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Article

Households' Electricity Consumption in Hungarian Urban Areas

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Abstract: The aim of this study is to examine the factors influencing the electricity consumption of urban households and to prove these with statistically significant results. The study includes 46 small and medium-sized towns in Hungary. The methodology of the study is mainly provided by a model that can be used for this purpose; however, the results obtained with the traditional regression method are compared with the results of another, more complex estimation method, the artificial neural network, which has the advantage of being able to use different types of models. The focus of our article is on methodological alignment, not necessarily the discovery of new results. Certain demographic characteristics significantly determine the energy demand of a household sector in a municipality. In this case, as the ratio of people aged 60 or over within a city rises by 1%, the urban household average energy consumption decreases by 61 kilowatt hours, and when it rises by 1%, the amount of pollutants expelled from urban households' average energy consumption may decrease by 22.8745 kg. The research area of our paper was greatly influenced by the availability of the statistical data. The results can be used in the planning of urban developments.

Keywords: environmental economics; energy consumption; CO_2 emission; non-linear estimation; urban pollutant; ANN

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1. Introduction

The relationship between energy consumption and economic growth is one of the most significant issues in environmental economics. The most significant problem related to energy consumption is the increase in CO_2 emissions and its harmful effects. This issue can be examined at both the macro- and micro-levels. In ecological analyses, indirect CO_2 pollution from electricity consumption is neglected. This was a strong motivation for carrying out this research.

Cities, as complex systems, concentrate different regional functions. Although these functions are networked at the same time as digital development, they interact with the systems of other settlements and cities, but their local characteristic has remained to this day. Our study uses a sample of cities in Hungary. Hungary is a country in Central Europe with about 9.7 million inhabitants. Hungary is a medium-sized member state of the European Union (Figure A1 in Appendix A).

The internal structures vary from city to city, which, despite the globalizing world, could not change much, as the built environment and other environmental conditions could not change slowly, or at all, over time. These internal structures determine the socio-economic characteristics and quality of life of the population living in them. All these factors also have a significant impact on the energy needs of cities. Energy demand is also one of the key factors in the concept of sustainable development. Energy consumption and the energy intensity of the economy directly determine the well-being of society and also indirectly affect economic growth [1]. From the extent of energy consumption, the resulting carbon dioxide emissions can also be approximated, which is not generated locally, but can be well estimated from the data characteristic of the settlement. The larger the settlement, the higher the volume of value added production. This will improve the living standards of the population and employment [2,3]. The aim of the study is to examine the factors influencing the electricity consumption of urban households, to provide a forecast for the next period—in our case, some in cities, the data of which will be defined as missing for the model—and to prove this with statistically significant results. The problem of the article is the estimation of electricity consumption of households. We present two methods for estimation. One method is a traditional econometric method that is nothing but regression analysis. The second method is a regression-based but methodologically significantly more complex method, analysis with an artificial neural network, better known as artificial intelligence. In addition, we try to classify cities into logically consistent groups by cluster analysis. The obtained results are also used to estimate the carbon dioxide emissions from energy consumption. No such study has been prepared in Hungary, so we can only rely on foreign literature and methodological peculiarities. In the first part of the study, the relevant literature is processed. The methodology consists of two parts: first, the general linear regression and then the application of the artificial neural network (software used: SPSS 24 Matlab 2019a). In this article, we examine the urban dimension of the topic in more detail. We apply these presented methods to the examined data.

We produced two theorems, as follows.

Theorem 1. *The closer a town is to the capital geographically, the higher the energy consumption per household.*

This follows from the territorial location that the standard of living within the country improves as we approach the capital. In the case of countries with a significantly larger area than Hungary, this fact also occurs in areas with a higher urbanization rate. As living standards rise, so does energy consumption per household.

Theorem 2. *Changes to the age structure of society influences energy consumption.*

Consumption by older generations differs significantly from patterns observed among younger generations. This means more restrained consumption for the older generation, and lower energy consumption.

The first step in this study is to review the main literature on the topic. Then, we present the econometric and statistical procedures which are then applied to the data. Finally, we interpret the results, draw conclusions, and make suggestions for further applications.

2. Literature Review

In this chapter, the general literature of this topic is presented. The literature on specific topics is discussed in the relevant section. At present, almost 40% of the urban population comes from surrounding settlements as immigrants [4–16], which is one of the main reasons for the rapid acceleration in the urbanization process [17–22]; however, the removal of the surrounding urban areas, previously agricultural lands, from agricultural cultivation to allow urban expansion and declaring them construction areas, enabling the construction of new residential areas, can also be considered as an indirect urbanization process. Overall, therefore, the economic potential found in urban space is a strong driver of settlement in the city, capable of automating the metropolitan system [23–27].

In Hungary—and throughout the world—the stages of urbanization take place in parallel. The network of settlements mainly consists of small settlements and cities with a low population in Europe, so they are characterized by the absorption power of the rural population. While the process of suburbanization can also be identified in the regional centers and the agglomeration of the capital. Around the cities, the urban sprawl took place without designer control, thus generating significant tension [28]. As a result of "spontaneous" suburbanization, land use around Hungarian cities has significantly changed, the shrinking of green areas has accelerated, and the proportion of artificial surfaces has increased exponentially. Another significant source of tension was that, with the mass exodus of the urban population, the former relative territorial balance of jobs and residences was upset, with more and more workers being forced to move with their jobs, i.e., the commuting. However, mass immigration also increases the environmental impact of cities [29,30]. Although one of the factors involved in moving to the city is access to better infrastructure and health care, at the same time, the health-damaging impact and ecological footprint of urban settlements will increase significantly [31]. Although the compulsion to reduce emissions should be more territorially concentrated, it should be directed towards a network of municipalities with lower energy consumption, as urban sprawl still seems unstoppable [32].

According to some studies, urbanization has a triple impact on the environment, as follows:

- Increases economic performance [33,34];
- Increase energy consumption [35–37];
- Increases the environmental impact [38].

In addition to economic growth, the urban population explosion as a result of capitalist development will significantly increase the rate of energy consumption and the impact of other environmental factors within a given area [39,40]. Several studies [41,42] demonstrated the findings of Newman and Kenworthy [43] that a more compact urban form is also more energy efficient in terms of transportation [44].

