a total amount of energy over a certain period, has the flexibility of shifting its energy usage in time, and therefore is in perfect position to exploit the volatile real-time market price through demand response. The demand response strategy may lead to not only maximize the profit of the energy customer, but also alleviate the supply-demand imbalance in the power grid, and even reduces the bills of other market participants [21].

The estimated rate of energy growth for the second group of higher load characteristics is presented in Figure 24 since the occupied houses condition (Av_{2act}) gives another behaviour in this rate. The actual case of occupied houses gives the exact rate decreasing, but the initial (Rate Av_2) readings (manual recoding) is increasing. This proves the necessity for treatment of raw recorded energies. The maximum consumption in second group during the first transient time is estimated, and the results are shown in Figure 25. The false conclusion comes with the raw data (Av_2) where the exact proves lower maximum (Av_{2act}).

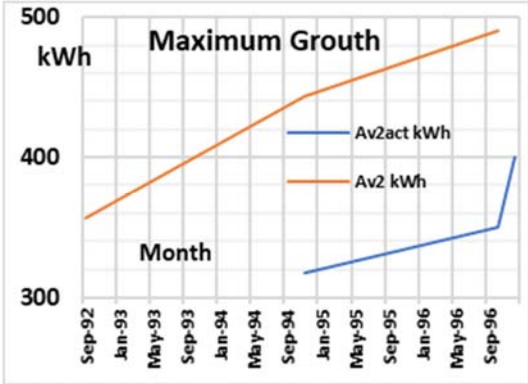

Figure 25. The evaluated maximum growth.

Figure 25 indicates the exact level of rise of maximum energy consumption (Av_{2act}) is less than the apparent one. Since the load is continuously varied, the consumed energy will not be a constant always. So, a new correlation factor may be required to adjust the performance of tariff as well as to bring the economic pricing in the right margin. Also, this process appears to be a direct reflection for the statistical type of variation, and consequently, it may be taken according to the load curves of the network either in the end locations or in the city as a whole [13, 14]. The case of end users is analysed while the next part of work considered the load curves in North Cairo City [15] as an example for the idea of correlation. This leads to the importance of statistical parameters to cover the probable values during the period of study. The major factors may be essential to represent all readings as they are tailored into the following items.

Traditional load frequency control concepts, which are suitable for large centralized power generation, are not suitable for power systems with small decentralized renewable generation units in microgrids due to the lack of large inertias. Variability and uncertainty associated with renewable energy. Disturbances usually result in voltage and frequency variations (since the desired grid frequency is maintained when the generated power matches the grid load) in microgrids [22].

7.4. Prediction

All existing research gaps are identified and future research directions around data-driven building energy consumption prediction (or another) are highlighted [2]. Buildings represent a large portion of the world's energy consumption and associated emissions while the building sector represents 39%

and 40% of the energy consumption and 38% and 36% of the emissions in U.S. and Europe, respectively. Prediction of building energy consumption is crucial for improved decision making towards reducing energy consumption and emissions, since it assists evaluating building design alternatives and building operation strategies (in terms of their energy efficiency) and improving demand and supply management [2].

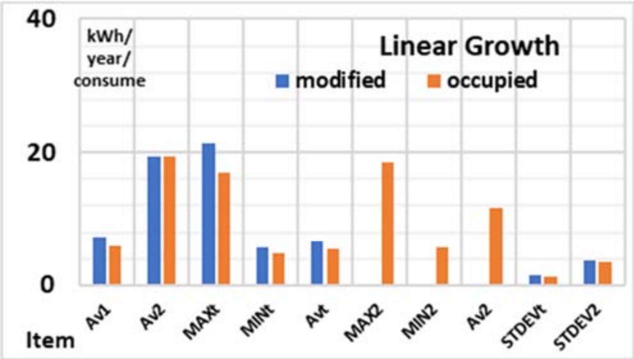

Figure 26. Linear growth (kWh/year/ consumer).

