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Grouping Analysis for the Energy Consumption of Domestic Loads in the Distribution Network at North Cairo Zone

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Abstract

This paper presents a statistical analysis for an ideal official model (15 customers) for electrical energy consumption in the domestic sector of Cairo, the capital of Egypt (mega city) during the last 26 years (Jan 1992-Jan 2018). The statistical dispersion parameters (Mean and Maximum Values, and standard deviation) for the populations of energy consumption are determined and analyzed. The original data of customers are grouped in diverse scale into 12 groups according to either mean value or standard deviation after the purification of original data (within two scales as multi-month reading and the occupied houses conditions). This is based on two title (mean value and standard deviation) where each of them is tailored into closed and wide range data. This creates 6 groups for each while the groups G10 and G8 are appeared for both classifications as the same. The effect of simultaneous, static and maximum values may be processed for the energy growth within the period of 26 years. Additionally, two issued groups for the same model have been inserted with the study and the relative factors have been analyzed. The created groups are investigated statistically for mean value and standard deviation so that the accurate prediction for the future electric energy consumption growth can be realized as the target of article. The given investigation determines the automatic random characteristics in the domestic demand loads of customers and then, important parameters for the studied model (grouped sampling) are deduced statistically. The growth rate of energy consumption is calculated within the period for all groups in details. The results, as a micro-scale base, approved the necessity of statistical parameters for planning problems in general. The prediction for not only energy needed but also for future power demand, which is a vigorous factor for the demand requirements of power stations in the united network, is simply extracted. The maximum value should be tested for the forecasting process as a vital item because it points to the future power demand for the power generation. The prediction for future annual loads is extracted mathematically. The proposed simple linear prediction can reach to the same results with an appropriate accuracy since the complex methods of prediction may consume both computational time and effort. The concept is easy for applications in different fields where the maximum prediction gives the value of power demand required for the united electric network. The grouping system for a lot of populations may be recommended for all similar problems because it facilitates the processing populations. The proposed grouping system can be considered for medical, industrial products, marketing products, weather, stocks, etc. to be a fundamental tool for the prediction in each field.

Keywords

Domestic, Dispersion Factors, Simultaneous Energy, Growth Rate, Prediction Performance, Statistical Grouping

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1. Introduction

Recently, the energy consumption floats on the surface in all countries because the power generation becomes a complex problem. The strategy of nations is directed today towards the renewable energy since petroleum is needed to cover future requirements. Therefore, the rationalization appears to be important not only to minimize the energy consumption but also to create new energy sources. Nowadays, this subject is a vigorous strategic item although the traditional fuel is enough till now. Either new or renewable energy has analyzed in most recent researches, but the solutions are still expensive. The improvement of energy consumptions comes from the modification of domestic appliances specifications despite the rating as a power consumption is always decreased [1, 2].

Contrary, the number of domestic appliances is highly increasing every day indicating the necessary regulations of rationalization implementation for energy. The international published per capita data for many countries may be slightly inaccurate as population data may not be for the same year of consumption data [2]. The published data for economic measurements (average energy per capita) that considered to be for the year 2016 because it depends on the populations of each country at the same time. The globally world value of energy consumption is 2,674 for 219 countries while the first rank goes to Iceland, but Egypt comes in the rank 124. The study of energy economics in Egypt is significant for macro scale national target. Whatever, energy is, now and tomorrow, the lifeblood of societies because the world's energy consumption increased rapidly due to population increase and comfort demands of people. Building energy consumption prediction is essential for energy planning, management, and conservation where models provide practical approaches to energy consumption prediction [3-6].

Thus, a suitable simple calculating method to reach the true prediction for the domestic consumption is needed. Therefore, the present investigation is a major title of energy where it represents the rationalization strategy to save energy consumption. So, the given samples of data can be treated to go away in a wider bandwidth through the grouping principle since the processing concept may determine good results. The grouping of data in different ways will create a new model for the real accurate statistical populations results if the difference is based on major factors in the study. The proposed analysis for forecasting can assist in the decision making in many countries in order to realize the optimal situation for the energy consumption.

2. Statistical Considerations

Since the huge commonly rise in energy prices, the need to control the power consumption became more important than ever. If occupied buildings are complex systems with social-technological interactions, as implied by more holistic approaches, novel concepts may be needed to improve the understanding of their dynamics [7, 8]. Thus, the analysis in this work will account an input ideal model of populations given above since all input data (*15 samples sorted in two primary groups*) are presented in Figure A1 (See the Appendix). So, the analysis becomes real although many other consumptions would be expressed in different cities or even in various countries. A mathematical formulation for the statistical investigation would be necessary so that some initial factors could be inserted. The domestic energy consumption appears as the vital today items because the rationalization of energy consumption became the principle target for human on the Glob [4, 9].

Various energy models may be inserted for determining regional or national energy supply requirements (*macro-scale*) as well as for measuring the consumption efficiency in specific housing with refurbishment strategies (*micro-scale*). For the specific purposes of macro-scale, building (*housing stock*) energy consumption models can help a decision making for refurbishment policy and regulations with the cost-benefit analysis. With micro-scale applications, models provide impacts on energy saving because of new specific materials and modern technologies. The common existing housing stock models are either statistical or engineering-based, but both were pointed out as limited due to accuracy, data collection, computational time, decision-making and flexibility. Statistical models are less flexible although more accurate than engineering-based methods sometimes, whereas engineering-based methods are more extensive with computational simulations than statistical models. With current development and aimed energy reductions, consumers try to invest in photovoltaic solar cells and electric vehicles lose interest in delivering their energy to the system level [5, 9, 10].