One of the most commonly measured indicators of this is the measurement of carbon dioxide emissions. Studies show that CO_2 emissions are often the only cause (fetishization) of climate change, with tragic consequences. Kondor, Kovács [14] (p. 686) quotes [42] "*climate change is seemingly sweeping all other environmental issues off the table, and communication on climate change has also narrowed: CO_2 is the main culprit, reducing CO_2 emissions is the only saving tool to save the Earth.*" Within these reasons, according to Kondor and Kovács [27] (p. 687), there is "*the logic of capitalism, which was able to integrate and internalize CO_2 emissions into its own operation*".

If the current unsustainable levels of consumption do not change, global energy consumption could triple by 2050. For this reason, striving for separation is important in achieving sustainable management. The most important question is whether energy consumption and CO_2 emissions start on separate paths [45]. Economic development and greenhouse gas emissions have been examined from many directions [46]. One important direction is the theory of decoupling. This examines the ability to separate economic production from pollution [47–49]. The second important factor is the Jevons paradox [50–53]. This occurs when technological progress increases the efficiency with which a resource is used, and the rate of consumption of that resource grows due to increasing demand, resulting in an increase in pollution. Eventually, the original plan, of efficiency and pollution reduction, is also lost [54]. In addition to energy consumption, carbon dioxide emissions are also generated during production processes. This can be reduced by prioritizing reuse, but it does not leave the system [55].

In terms of energy intensity, in the case of cities, the difference in the mass and economic development of a country affects [56] consumption in different ways [57,58]. In countries with a low level of development, economic development reduces energy consumption. For medium and highly developed countries, the urbanization process leads to an increase in energy consumption. Hungary is currently classified as a moderately developed country [59], so, based on this, we assume that the urbanization process in Hungary will lead to an increase in energy consumption. However, the relationship between the two factors is significantly more pronounced in the case of higher-income countries than in middle-income countries [60]. However, in cities with a growing population, due to the higher population density and economic productivity, energy investments can also be made that are not feasible in rural areas. However, these investments are by no means based solely on technical factors in terms of efficiency. They are largely determined by the society's level of environmental awareness, culture, and social affiliation [61]. In addition, the problem of energy supply was strongly influenced by political threads, with various interests in either green or conventional energy production. However, the energy policy also has a major impact on the daily lives of local actors. On the producer side, there is a growing need to set up power plants with sections that can be switched on and off according to the time of day and changing needs, while on the consumer side, the amount and generating factors are the determining factors, as there are significant differences between rural and urban areas. This may arise, for example, from the less modern equipment used in the countryside, the number of electricity-consuming devices, income conditions, etc. [62,63].

3. Data and Methods

3.1. Application of Artificial Neural Networks

ANN's practical application can be traced back to the following types of task:

- Classification tasks;
- Optimalisation;
- Approximation;
- Analysis of nonlinear dynamic systems [64].

In the case of settlement studies, the ANN procedure was used in the following studies (Table 1).

Table 1. The summary table of literature background.

Research Problem	Applied Methodology	Literature
Prediction of Ecological Pressure on Resource-Based Cities	radial basis function (RBF) Neural Network	[65]
Urban and economic Development and ecological footprint	Back Propagation Neural Network (BPNN) adaptive fuzzy-neural-network (RBNN-FNN)	[66–70]
Air pollution in cities	Multilayer Forward Neural Network (MFNN), FFNN	[71–74]
Territorial expansion	multilayer perceptron (MPL)	[75]

We used the basic MPL due to its simplicity and ease of interpretation. Our research focused on the uses of the methodology.

The two most-used tools in the econometric toolbox are the trend function analysis, as well as the regression analysis. Trend function analysis can be divided into two consecutive parts. The first step is the trend function definition, as well as the estimation of its parameters. The economic time series usually applies to predetermined seasons or periods, which fluctuate significantly, and is detrimental to the model's overall prediction abilities [64]. The most regularly occurring problem among the times series is autocorrelation. The order of times series' datum is already determined, and cannot modified, yet this is not the case regarding volume cross-section data, and thus it is necessary to examine homoscedasticity. The testing of primary autocorrelation is carried out with a Durbin–Watson Test, with a hypothesis zero of $H0$: $p = 0$, where p is the primary correlation coefficient. We are able to make fairly accurate predictions one season ahead, while secondary and tertiary autocorrelation tests, that are considerably more complicated than primary examinations, are necessary for predicting multiple periods in advance. The regression analyses become confounding factors, and the interval estimation and the statistical trials connected to it become distorted [76,77]. The frequent problem of cross-section data is multicollinearity [78]. This raises the problem that our regression model "is not able to determine", the explanatory power of some variables within the model. In the times series analysis, the second most frequently occurring problem during econometric analyses is the problem of stationarity [79]. A times series is not stationary if it contains a so-called unit roots; thus, a sort of trend is observable in the given season (its mean and variance are not affected by the shift in time). The majority of economic time series are this type of data series. The nature of stationarity is explained by the following autoregression formula:

$$Y_t = \alpha + \varnothing Y_{t-1} + e_t \quad (1)$$

In the above model (1), α is axix section, e_t is regression error term, explanatory variable Y itself is a delayed-action, taken during one period, named as stationary, in as much as $|\varnothing| < 1$, yet it is simultaneously not stationary, if $|\varnothing| = 1$. A third option can occur, although rarely, which is $|\varnothing| > 1$ (often called "explosive series"), which describes an outstanding case, for example, hyperinflation. As the Y time series is not stationary, it is important for us to note, however, that ΔY is already considered a stationary time series. Non-stationarity raised yet another problem, that of integratedness. Integratedness shows which time series differential (derivative) becomes a constant with the expected value, and, over time, an unchanging probability variable. Therefore, as long as the time series is non-stationary, it cannot be integrated in zero-order.

In the event that, during regression, we are in absolute need of one of our given variables, we first must transform the data string, so that the string changes into a stationary time series. Here, we mention one exception: when the data are cointegrated (in case of cointegrated series, linear combinations of non-stationary time series result in a stationary time series).

In the above section, without the need for completeness, we highlighted a few problems that often occur during econometric analyses. Our goal was to (ourselves) perceive and, in the following chapters, to make more perceptible, the accuracy and simplicity in of application, as well as the resistance and flexibility, of predictions carried out via neural networks, although it is often cumbersome to use traditional statistical methods to discover this.