However, building energy consumption prediction remains to be a challenging task due to the variety of factors that affect the consumption such as the physical properties of building, installed equipment, outdoor weather conditions, and energy-use behaviour of occupants. Many statistical algorithms for prediction have advantages and disadvantages while an artificial concept requires many parameters and computationally expensive, but the accuracy is acceptable [2]. Although there are many types of growth estimation, only four of them may be evaluated shortly. The future vision for the level of energy consumption can be deduced easily in the present research since the period of study is long term (26 years). The aimed value generally is the energy consumption for a short and terms although the most important factor for future prediction is the peak value (Maximum) because it means the demand power of generating system. Thus, the detailed investigation can be implemented for the model in this section.

Firstly, linear principle for growth (kWh/year/consumer) is considered for the studied model where the results are illustrated in Figure 26. The estimated values in Figure 26 are different for all parameters identifying the model and its contents where the symbols 1, 2 and t mean groups 1 and 2, and the total model, respectively. Secondly, the exponential growth base is given in Figure 27. Thirdly, the static growth is calculated for the model and the results are drawn in Figure 28.

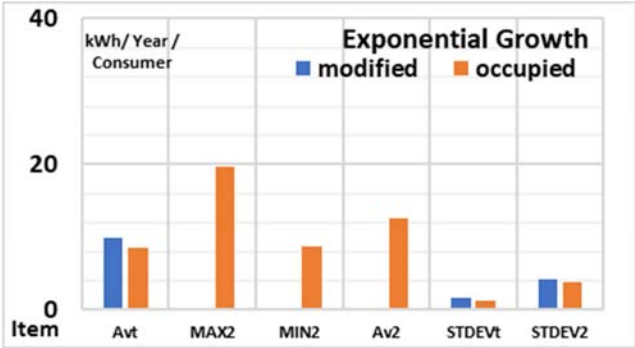

Figure 27. Energy growth (Exponential base).

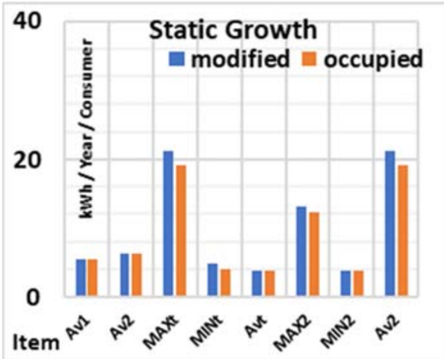

Figure 28. The computed growth statically.

Fourthly, the dynamic principle is accounted w. r. t. the maximum values of energies according to the appeared maximums during the period where Figure 29 illustrates the dynamic growth of maximum appeared. The dynamic growth rate is accounted as given in Figure 30 for the second group. Notably, clusters of comparable houses were categorically and statistically different when using descriptors based on normality (e.g., mean, variance, skewness, kurtosis) versus those based on fractality (e.g., Hurst exponent, multifractal spectrum width).

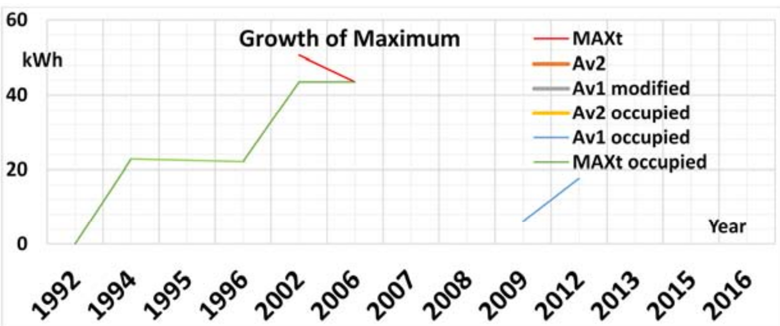

Figure 29. The evaluated growth for Maximum.

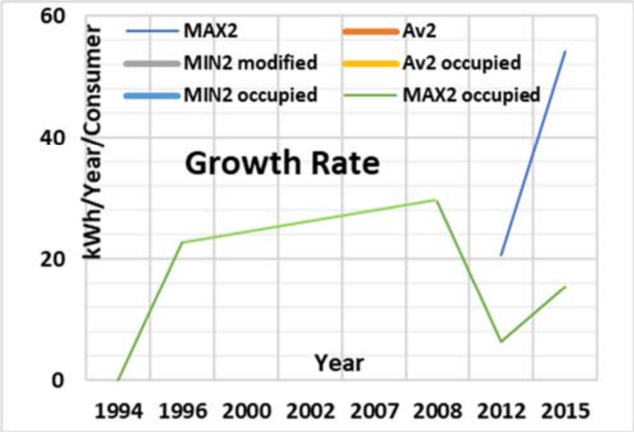

Figure 30. The dynamic growth for 2nd group.