2.1. Mean Value

However, the energy price must be updated sequentially, according to the economic system modification so that the energy tariff in Egypt (For example) may be considered for study. Although there are many other tariff systems, the Egyptian tariff is introduced as a sample for developing countries. Otherwise, the principle of tariff has been widely investigated for a long time according to a social dependency with the official support based on the social content of society [11, 12].

Generally, the energy pricing contains two sections (*Fixed & Variable*) as a micro term of economics. It must depend on, firstly, the capital cost of stations (*Power Stations and Substations*), the connection between them (*Transmission System*) with the ends of utilization containing transformers, and boards and cables (*Distribution System*). This is expensive because of the price of lands for the networks (*Stations and Lines*). Secondly, the running cost, including both generated and consumed powers while the presented research is concentrated to investigate the part of energy consumption. The average monthly price P_{mean} in the units of L. E. for the total energy E_m may be formulated as a function of the strip instance price P_a and total energy kWh_a used in the measuring units (kWh) for the instance ($a = 1- n_c$) by:

$$P_{mean} = (1 / E_m) \times \Sigma (P_a \times kWh_a),\ a = (1- n_c) \qquad (1)$$

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 (1-9) [13]. Then, the average price will obey the expression in equation 1. All values are based on P. T. units (L. E. = 100 P. T.). This reflects the interaction between energy consumption and operating cost (Running Cost) so that the energy investigation may be a major factor for the determination of energy price. Then, evaluation of the price could be energy utilization dependent where consumers would be classified into strips.

2.2. Grouped Populations

Since the load curves and consequentially the energy curves have a wide spread style of readings, the scattered data principle may be inserted. This means that, the grouping statistical base can be accounted because the scattered populations in readings must be red well and analysed theoretically to find the final corrected results. Thus, the grouped population for the original input data must be introduced to catch the target of prediction for not only future energy but also maximum power demand of stations necessary.

It should be remarked that, data may be scattered in a wide range as in the studied case in this work and then the system of grouping will be a suitable idea for the evaluation of the given model characteristics through a lot of original samples. This principle appears to be necessary when the mean value, as a *Grouped Mean* (X_p), which defined as a function of readings frequency f and the midpoint point of each class (group) M for the number of samples n ($n < N$ where N = number of populations) as:

$$X_p = (\Sigma f M / n) = (\Sigma f M / \Sigma f) \qquad (2)$$

Clearly, this type of computations will be required, too, for the estimation of annual average load or even the monthly mean value so that a median for readings may be necessary as a function of class interval of median class C and the boundary of middle class L_m, lower frequency of the middle class f_m and the cumulative frequency for the class before middle F in the mathematical form:

$$Median = L_m + \{C\,[½\,(n) – F] / f_m\} \qquad (3)$$

The group mode as one of the most important parameters for grouped populations would be necessary to determine the general form of data distribution where it is a function of difference between frequency modal and before one D_a and frequency difference between middle class and next D_k as

$$Group\ Mode = L_m + \{C\, D_a / (D_k + D_a)\} \qquad (4)$$

2.3. Standard Deviation

This research deals with the importance of domestic energy consumption in mega cities in future where the domestic energy consumption in Cairo takes the priority for analysis. The 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 given work is concentrated in electric domestic [2]. However, some concepts would not be accurate enough to be used for actual implementation, especially for existing buildings that necessarily need a calibration process for building energy models. High-rise apartment buildings were studied, disregarding the variation of individual units with different locations and occupants where energy resolution of building was estimated. The apartment buildings have been evolved to hand over controlling energy systems to occupants [5].

Scattering values around the mean value notify the shape of data distribution along the studied period where their origin 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:

$$S = \frac{\sqrt{\Sigma[f\,M^2 - n\,X^2]}}{n-1} \qquad (5)$$

Consequently, the cumulative frequency can be accounted for the different cases of readings where their classes are determined. These cases are denoted because the factor of skewness H is required to understand the overall shape of data along the distribution axes as:

$$H = \frac{\text{mean} - \text{median}}{S} \qquad (6)$$

The peak effect on the load curve appears to be the most important item for economists and so, the statistical study for either peak or light loads may be applied as the weight load mean X_{vv} according to the reading weight of i^{th} month or day or even hour:

$$X_{vv} = \Sigma (X_i W_i) / \Sigma W_i \quad (7)$$

Secondly, the sampling style can be used as an appropriate tool for the statistical evaluation where the readings are divided into n samples. The standard deviation of samples leads to its principal value σ for sampling while the mean value would be known as μ, defined mathematically as:

$$\sigma = \frac{\sqrt{\Sigma (Xi - \mu)^2}}{(n - 1)}, (i = 1, \ldots, n) \quad (8)$$

Thus, the standard deviation for each sample would be derived while each of energy consumption and corresponding cost may be treated individually.

3. Modelling

However, the point of simulation will go to another view for the characteristics of consumption as it is presented below. The original populations of investigated model (15 customers) are given in Figure A1 of Appendix while the results (monthly and annually) for statistical parameters are mainly illustrated briefly in Figure A2 [1]. It is stated that, the results represent a summary for the effect of occupied houses consideration on the original or modified samples for multi-month readings. Otherwise, the present work takes the model for a bottomless investigation so that this paper gives more details according to the statistical attitude. The effect of annual actual energy utilization *(OCCUPIED HOUSES)* on real domestic consumption profile will be the target for the period Jan 1992 to Jan 2018. Whatever, the profound investigation can be controlled by the scientific base for grouping because the grouping for multi-group style would be a real effective model for original populations. Thus, a classification base may be tailored.