The Operational Principles of Network Theory and Artificial Neural Networks

Networks are systems made up of many parts that impact each other through their interactions, thus influencing the system's working as a whole [80]. The network theory's foundation is given by the graph theory. Networks in every corner of the world can be found everywhere, from cell function and epidemic spread, all the way through chemical reactions, airline flight paths and human interactions, to computer networks. Thus, we call every such factor "a network", in which more than one factor can be identified and where the given factors affect each other's functioning [80]. We usually differentiate between networks' two distinct forms: static networks and dynamic ones. Static networks are those which have fixed and permanent points and bonding elements. Such networks are, for example, formed of consciously pre-planned and manufactured technical instruments like a computer or a solar panel system. The parts fitting them together are often permanent, or only partially expandable, and usually only used for predetermined tasks. The other network type is dynamic networks, in which both the points and their bonding elements are able to change, with an example of this being human relationships—e.g., friendships, various workplaces relationships, or new blossoming communities brought about by migration, but the neuron connections in the brain can also be listed here [81]. Network research is the science of mapping networks, uncovering network birthing processes and describing various network control processes and their predictability and influenceability [82].

The artificial neural network is one of the important factors in machine learning and artificial intelligence (A.I.). We may also think of artificial neural networks as a graph, differing from static networks, in that their foundation was given by the nerve membranes found in the human brain, that is, the mathematical prediction and analytical model, based on the operational principles of Man's complex nervous system network, which is capable of executing complex learning processes. The basis of the artificial network is the so-called "*perceptron*", a neuron's mathematical model (Figure 1).

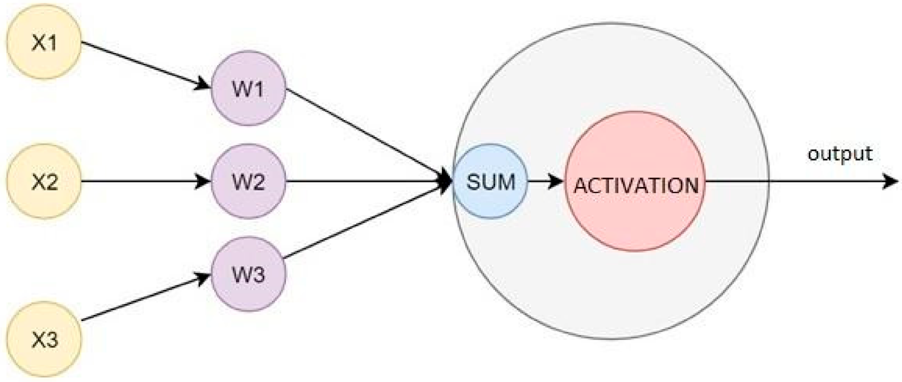

Figure 1. Perceptron—A neuron's mathematical model [83], based on our own editing. Legend: (X1, X2, X3) Input, (W1, W2, W3) Weight.

The perceptron weighs (W_1, W_2, . . . , W_n) the input values (X_1, X_2, . . . , X_n), then the activation function provides the final output value. To see the learning processes through which the network determines the weights and the activation function, as well as how it modifies the interior structures during process, countless complicated procedures are needed. The procedures we used during our analysis are written down in rather simplified fashion. As this is an economic article, we will overlook the precise derivation of the mathematical model. Nevertheless, it is important to note that much of the neural model visible in the following model is a base model, which can be condensed into a complex network through the analysis, just like the network of neural pathways in the human brain [84]. The basic neural model consists of three parts (Figure 2).

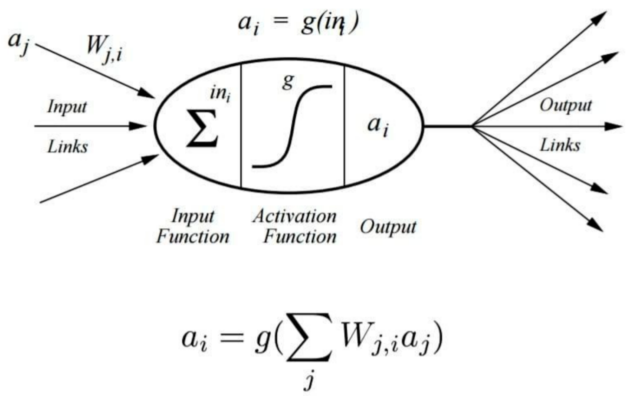

Figure 2. Basic Neural Model. Legend: (g) means Activation Function: Determines whether or not the perceptron "reacts to input stimuli".

The a_j points are the input values, the actual values of observation. The set of middle—hidden layer—nodes is the first hidden layer. The simple neural model contains a hidden layer. The one—output—node is the output point. Every hidden layer is made up of perceptrons, to which every input layer individually connects. The input points' edges forward information in the direction of the hidden nodes. Upon arriving here, the information is weighed w_j, and is later used for the formation of the activation function's inner structure. Every single input point has a net input value, which we obtain using the following equation

$$Y_{net} = \sum_{i=1}^{N} Y_i w_i + w_0 \tag{2}$$

where N is the number of neurons in the input layer, Y_i is the i-th neuron's information arriving from the previous (input) layer, w_i is the weight of the i-th relationship and w_0 is the neural threshold value. The neural threshold value ensures that the value of $\sum_{i=1}^{N} Y_i w_i$ is always within the domain of acceptance, increasing the network's flexibility [85,86].

Following this, the net input value transforms into an output value, which we obtain as follows

$$Y_{out} = f(Y_{net}) = f(\sum_{i=1}^{N} Y_i w_i + w_0) \tag{3}$$

where $f(Y_{net})$ refers to the selected neuron transmission function. The w_i neuron's weight can in reality be understood as the given input value's relevance within the entire model. The structure of the internal functions also depends on the current problem and the measurement level of the input data. However, a simultaneous combination of each function type is also possible. The neural networks, both linear and non-linear, are extraordinarily suitable for the modeling of correlations, which among other things, is made possible by the S-shaped threshold value function. The shape of this can be given the parametric form shown below

$$Y_{out} = f(Y_{net}) = \frac{1}{1 + e^{-Y_{net}}} \tag{4}$$

The function's output can, however, have a value between 0 and 1. Thanks to this, the above procedure (Equation (4)) is also appropriate for use in the estimation of binary variables (Figure 3).

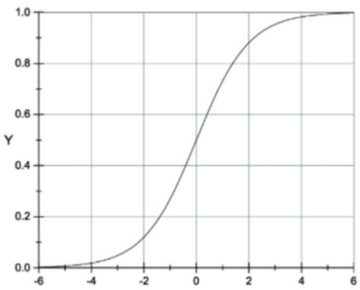

Figure 3. Logistical function with a border value between 0 and 1.

Therefore, for the final result, from input neurons made of close linear parameters, we obtained an interior learning model touting non-linear parameters, the output values of which, thanks to further transformations, become linear as well.