To resolve gaps between predicted and actual building performance, more recent modelling efforts are derived as approaches. Rather than framing buildings as a simple series of compartmentalized, independent components to be optimized, these more holistic approaches try to treat buildings and their inhabitants as interdependent across their design, construction, and operational management. Exploratory data analysis descriptors, such as the sum of household electricity over some period, and classical distribution-based descriptive statistics presuming data normality, such as mean and variance, may suitably serve as tools to record the aggregated consumption of building utilities for periodic billing purposes [3, 7].

8. Conclusion

Since the raw data readings of energy consumption depend on the manual system, their correlation to the real are necessary. Therefore, two corrections (multi month readings and occupied houses style) may be done. This process doesn't change the data but transfer any distortion into right as the same readings. Thus, the original raw data must be transformed into actual because the actual readings present the real results.

However, the correlation is implemented for the domestic energy model where the results of computations for actual deduced model go to real value estimated. So, the statistical parameters identifying the studied function should be determined. The results for main parameters such as Mean Value (Average), Maximum and Minimum Values indicates the importance of purification of original raw readings from impurities.

Therefore, the main statistical factor such as Standard Deviation of the domestic energy model may be introduced where the results are analysed. Thus, the widespread factor has been remarked because the characteristics of energy consumption are variable with either time, place, person, tariff, society, etc. This indicates that samples must be applied on different load characteristics.

Moreover, prediction of future domestic energy should be based on the maximum energy growth not on the Average Value because the maximum value is corresponding to the peak value of the load curve. Thus, the prediction of maximum value growth leads us to the demand power that required to be generated in the future.

Since the society performance in Egypt within the building market characteristics has a special type, the transient's cases are appeared in the model. However, the first transient state is occurred at the starting occupation of houses where the finishing details are required and consequently the presence of energy variation in steeply form.

A great fluctuation is generated after steady state operation for a long time, but the new types of transients is floating in readings. The reason may conclude with updating process of tariff in Egypt since the unbalance in reforming the use of energy by each consumer.

Although the long term of 26 years for the consumers in the model, the middle time (steady time) has another type of transients. Then, this steady state condition of transients is studied for the model and parts while the high fluctuations appeared to say that the reason is referred to the manual recording of readings. Thus, an automation system for recording readings is recommended, especially, the modern applications in internet and communication systems and wireless facilities to maintain this implementation in the field.

If the raw readings are considered for analysis, the results will go away from the real. This is proved for the rate of maximum growth tendency where the actual proves decreasing rate, (the raw readings say opposite). Otherwise, the future growth has been analysed by (Linear, Exponential, Static and Dynamic) principles where the dynamic response may be suitable than others. Also, the linear base is simple, and readings is fair so that both concepts of Dynamic growth as well as the linear prediction can be utilized for the domestic energy consumption.