Serially, the initial data have been modified where the general characteristics are based on three categories. The published double (*1st and 2nd*) grouping for original data may be the ignition for the present work since the given paper will rearrange the model according to the results determined. Therefore, the grouping system may reach good conclusions that would be valuable and effective [1]. Original populations and their sequential modification with purification were studied, but the current article will be directed for a deep analysis [2]. This means that, the present work will classify the model based on statistical fundamentals. However, new grouping depends on results of the basic statistical parameters where both mean value and standard deviation could be accounted (*Table A1 in the Appendix*).

3.1. Grouping Base

Whatever, the statistical major parameters (*Mean Value & Standard Deviation*) lead to four types since the choice could be dependent on the original 15 consumers individually. The base will account the mean value for closed values and the wide spread range while the standard deviation is similarly inserted too. The results are listed in Table 1 where the final vision should be determined for a wide range of variety.

Table 1. The grouping according to classification.

Selection Base	Groups	Mean Value Range	STDEV Margin
Closed Mean Value	G1	83	55
	G2	31	46
	G3	44	293
	G5	72	457
Wide Mean Value	G10	530	335
	G12	206	117
Closed STDEV	G6	119	19
	G7	206	40
	G9	122	55
	G11	105	62
Wide STDEV	G4	430	457
	G8	530	335

Furthermore, the scientific rules are considered for the statistical parameters, mainly, mean value and standard deviation of 15 customers [2]. Firstly, lowest consumption is 87.3676 kWh for the customer No. 1, but the maximum is 761.97 kWh for the customer 14. Therefore, both parameters have been accounted separately where each parameter should be measured for two cases. The first case would be the close values for customers to be grouped although the second may be for far values. Thus, the grouping is done, and the results of grouping are tabulated in Table 1. The close mean value groups are G1, G2, G3 & G5 but the wide spread mean value will be G10 and G12. Similarly, for the standard deviation consideration the close value groups are G6, G7, G9 & G11 but for wide spread G4 & G8 appeared. These groups should be analyzed and discussed below.

Also, the mean value (*Average*) of energy consumption represents the fundamental mathematical and statistical factor for the spread-characteristically data however the need of analysis may be necessary for the development in future either long or short term in micro-scale. The significance of mean value is induced since the subject of energy is significant not only in a specified country but also for all on the Glob. Therefore, the average values for created groups may be accounted and analyzed because the accurate prediction for energy consumption is the target. Then, the domestic sector is representing the society activity depending on the power demand available. The mean value for the selected groups is computed and the results are drawn in Figure 1.

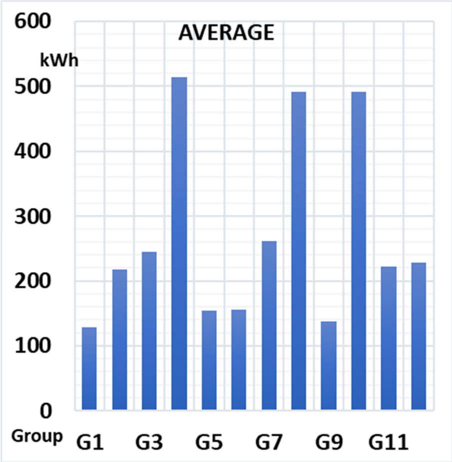

Figure 1. The mean values of groups.

There are three levels for three groups where the lowest level consists of G1, G9, G5, and G6, sequentially, corresponding to 127.8 - 154.8942 with a maximum variance range of 27.1. This indicates that, the groups are written in ascending series. Otherwise, the middle level contains G2, G11, G12, G3 and G7 within the maximum variance of (261.2-217.8 = 43.4) while the highest-level collects G10, G8 and G4 at a maximum variance of (514.8486 - 492.4087 = 22.4). These results prove that, the chosen grouping is a suitable since the maximum variance of mean value is low (not exceeding 43.4 as a maximum value) where the maximum value comes as 514.8486 with G10.

3.2. Simultaneous Value Base

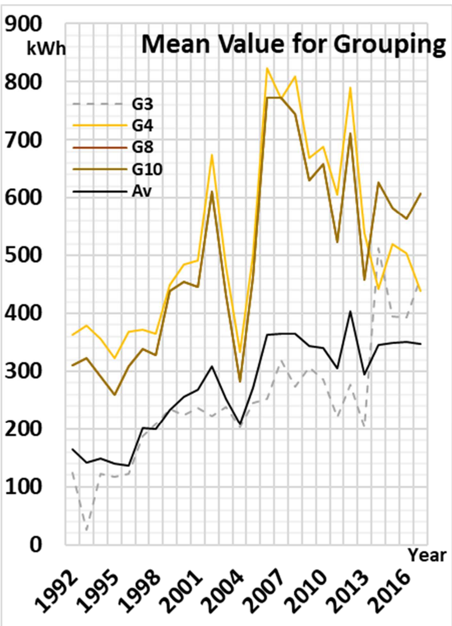

Figure 2. The mean values for biggest four groups.

However, calculations of the mean value for groups illustrate the presence of 4-groups for biggest mean values if history of the period is introduced. These mean values are varying each year as shown in Figure 2 where G3 comes in a wider margin. But G4 is the narrowest. Thereafter, the effective customer/s may be deduced as the common one between all although it may not be the cases in all conditions. The shown level in Figure 2 may be identified as groups G3, G4, G8 and G10 while the common member in groups totally or partly can be determined as C9, C10, C13 and C14.

Secondly, a middle span for the history of mean value is given in Figure 3 where 5 groups are appeared.