The methodology described above, and some of its details, are presented without the need for completeness, since the artificial neural network's, that is, A.I.'s, internal processes, learning, testing, and validation are an extraordinarily complex process. Its description, detailed introduction and elaboration would demand a separate study, thus we only touched upon the most important details.

3.2. Data

Hungary has 3152 settlements, including 346 towns, but the terminology we use does not distinguish between cities and towns. Hungary is a unitary state nation divided into nineteen counties, and these are the NUTS third-level units [87] of Hungary [88,89].

The following data were used for the analysis. Data source: Hungarian Central Statistical Office, period: 2004–2018.

- Electrical power use (kWh);
- Registered employment seekers (%);
- Ratio of those 60 years-old and older within the permanent population (%);
- Number of people per household (person/household);
- City size (km^2).

During our research, we analyzed cities whose number of inhabitants reached or exceeded 20,000 persons. This way, a total of 55 cities made it into our sample. From this number, 18 cities were county seats, 37 were not. We deem it critical to note that Budapest, due to its unique features, was not logged into the analysis, since it would produce salient values in every topic. A comparison with Budapest would be the subject of its own study.

Looking at the size of the inhabitant population, 67.3% of settlements belong to the settlement group with populations between 20,000 and 49,999, totaling 37 cities. Eleven more settlements follow this, in which the number of inhabitants is ranked between 50,000 and 99,999. This makes up 20% of our sample. Finally, we have seven large cities in which the number of inhabitants exceeds 100,000 persons, which comprises 12.7% of the sample.

The settlement size, we displayed the measure of yearly electricity consumption per household (Figure 4). The graph shows that the sample can be broken into three groups.

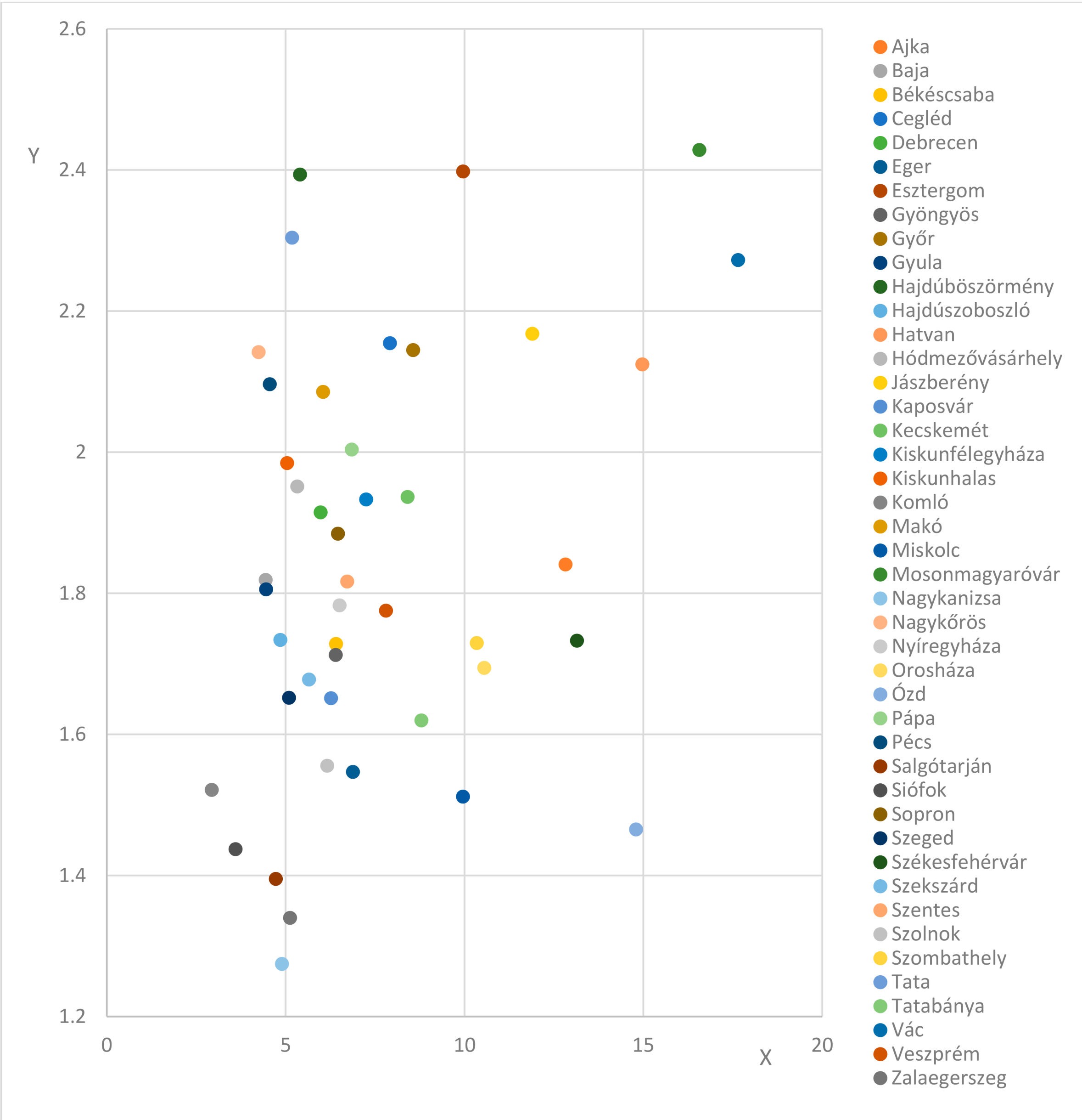

Figure 4. The amount of electrical energy provided to households yearly based on amount/person and city size. Legend: Axle Y = The amount of electricity provided to households (1000 kWh/ household) Axle X = Size (km^2) (n = 46).

The other focal point is somewhat contrary to this (the cluster circled in green Figure 5). Here, such settlements were added as, Hódmezővásárhely, the second largest settlement in the country. This is followed by Debrecen, the country's third largest city, though the second largest in terms of inhabitants. The fourth largest settlement in terms of land area is Hajdúböszörmény, Kecskemét is the the seventh largest by administrative size and eighth in number of inhabitants, and Szentes comes last. However, we can observe that these settlements, in contrast to the members of the previous cluster, do not represent considerably high values regarding energy consumption. It is only due to their area spread that they can form a separate cluster, upon applying the arbitrary method of ascertainment. We also tested whether a significant connection could be found between the area and energy consumption per household.