Appendix

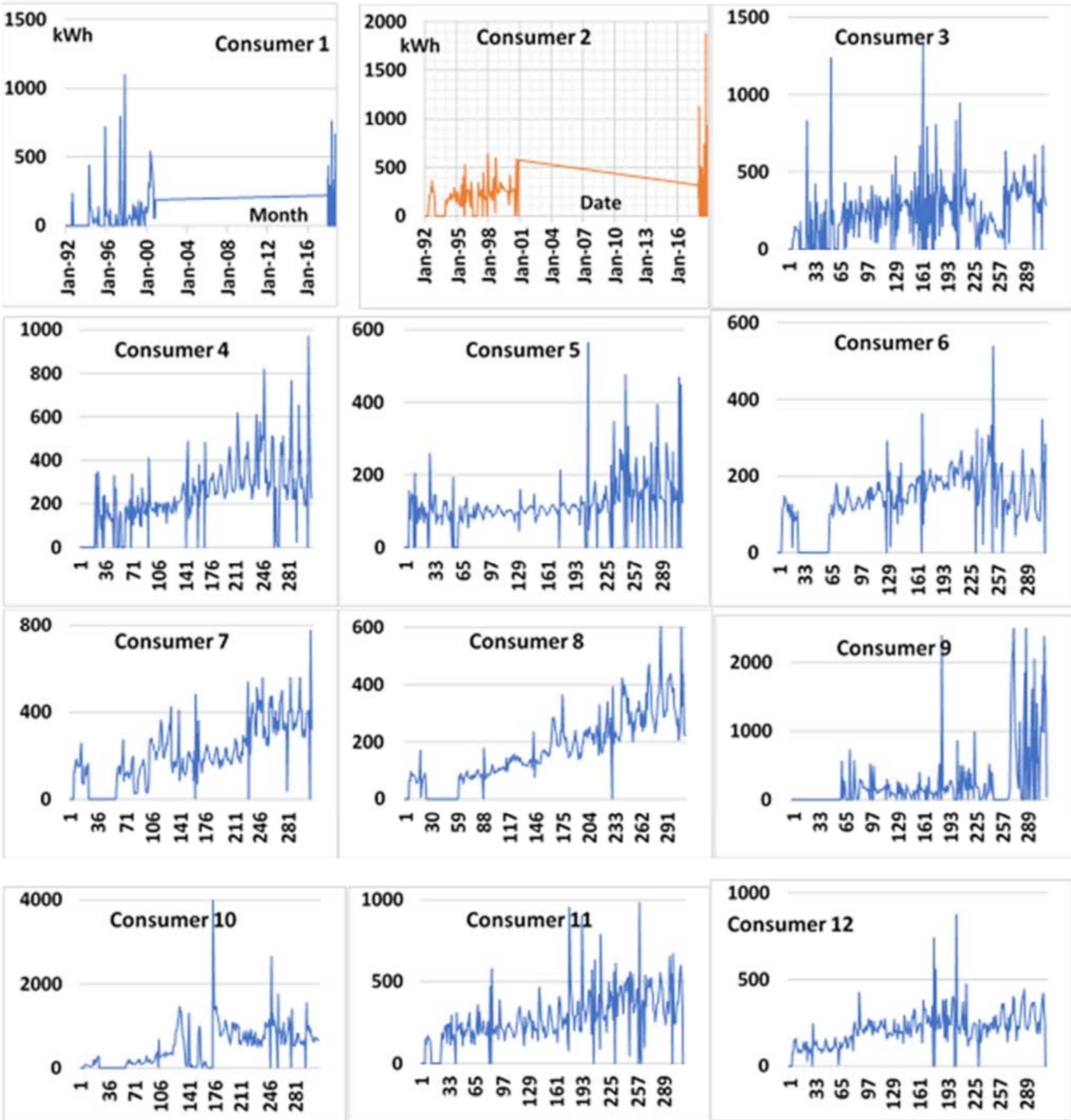

Figure A1. Readings for the original ideal model (Jan 1992–Jan 2018).