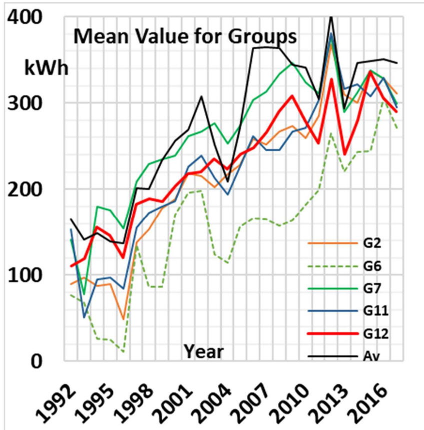

Figure 3. Mean values for middle consuming group.

These groups are practically close to each other where they are G2, G6, G7, G11 and G12 (overall mean values diverse from the history). Similarly, the shown level in Figure 4 may be identified as the groups G2, G6, G7, G11 and G12 while the almost common consumers can be extracted as C4 and C7.

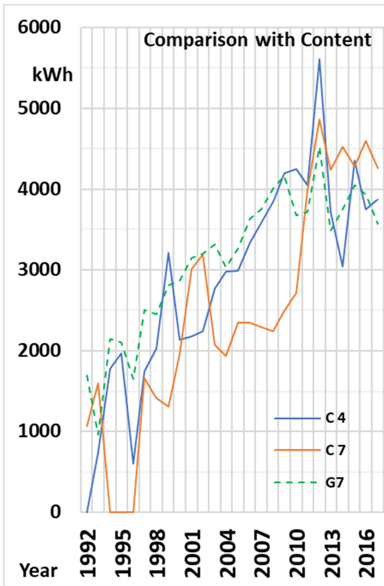

Figure 4. The comparison with the content effect.

Thirdly, the lowest groups for energy consumption are given in Figure 5 since the history illustrates similar characteristics.

Then, the shown level in Figure 5 may be identified as groups G1, G5 and G9 while the common consumer can be found as C1, C5 and C6.

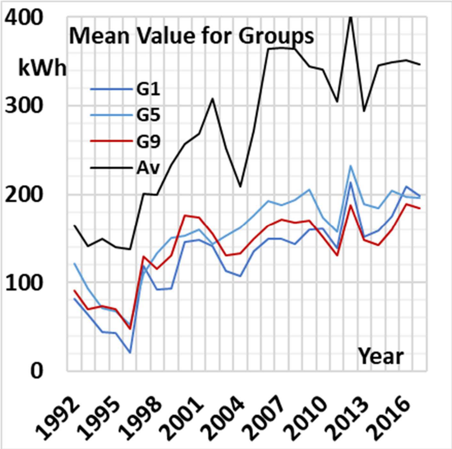

Figure 5. Mean values for lowest consuming group.

The lowest level is subjected to the effect of repeated content as above and the contented common consumers C1, C5 and C6 are introduced with the groups in the level G1, G5 and G9 (Figure 6). The shown characteristics may not be completely overlapped but the summation of C5+C6 may give this overall shape, sharply. Otherwise, the points of peaks are synchronized too with all so that it can be said that, the contents have the same characteristics of the determined groups G1, G5 and G9. On the other hand, the mean value characteristics for the selected highest groups as given above (G4, G8 and G10) are shown in Figure 1 where both groups G8 and G10 are identical despite the principle of selection is different as indicated in Table 1.

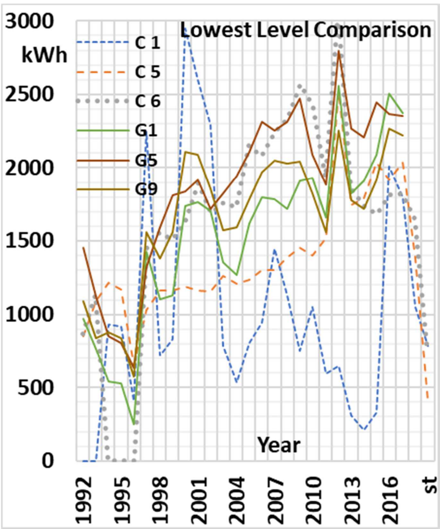

Figure 6. The illustration of divergence with content.

Essentially, small power is a substantial energy end-use in office buildings and significantly contributes to internal heat gains. Technological advancements have allowed for higher efficiency computers while current working practices are demanding more out of digital equipment. Designers often rely on benchmarks to inform predictions of small power consumption, power demand and internal gains, but alongside typical power demand profiles have been studied through two models. Prediction ranges for power demand profiles were also observed to be representative of metered data with minor exceptions. As buildings become more energy efficient, small power equipment as computers are increasing in use, but office buildings are likely to have higher cooling demands more than domestic due to the climate change, emphasizing to better IT equipment [14].

3.3. Static Value Base

The selection of closed base average (mean value) for grouping is introduced and the results are driven in Figure 7. The static base calculations have been considered in this process.

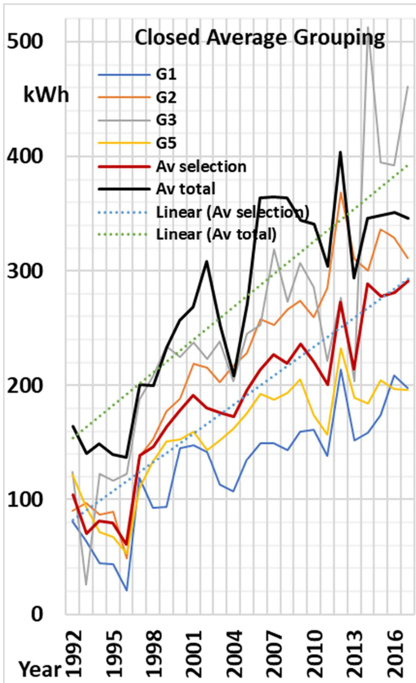

Figure 7. The closed average grouping.

The derived mean value for each group in the chosen characteristics is illustrated clearly although there are high variety sometimes. Whatever, the choice concept gives a spot-on population of high divergence like energy consumption in general while all types of consumption may take the same behavior for analysis.