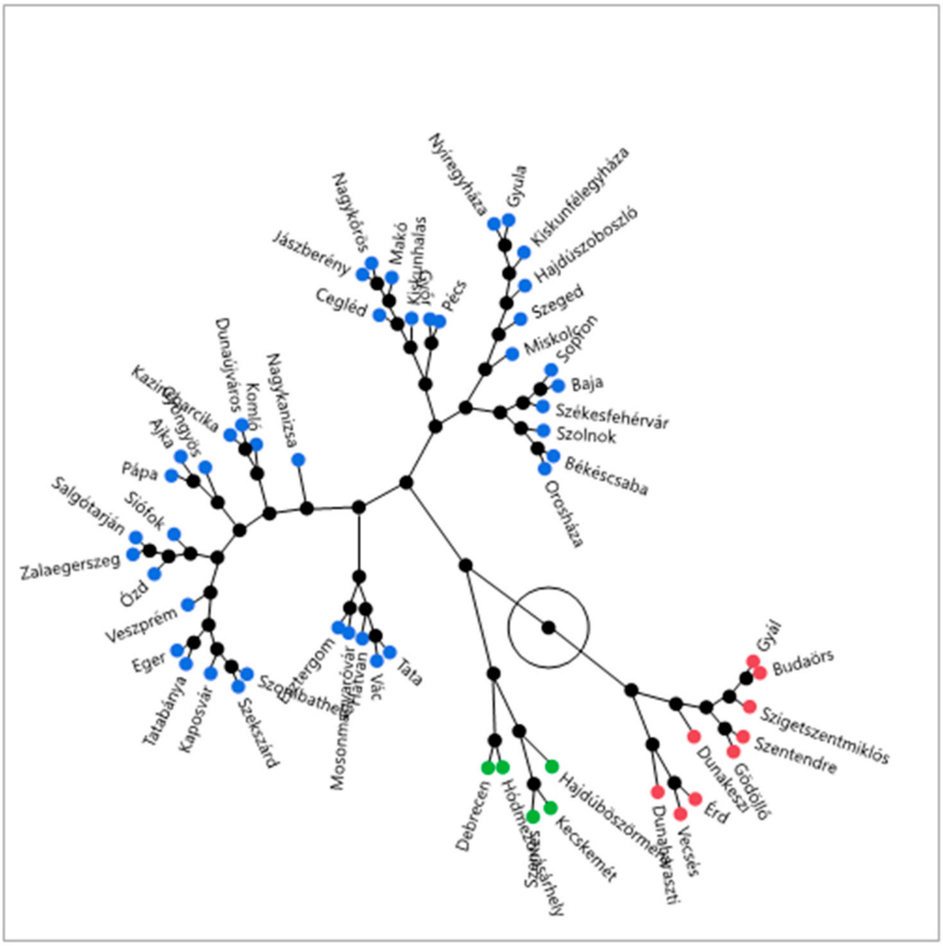

Figure 5. The groups created by the K-center clustering procedure (n = 46).

Naturally, Gyál, Érd, Dunaharaszti, Budaörs, Szigetszentmiklós, Vecsés, Szentendre, Gödöllő, and Dunaharaszti (the "orange cluster") (Figure 6) were all disqualified from the analysis, as they would have terribly distorted the results for that cluster. However, it became clear and easily deducible that, by itself, the relationship between the area and the measure of energy consumption within the settlement was weak (r = 0.240). Besides this, the result's 5% significance was not actually significant. Thus, we came to the conclusion that the following observable groupings (Figure 5) are the consequence of the fact that the greater expansivity in the east means that settlements are less frequent in their geographical location than in Hungary's central and western regions. Thus, since this is considered "no man's land" at present, there is no area under the administrative control of the surrounding settlements. In other places, far less free space was available to divide up among more tightly packed settlements. We can also support this hypothesis by carrying out a cluster analysis based on the observed settlements' size and the amount of energy used per household.