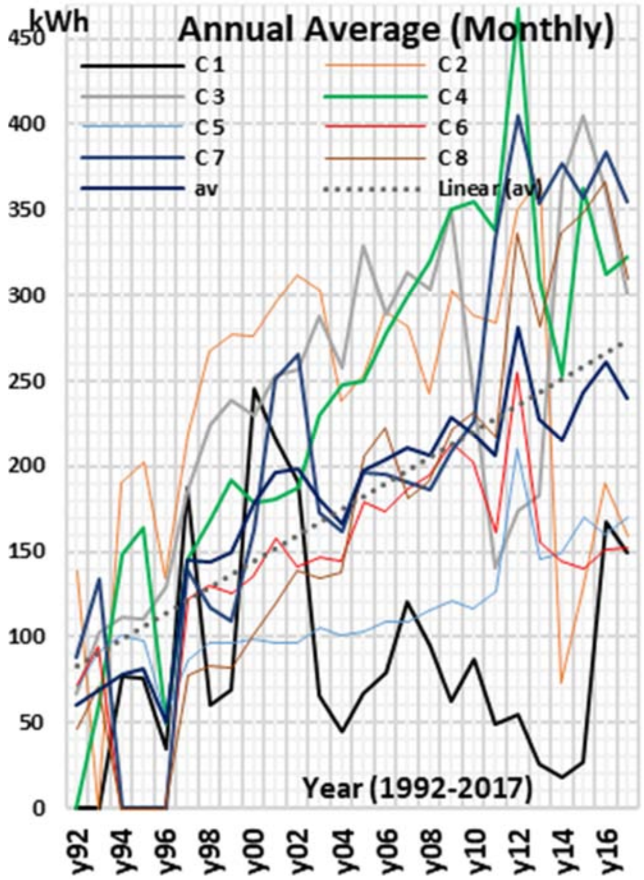

Figure A2. The mean value for original readings (1st group).

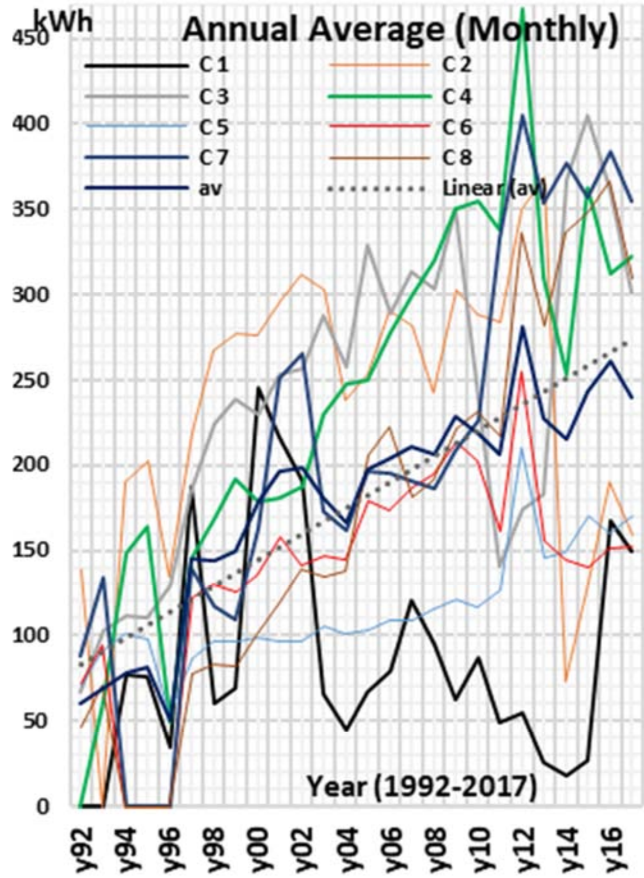

Figure A4. The mean value of annual consumption (occupied house), 1st group.

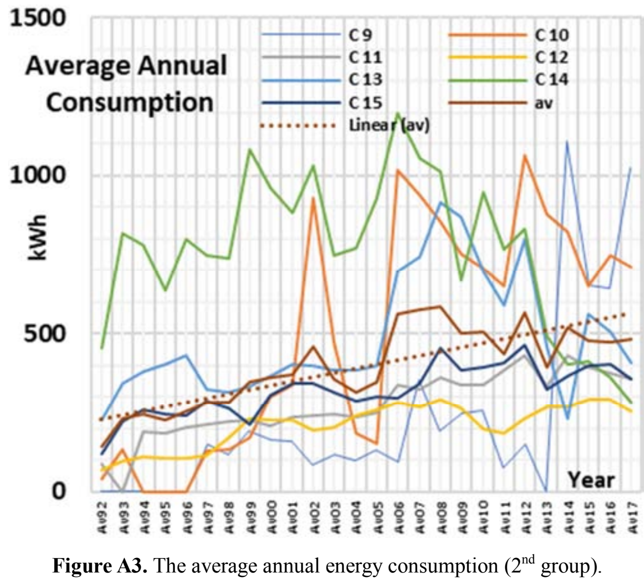

Figure A3. The average annual energy consumption (2nd group).