Consequentially, the second type of selection at static values would be accounted as shown in Figure 8 where the average selection can be analyzed for the future prediction of energy consumption in domestic sector.

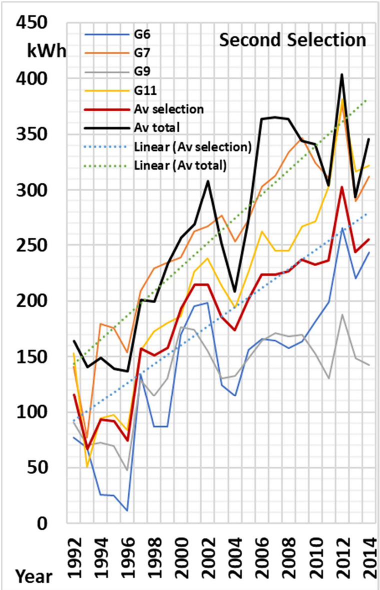

Figure 8. The Performance of the second selection.

It should be mentioned that; the community culture plays a great role in the shape of load curve (energy consumption) not only in the domestic sector but also in all other sectors (private, industrial, commercial & governmental). Thirdly, the last selection based on static values is drawn in Figure 9 although it depends on the borders of consumptions in general. The deduced performance is shown for both selections of wide spread values while the results may be introduced for discussion.

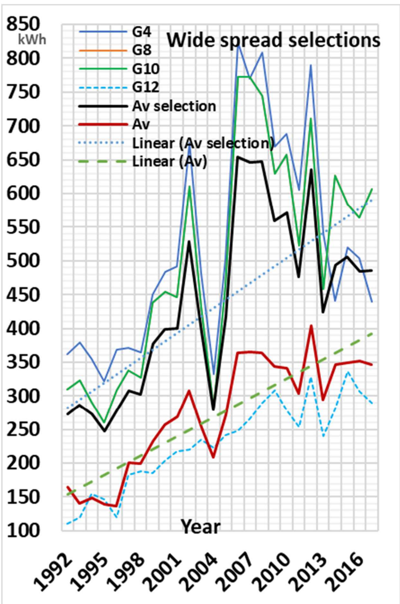

Figure 9. The performance of both selections.

3.4. Maximum Value (Peak)

Since the target is the future requirements for energy generation in a country network, the energy consumption can't give the indication needed. Therefore, the maximum value of energy consumption represents the peak load so that the maximum value may be the target. Then, the maximum value for all groups is calculated as shown in Figure 10 although the same maximum is appeared for group G10. This means that, a certain group can express the maximum value, but this is impossible for the mean value in general. The reason may be referred to big customers in the domestic sector as usually classified by companies of electricity. This rule may be changed if there are several big customers.

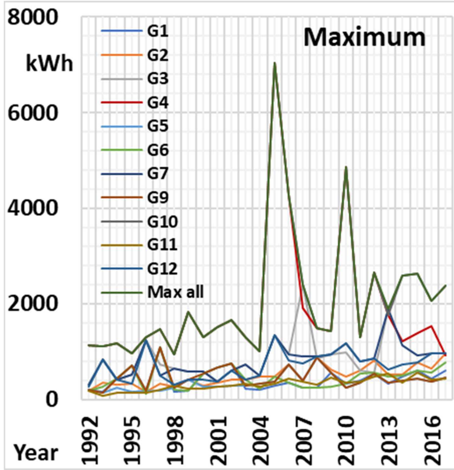

Figure 10. The deduced annual maximum of groups.

If the maximum value for a lot of data as the problem studied here needs more analysis, the maximum value in annual-scale is evaluated as shown in Figure 10 for all groups. The curves say that, the analysis of maximum value for energy consumption may be an important target for future prediction while the maximum energy expresses the peak load required for power stations in future. Thus, micro-scale for energy consumption can be defined and utilized for planning towards allocation and timing of necessary stations.

3.5. Standard Deviation

Essentially, the standard deviation factor can be used in many fields as a statistical parameter because it provides an indication of how far individual responses to a question vary or "deviate" from the mean value. It usually tells the researcher how spread out the responses are if they concentrated around the mean value or scattered far & wide [15, 16].

Therefore, the fundamental factor for the data analysis appears to be the standard deviation, which is attended with the mean value, generally. Thus, the standard deviation for the groups may be computed where the sorting or evaluation of results may be presented. Otherwise, the modification effect on raw data is estimated and the deduced results are drawn in Figure 11 since the modified data reduces the standard deviation for all groups.

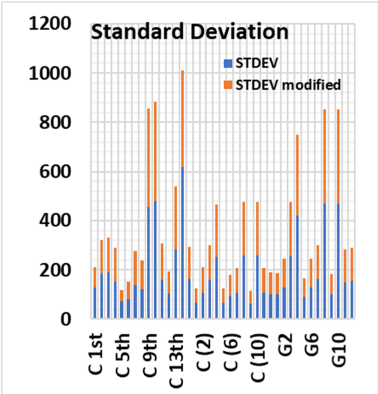

Figure 11. The values for consumers and groups.

Whatever, the data of customers are considered, and the results show no difference. The accounted standard deviation for both original customers and the created groups is introduced, and the deduced results are sketched in Figure 12. The effect of treatment of raw data is clear for the evaluated standard deviation factor per customer and group since the treatment reduces the false deflection in readings. This process is important because the readings become real.