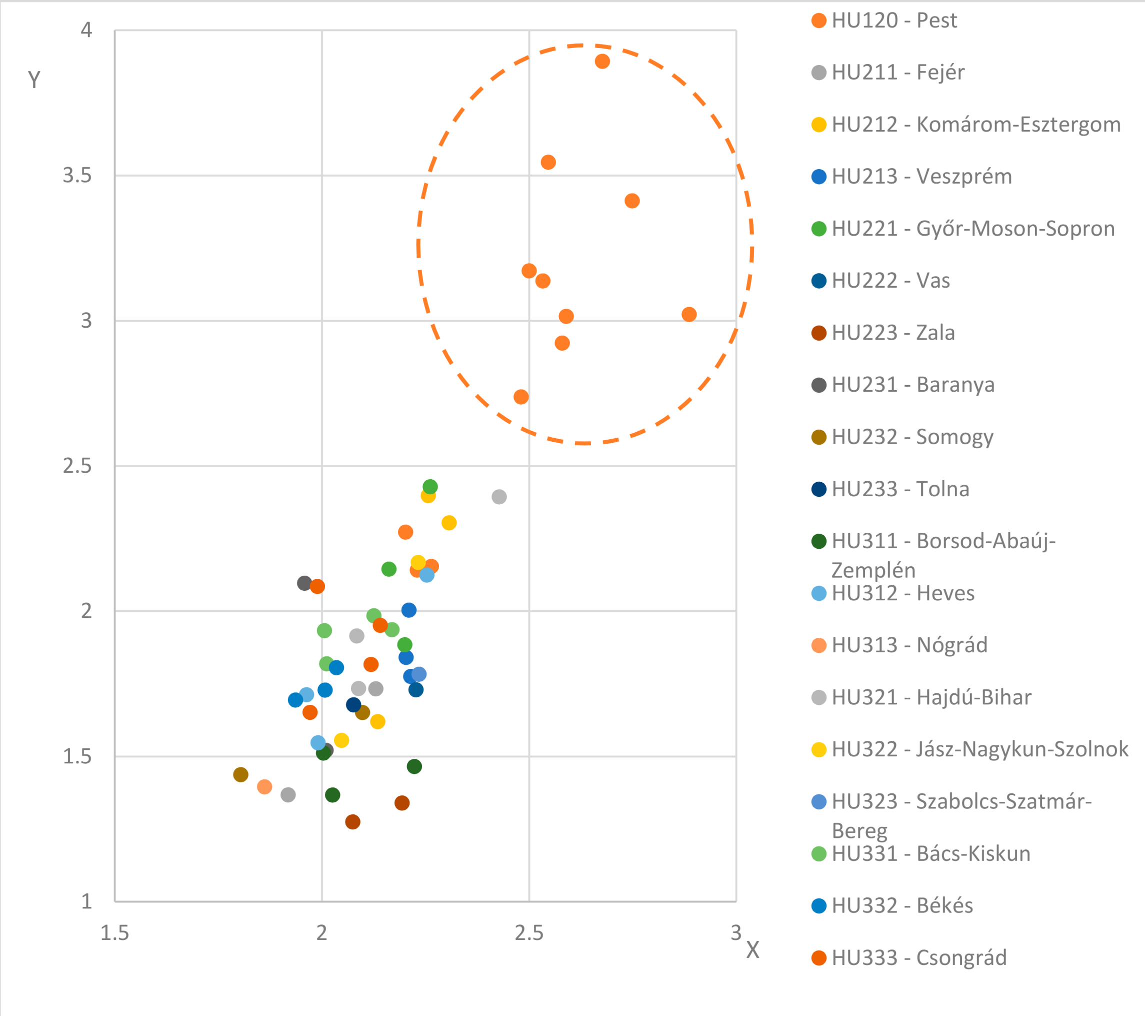

Figure 6. The number of persons per household and electrical energy expended by amount. Legend: Axle Y = The amount of energy provided to households (1000 kWh/household); Axle X = The number of dwellers per household (person/household) (City: n = 46, country (NUTS 3) n = 19).

With the cluster analysis protocol, we aim to classify these settlements into homogenous groups. Our goal is that the monitoring units, found within the clusters and based on the chosen criteria, are more homogenous, and the attributes of some of the clusters are more heterogenous. In practice, we often implement hierarchical and non-hierarchical cluster analysis procedures simultaneously. Now, however, it is not necessary to complicate the procedure, since, due to the low number of items and existence of only two dimensions, the cluster center and cluster number can be determined through the visual method. In reality, this protocol does not provide the main method for the study; we simply wanted to test observations with it.

Ergo, in our case, we applied the K-center clustering procedure. We are requested classification into three clusters, and maximized the iteration–reiteration processes to a total of ten. We did not report on the exact numeric results, save in a single, two-dimensional figure (Figure 5), where we illustrated the clustering.

The results support the prior supposition of ours, according to which the measure of power consumption per household is most dependent upon their positioning within the interior of the country and the multitudinous other social and economic factors, and least dependent upon the geographical scope of the examined area.

In the next step, we examine what type of relationship is found between the energy consumption and number of residents within a settlement. In and of itself, population density and the measure of consumption do not display a significant connection, which is not surprising when taking the previously displayed ties to settlement size into account. However, as regards specific data, like the number of persons per household and the energy usage thereof, clear results can be observed.

The first which we deem worthy of highlighting (the focal point circled in red, Figure 6) is a settlement group which, in comparison to its area spread, has high residential electricity consumption, with those settlements being Gyál, Érd, Budaörs, Szigetszentmiklós, Vecsés, Szentendre, Gödöllő and Dunaharaszti. The cities in this cluster are all found within Pest County. This outstandingly high value may result from, one, the fact that the people living here, in a good part of the country, within close proximity to the capital, all live within comfortable means, and thus are able to possess more high-consumption products (perhaps for entertainment or other purposes) than the average Hungarian household. Two, we cannot speak about conscious consumers, regarding the level of consumption, when the discussions pertains to solutions that are money savers—which still produce higher consumption levels per household.

Once again, a pretty cluster is formed (circled by the dashed line (Figure 6)), in which every single member is a settlement found in Pest County from the previous discussion. In this area, the number of persons under one roof is also considerably larger than the national average. Thanks to this, the level of consumption also produces a much higher values. The correlation analysis underlies the relationships displayed on the graph.

The results show a stronger than medium result between the two criteria ($r = 0.618$); this value is significant even at the 99% trustworthiness level. Overall, the number within a household explains 38% of the total variance.

By itself, the higher population per household, observable in Pest County, can first be explained by the fact that, in this region, the living costs and real estate prices are considerably higher, making youths' separation from their parents much more difficult to execute in many families. Besides, in this region, although living apart from parents is not easy, the income per capita is much higher than the rest of the country. Based on this, it is possible to find more electronic devices in households than the average, from big or small household devices to entertainment electronics. Thanks to the better financial standing and the discernible decrease in air conditioning unit prices in recent years, the number of such facilities in this region can be considered high, which explains the increased consumption. All of these, however, are only hypotheses, and proving them would require more research.

As shown in Figure 7, Kazincbarcika and Dunaújváros represent an extremely high value of the total electricity usage in the settlement, while the populace's consumption is said to be around average. We know that Kazincbarcika began to grow considerably following the Second World War, maturing into a true city. Industrial facilities can be found here in a large number, as the industrial boom brought about its development. Power and chemical plants, along with many other industrial installations, find a home here, which greatly increases its energy usage. Dunaújváros also began its growth spurt in the 1960s, becoming one of the country's most important economic centers.