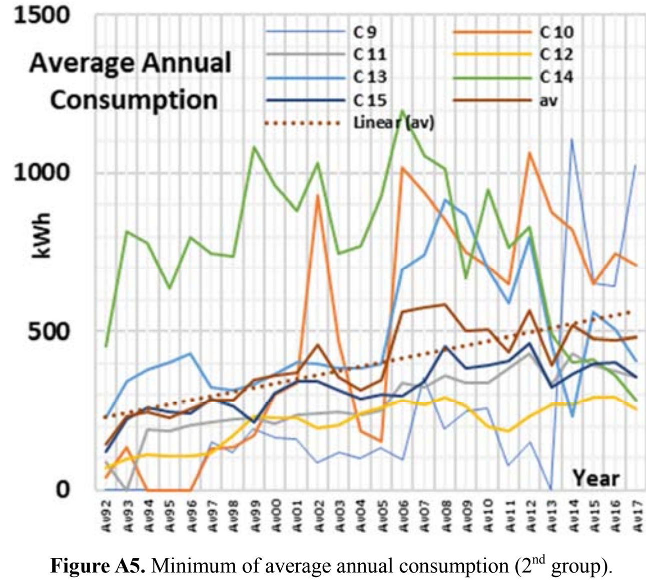

Figure A5. Minimum of average annual consumption (2nd group).

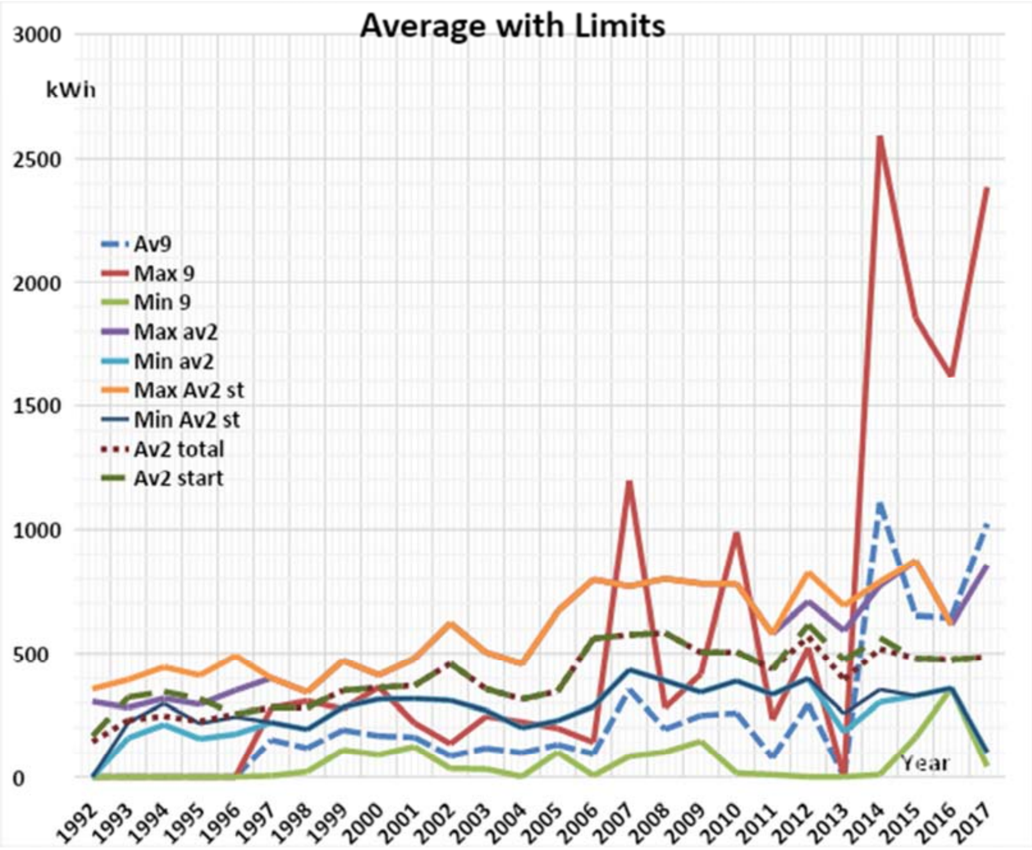

Figure A6. The performance of the model.