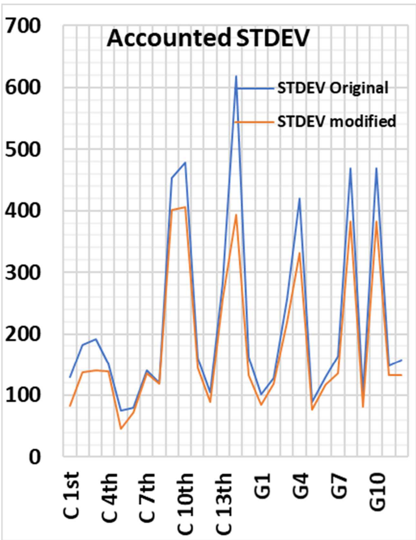

Figure 12. Deviation (σ) for groups and consumers.

The estimated standard deviation in Figure 12 is taken simultaneously as grouping for each so that the results may be closed. It is seen from Figure 12 that, the original data (without any correction or correlation) give a false vision because the rigid data can't reveal the real situation. So, the treated data give a real vision for the studied case where a modification for data in two steps (multi-month readings and occupied houses conditions) have been processed [2]. The deduced standard deviation (σ) for all consumers and created groups takes always a lower value than that for the original one (without purification) so that the readings become more concentrated with the mean value. It should be mentioned that, the same readings are indicated in Figure 11, too.

3.6. Overall Performance

However, the results of computations are listed in Table 2 for both statistical parameters (mean value and standard deviation) although the old concept for double-group model is characterized, too [2].

Table 2. Groups Classification.

Group No.	No. of Customer	AV	STDEV
First	1+2+3+4+5+6+7+8	178.4143	108.8835
Second	9+10+11+12+13+14+15	396.3387	260.6101
All	1-15	287.3765	184.7468
G1	1+5+6+8	127.803	67.372
G2	4+7+12	217.837	107.736
G3	2+3+9+11	244.68	158.581
G4	10+13+14+15	514.849	253.500
G5	5+6+12	154.229	158.581
G6	1+7+8	154.894	94.079
G7	2+3+4+11+15	261.167	108.144
G8	9+10+13+14	492.4087	257.829
G9	1+5+6+12	137.514	62.131
G10	9+10+13+14	492.4087	257.829
G11	2+7+8+11	221.4439	107.582
G12	3+4+5+15	228.173	101.784

The detailed computational results are given in Table 2 as well as the mean value and the standard deviation factors have been developed [2]. Nowadays, the energy saving has the priority importance in the world since the lack in traditional energy is acting for future. Therefore, the prediction for energy required for populations may be necessary because the domestic sector is a vital for any country. The target is saving with sampling and modeling concepts. Sequentially, the results of both factors for given groups may lead to explanation of deduced results while calculations are transferred in Figure 13.

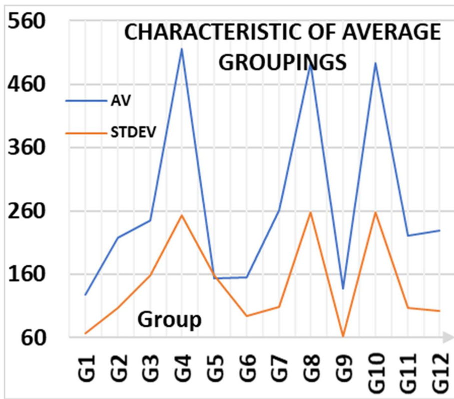

Figure 13. The overall characteristics for groups.

Similar performance for mean value and standard deviation is produced although the values are different. This is confirmed by the repeated oscillation for both since large mean values have a high standard deviation and vice versa. Thus, the maximum value will be corresponded to the highest value of standard deviation because the maximum value determines the maximum demand of a power generation.

4. Prediction Performance

The distinction between post-detection and prediction is appreciated conceptually but it is not respected in practice. Mainly, a variety of practical strategies is required to make the best possible use of preregistration in circumstances that fall short of an ideal application, such as preexisting data. Widespread adoption of preregistration will increase distinctiveness between hypothesis generation and hypothesis testing and so it improves the credibility of research findings. The real time data were taken from a street while it is possible to manage the demand and supply, planning of power grid and prediction of future energy requirement in the smart grid [17, 18].

Since the micro-scale is introduced for the planning of annual future energy consumption, the domestic sector may represent all other sectors. Then, the current analysis for the prediction of future electric energy may be repeated for gas or petroleum or any product (in marketing) consumption because the analysis is valid for the pattern of similar problems, absolutely. Therefore, the annual domestic energy consumption can be accounted to reach the goal which is appeared as the future necessary annual energy for Cairo. The principle of linear prediction may be the simplest although there are many other methods for such problem. The time dependence of social practices at specific points of the day shapes the timing of energy demand per hour.

A research paper aimed to assess how dependent energy-related social practices in the household in relation to time of a day. It analyses the 2005 UK Office for use of statistically-derived time dependence metrics for six social practice: preparing food, washing, cleaning, washing clothes, watching TV and using a computer where the washing has the highest value for the time dependence [19].

On the other hand, the given groups for the studied model are introduced on the micro scale for the annual energy prediction based on the linear characteristics while the determined results for the annual rate of rise of consumption growth are listed in Table 3. It tabulates multiplicity for extracted values corresponding to different selections either for closed or wide spread bases although the single base of selection (closed or wide-spread) gives also some diversion.

Table 3. The estimated rate of future growth.

average Base	Growth Rate	Figure
Closed 1	8.1	7
Closed 2	3.3	8
Wide-Spread 1	11.5	9
Wide-Spread 2	9.6	9

These values indicate the amount of energy required in future at least in the short term despite the lower values for the rate of growth in some samples. Thus, the rate of annual energy growth in short term may vary between 3.3 and 11.5 kWh/year, but the original data detected a higher level of consumption. It must be noted that, this high-level of consumption went to be lower and it takes similar values for others widespread. Thus, the elimination of very high (non-ordinary) readings is a step to find the realistic rate of consumption growth so that the third row in Table 3 can be canceled. Then, the variation zone becomes between 3.3 and 9.6. Exact single figure can't be accounted because the populations are highly varied. Since a lot of new consumers may be joined other than, the single customer can behave in a dissimilar way. The vision of energy consumption is revealed to the amount of energy required because this means the needed amount of fuel as a source of energy for the electric generation in the united network.