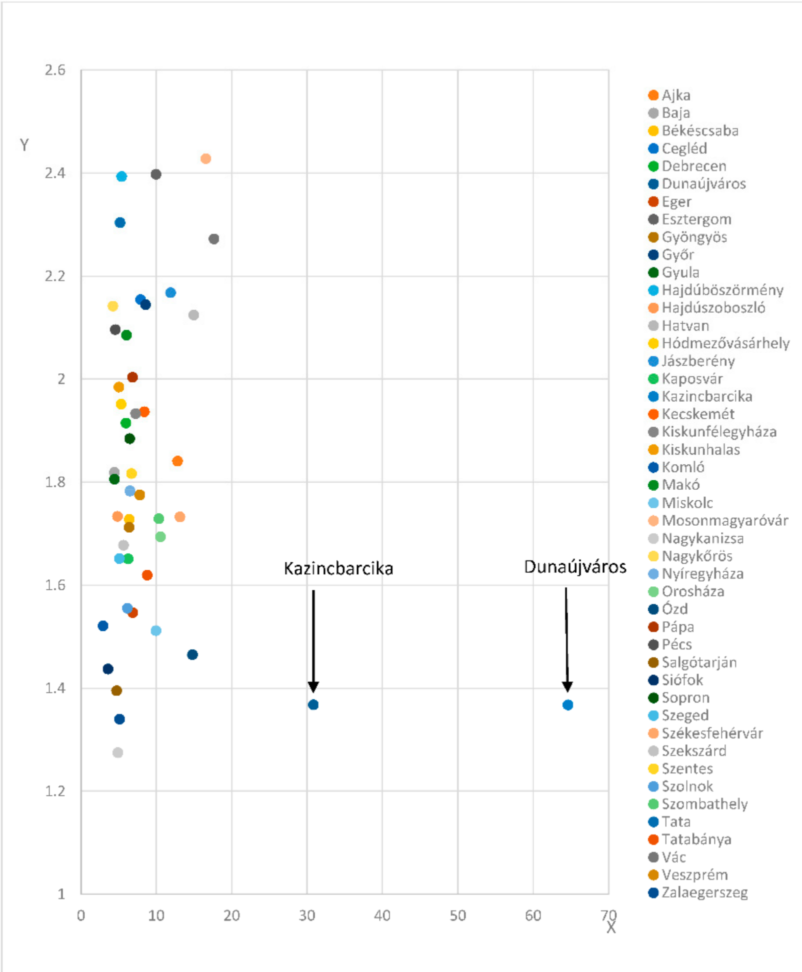

Figure 7. The entire amount of electrical power used in the settlement and by households. Legend: Axle Y = The amount of electricity provided to households (1000 kWh/household); Axle X = The total amount of electricity provided (1000 kWh/total consumers) (n = 46).

If we exclude these two outlying values from the analysis, it becomes apparent that one cannot truly find a connection between the amount of power used by the populace and by the entire town. This leads to the conclusion that industrial energy consumption and population energy consumption, due to the town's attributes, ought to be handled separately, since industry significantly influences the total consumption. Naturally, however, the size of lit public areas, public buildings, and many other factors affect the level of consumption. Figure 8 shows the share of household consumption in the total energy consumption of cities. Areas where the share is lower, are likely to be in industrial cities (as shown in Figure 8).

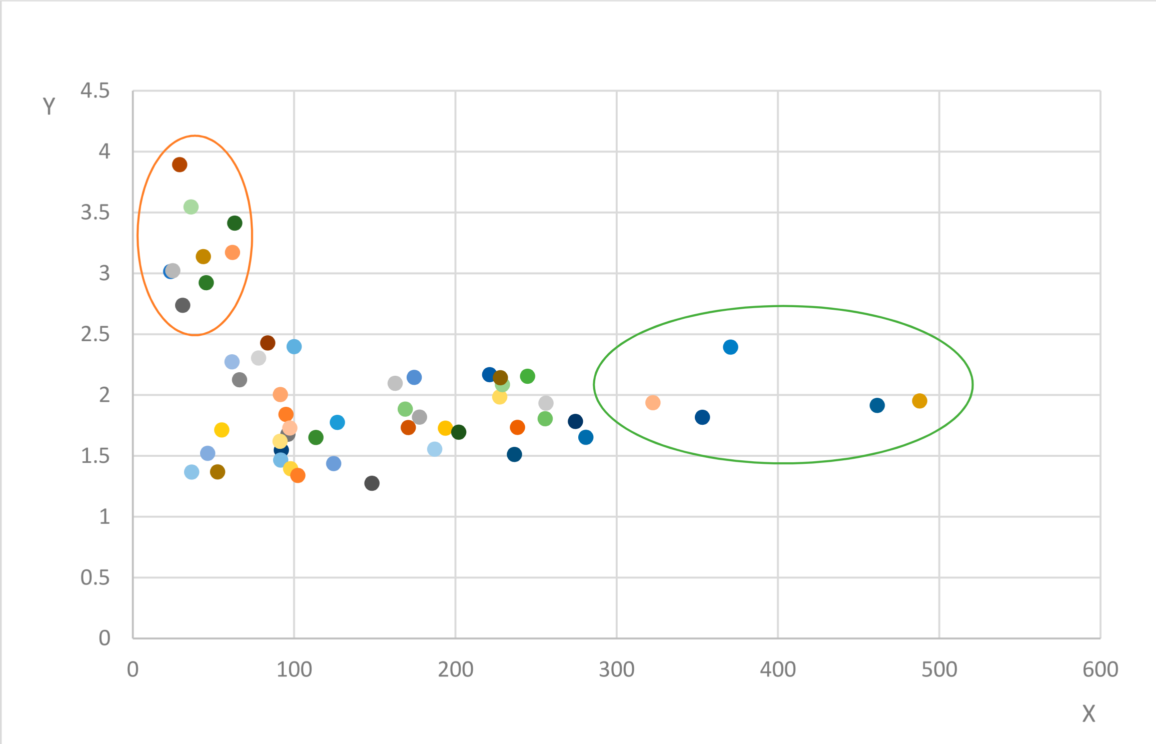

Figure 8. The total electrical power used in the settlement and by households—following the exclusion of two extreme factors. Legend: Axle Y = The amount of electricity provided to households (1000 kWh/household); Axle X = The total amount of electricity provided (1000 kWh/total consumers) (n = 46).

4. Results

4.1. The Modelling of Energy Consumption Using Various Statistical Tools

During our analysis, we applied two procedures: linear regression and artificial neural networking. These two procedures have both advantages and drawbacks. Regression is a developed, long-used method, an appropriate criteria system. Artificial neural networking has far fewer conditions and, being less sensitive to protruding values, it applies some of the regression calculation types during estimation.

The greatest advantage to utilizing artificial neural networking is that it is able to handle far more problems in a far simpler user session than regression analysis. Neural nets are extremely flexible, capable of solving both prediction problems and classification problems. They are able to take in massive amounts of input data, which, for its non-linear predecessor, was no problem during the course of the analysis. Tasks can be divided up into multiple layers of sub-problems, decreasing the chance of mistakes in some phases. Following the learning–testing–validation phase, the creation of outputs occurs more quickly. The number of inputs and layers in the model is customizable according to personal preference, although it is critical to note that increasing the number of hidden layers can cause further problems. In contrast, its disadvantage is that, contrary to the regression estimate, we can consider the innerworkings of these neural nets as akin to a "black box", meaning that we do not know as much detail regarding factors in the estimation process as we would during a regression analysis. Aside from this, the artificial nets are capable of so-called "overstudying", which falsely produces good results, thus making any future estimates far less accurate in their calculation.

4.1.1. The Regression Procedure and Its Outcomes

In order to determine with which variables (source: HCSO) it is possible to predict, with the utmost accuracy, an urban household's energy consumption, we implemented the so-called "Forward Stepwise" procedure. This the course of action draws the variables into the analysis one-by-one. This is the so-called "bottom to top" procedure which, in every step of the model construction process, draws a variable from the pre-specified list of explanatory variables with the goal of improving the model's fit from a statically significant standpoint. The operation continually repeats until the model's improvement remains above a certain value. The considerable advantage of this process is that, in the model, relatively few explanatory variables remain, which significantly eases the model's analysis (Table 2).