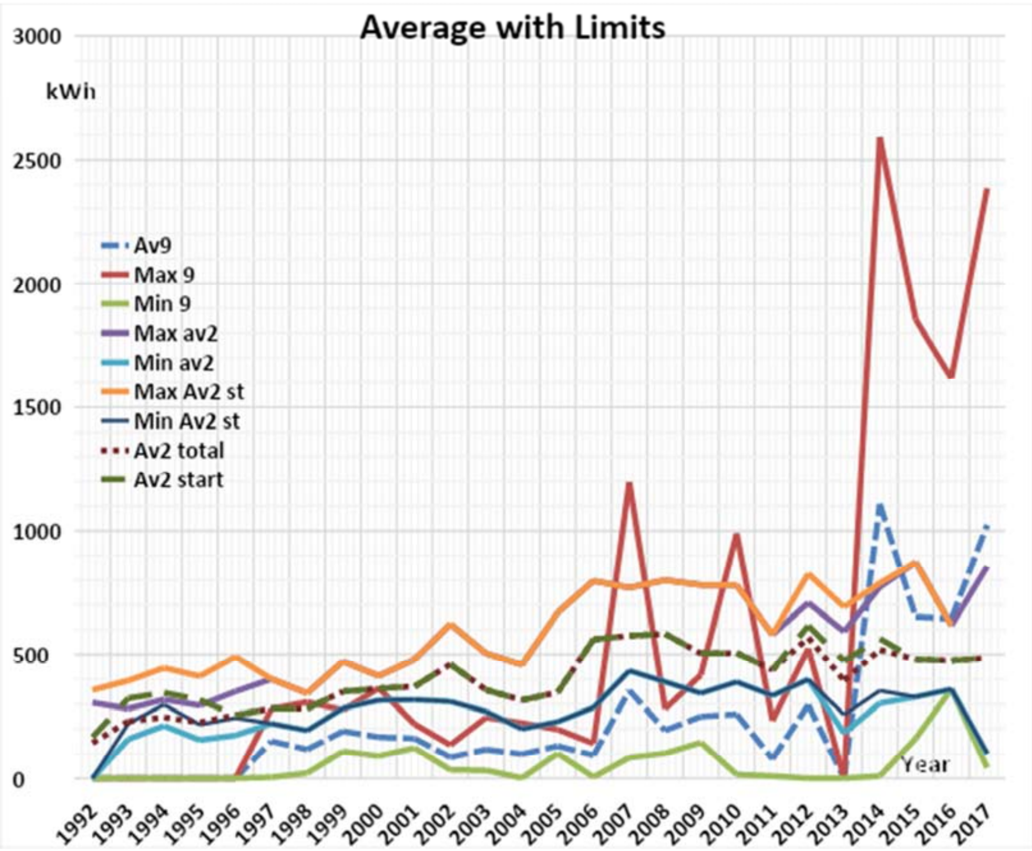

Figure A7. Original modified readings (month).

Nomenclature

Symbol	Meaning
E_t	total energy consumed
μ	mean value of samples
P_i	instant reading for the i^{th} month
X_i	reading at i^{th} month/day/hour
P_o	average month reading
f_{md}	frequency of the middle class
C	class interval of median class
$RREC_i$	Rate of Rise of Energy Consumption
L_{md}	lower boundary of middle class
P_{i-1}	recorded reading for the i^{th} month
R_i	energy reading for i^{th} (Month/Year)
kWh_i	energy for the i^{th} month
N	number of populations
n	number of samples ($n < N$)
T	month time (period)
X_w	weight load mean
X_g	grouped mean
σ	samples standard deviation
S	population standard deviation
t_i	time increase in i^{th} month
T_i	the period of i^{th} month
LS	load shedding
n_c	customers numbers in distribution network
E_i	Energy Consumption in the i^{th} (Month/Year)
W_i	reading weight of i^{th} month or day or hour
X	mean value of population measurements
F	cumulative frequency for the class before middle
D_a	difference between frequency modal and before one
D_b	frequency difference between middle class and next
$Av_{1,\,2\ start}$	Average energy occupied houses for 1^{st}, 2^{nd} groups
Av	Average energy total multi-month modified
$Av_{1,\,2}$	Average energy modified for 1^{st}, 2^{nd} groups
Av_{start}	Total Average energy occupied houses

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