Otherwise, the prediction for the future necessary power will be estimated if initial values have a good view for populations. The current target is accurate prediction or at least the most closed vision for the real future requirements. Then, the maximum value of all grouping selection as given in Figure 10 could be considered for the prediction analysis where the results are drawn in Figure 14. It must be indicated that, the results of Figure 14 express the real future for the presented ideal model of energy consumption in Cairo. Similarly, this concept may be implemented for the energy consumption not only in the domestic sector but also for all other sectors either in mega-city or in a small village.

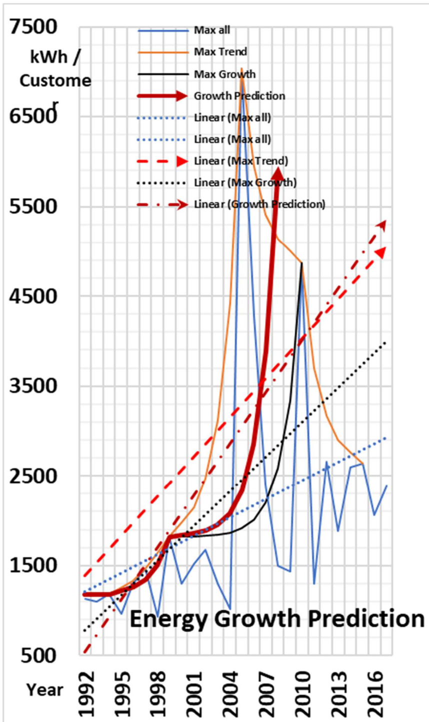

Figure 14. The Prediction for future Annual loads.

Otherwise, the maximum value of energy consumption can be transferred into the peak value of electric load so that the statistical analysis for the maximum value of energy consumption may be necessary. Thus, the curves of maximum energy consumption for each group have been introduced for the annual calculations if the target is the future peak load for the required electric generation in the united power network. The results for the rate of rise (growth) of maximum energy consumption per month per year are tabulated in Table 4, where 4 cases are proposed (normal or maximum growth, maximum style, & maximum all).

Table 4. Rise rate of maximum growth (Figure 14).

Selection Base	Selection Growth
Normal growth	15.7
Maximum Style	1.38
Maximum Growth	10.3
Maximum (Original)	27

The original curve (Max all) for the summation of proposed groups represents the maximum behavior instantaneously where the oscillation character is shown in Figure 14. The study of peak value would be referred to the maximum only so that low values should be eliminated. The envelope of maximum oscillated curve is the physical output for maximum values while the envelope is deduced in exponential style (not linear). The appeared unordinary peak (suddenly registered) is sharply dropped in the original readings because of a special consumption for any reason. Thus, it should be eliminated from the data for the analysis of peak to find the range of real maximum and so the predication can be implemented. This assumption generates the curve of exponential envelop (Max. growth), but it should be dropped, too. This may lead to the linear consideration of maximum style in the prediction for actual readings because of the deviation of exponential cases away from the possible vision.

The growth here is determined in high rate reaching 27, relating to the above said customer, since it may be annulled, too. The linear prediction is considered while the computed rates for the normal growth is 15.7 as a normal for the total consumption. Contrary, maximum growth is appeared as a nonlinear curve if Figure 14 is illuminated for discussion. So, the real growth will contribute the maximum style because it represents the actual development of maximum energy consumption. Therefore, the peak value will be taken as 1.38 kWh/year/consumer while other values were inserted on behalf of explanation. Consequentially, the coin of demand power growth can be expressed by the multiplication of this taken coin by the customer populations (Present + New) where the deduced value of 1.38 is a factor for growth in Cairo.

5. Conclusion

Initially, Since the readings as populations have a variable character, the treatment of the subject could have a probable based result. Therefore, the energy curves may be primarily treated to purify the original data from any impurities because the analysis proves the importance of such treatment. Thus, the data can be transparency output and the next sequential processes will be accurate.

However, the statistical treatment for the populations of energy consumption in the domestic sector addresses the suitable method for the mathematical analysis of energy consumption estimation not only in domestic sector but also in all other sectors. Moreover, this conclusion is valid for any field related to energy or not because the proposed concept for the analysis proves the validity to evaluate the similar styles.

Therefore, the dispersion factors of statistical mathematics lead to a good illuminated page for both understanding and good conclusions for the analysis. Thus, the mean value besides the standard deviation factor may explain the output of readings because the integration between both is enough. Then, the mean value of energy growth can open a way for future works.

If the target of work is the determination of the future growth of energy required in a mega city such as Cairo, the subject will be divided into two steps. Firstly, the amount of energy requires in the micro scale when this can be implemented through the mean value and standard deviation. Secondly, the maximum energy consumption should be tested for the future requirement in microscale, too.

Whatever, the prediction of energy consumption must be deduced since the micro consumption for short term is needed. Then, the maximum value should be tested for the prediction as a vital item because it points to the future power demand for the power generation. Thus, the deduced value /customer is a precious figure for the extension of the united electric power network.

Since the complex methods of prediction may consume both computational time and computational effort, a simple linear prediction can reach to the same results with an appropriate accuracy. It is easy for applications in different fields where the maximum prediction gives the value of power demand required for the united electric network.

Furthermore, the grouping system for a lot of populations may be recommended for all similar problems because it facilitates the subject and summaries well the results after purification. The grouping system can be recommended for medical, industrial products, marketing products, weather, stocks, etc. to be a fundamental tool for the prediction in each field.

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Appendix

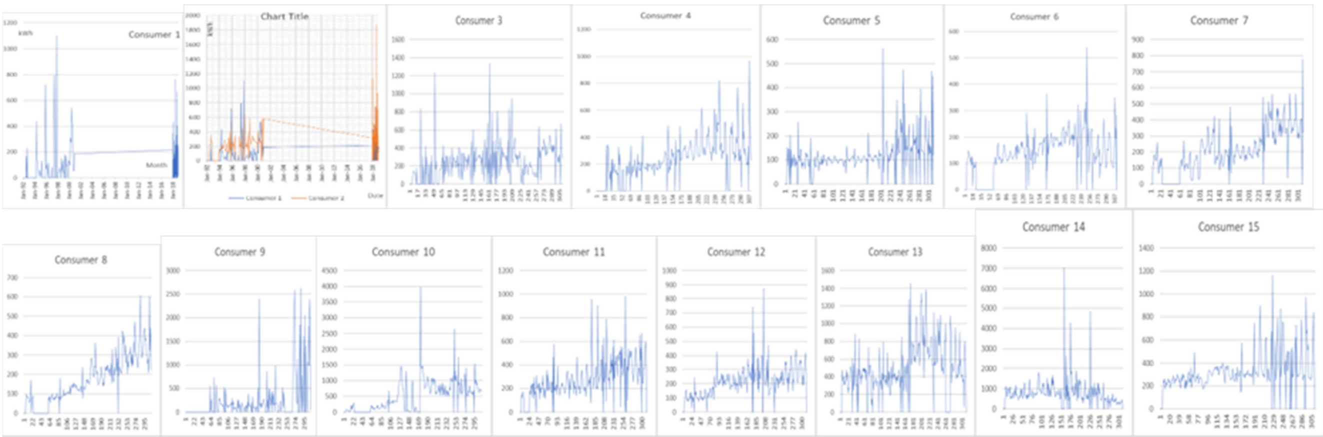

Figure A1. Readings for the ideal Samples (Jan 1992 – Jan 2018).

Source: North Cairo Electricity Distribution Company

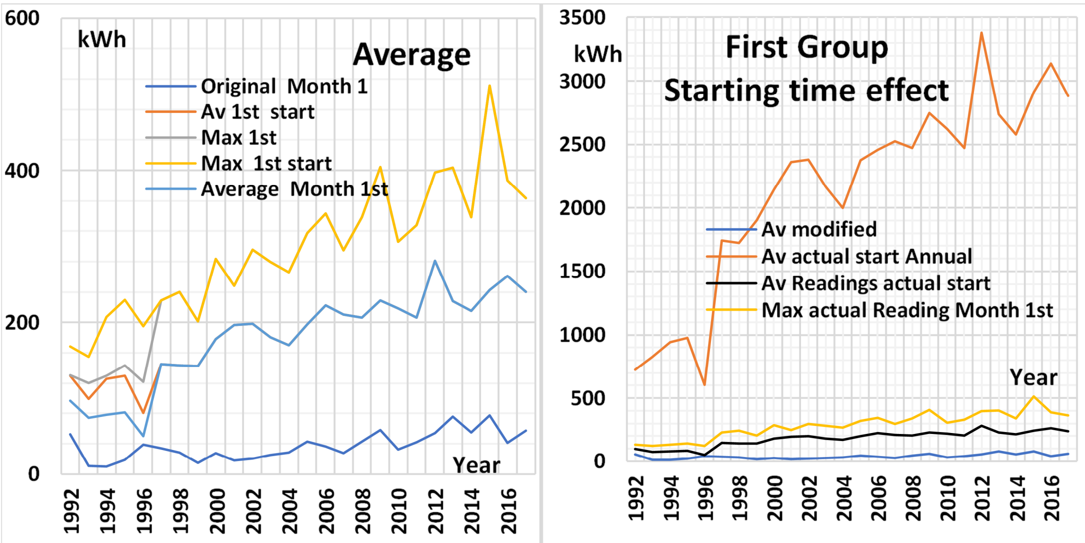

Figure A2. The results of double group modelling (with/without) occupied houses consideration.

Table A1. The Average & Standard Deviation of initial data.

C	$Av/Av_{modified}$	STDEV	$STDEV_{modified}$	G	$Av/Av_{modified}$	STDEV	$STDEV_{modified}$
C1st	87.36763	129.619	82.893	G1	127.803	101.473	84.160
C2nd	233.4263	182.831	136.608	G2	217.837	128.09	118.941
C3rd	238.8526	191.644	140.731	G3	244.68	255.966	219.754
C4th	237.3526	151.579	138.371	G4	514.8486	419.5	330.700
C5th	115.3186	74.894	45.187	G5	154.229	89.743	76.37
C6th	137.6827	79.811	72.397	G6	154.8942	129.515	116.694
C7th	206.4744	139.868	135.527	G7	261.1667	164.3	136.391
C8th	170.8397	120.603	119.354	G8	492.4087	469.558	382.78
C9th	231.4234	453.893	401.143	G9	137.5138	101.794	80.944
C10th	491.4968	478.501	405.103	G10	492.4087	469.558	382.78
C11th	275.0673	160.778	145.326	G11	221.4438	148.658	132.901
C12th	209.6827	105.173	88.417	G12	228.1733	156.898	132.823
C13th	483.8622	283.223	257.011				
C14th	761.9705	618.309	393.994				
C15th	320.8679	161.471	133.277				

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