Table 2. The result of the variance.

Model Summary [b]									
					Change Statistics				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**	**df1**	**df2**	**Sig. F Change**
1	0.742 [a]	0.551	0.519	0.21103494	0.551	17.201	3	42	0.000

[a] Predictors: (Constant), (78) = The ratio of registered employment seekers (%), (12) = the ratio of those 60 years and older within the permanent population (%), (22) = the number of people per household (person/household). [b] Dependent Variable: (47) = The amount of electricity provided to households (1000 kWh/household).

As a result of this, three independent variables were found in the model (Figure 9 and Table 3):

- The number of people per household—its explanatory power within the model is 49%;
- The number of registered employment seekers, the predictive power of which is 28%;
- The ratio of those 60 years and older within the city's permanent population—its predictive value is 22%.

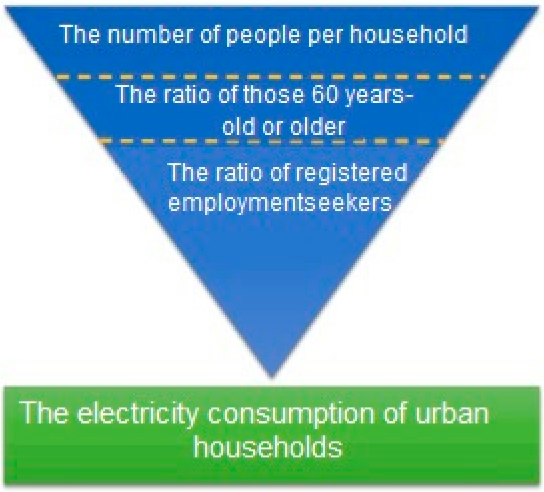

Figure 9. The model of the factors influencing the electricity consumption of urban households.

Table 3. The variables draw into the final model.

		Step		
		1	**2**	**3**
Information criterion		−121.73	−125.215	−100.642
Effect	@22	✔	✔	✔
	@78		✔	✔
	@12			✔

Legend: (22) = the number of people per household (person/household), (78) = the ratio of employment seekers (%), (12) = the ratio of those 60 years-old and older within the permanent population (%) (n = 46).

Therefore, these are the three important factors, which, according to the model, determine the amount of energy consumption for a household in the city. In the following sections, we will found our model setup upon these three key factors. In the first round, we summarize the regression process' results.

This explains 51.9% of our model's total variance, which can be deemed a moderately good model.

Based on the results of the ANOVA table (Table 4)—the zero hypothesis—according to which there is no significant correlation between the variables, the value of R^2 is 0. The significant existence of the F statistic implies the rejection of the zero hypothesis; therefore, we can be sure that there are significant ties between the variables we drew in.

Table 4. Aggregated model parameters.

ANOVA [a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	2.298	3	0.766	17.201	0.000 [b]
	Residual	1.871	42	0.045		
	Total	4.169	45			

[a] Dependent Variable: (47) = The amount of electricity provided to households (1000 kWh/household). [b] Predictors: (Constant), (78) = The ratio of registered employment seekers (%), (12) = the ratio of those 60 years-old and older within the permanent population (%), (22) = the number of people per household (person/household) (n = 46).

Every one of the examined variables has a significant effect upon the dependent variable. The greatest effect, according to the standardized beta coefficient, is that of the number of people per household on the energy consumption of municipal households. When the number of persons per household rises by one, the amount of expended energy in the urban household grows by an average of 729 kW/h. This value, based upon the estimate, can be a minimum of 67 and maximum of 1390 kWh, a 95% probability. The width of the interval is due to the fact that the household equipment and the modernity of their technical devices is spread across the various regions of the country, thus explaining Pest County's extremely high ratio of consumption.

Second is the ratio of those 60 years and older within the permanent urban population. When the ratio of people 60 or over with in a city rises by 1%, the urban household average energy consumption decreases by 61 kW/h. The possible reason for this reversed correlation might be that, in those households where the older generation lives, there are far fewer electronic devices, and, due to their lower income, they pay better attention to consumption expenses.

The third key factor is (Table 5) the rate of unemployment within the urban population. When the ratio of the unemployed rises by 1% within the resident population, the urban energy consumption average decreases by 110 kilowatt hours. The effect of this last factor proved to be significant on the 99% trustworthy scale.

Table 5. The summary table of the regression estimate results.

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	t	**Sig.**	**95.0% Confidence Interval for B**	
		B	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
1	(Constant)	2.234	1.244		1.795	0.080	−0.278	4.745
	@12	−0.061	0.024	−0.353	−2.611	0.012	−0.109	−0.014
	@22	0.729	0.328	0.309	2.223	0.032	0.067	1.390
	@78	−0.110	0.030	−0.407	−3.649	0.001	−0.170	−0.049

Dependent Variable: (47) = The amount of electricity provided to households (1000 kWh/household). Legend: (12) = the ratio of those 60 years and older within the permanent population (%); (22) = the number of people per household (person/household), (78) = the ratio of employment seekers (%) (n = 46).

4.1.2. The Results of the Estimation Carried Out by the Artificial Neural Network

Our second procedure was estimation and prediction using artificial neural networking. We input household energy usage data into the system as the dependent variable, making the three independent variables the number of people per household, the ratio of those 60 years or older within the entire resident populace, and the ratio of registered employment seekers.

Before inputting the variables into the model, they were standardized based on the below formula

$$Z = \frac{x_i - \mu}{\sigma} \quad (5)$$

where:

x_i was the measured value in the given city;
μ the given variable's average value;
σ the given variable's standard deviation, that is to say, its average detour from the mean.

We used three units in the networking model, while, during the course of the procedure, we used a total of one hidden layer. The neural network with a single hidden layer is capable of learning any continuous function. The perceptrons' activation function contained a tangent function, and, since we aimed to discover how capable some of the methods are of estimating an urban household's energy intensity, with knowledge of certain parameters, we deleted the energy consumption values of 16 cities from the previous regression model—defining them as a quasi-missing value. We will expand on all of this in more detail; however, the decreased item numbers still play an important role in the case of artificial neural networks.

The model is the remaining sample. After the deletion of the output information of 16 cities, it used up to 70% for learning, 20% for testing, and 10% for validation. The learning process was the observed learning procedure, the point of which was to compare the created output values with the real ones (the known electricity consumption), and, depending on the difference, to modify the weight matrix's connections. We finally maximized the learning process' time in 4 min, though, with this large of a chunk of data, this has no great significance.

Regarding the importance of each of the criterion, the artificial neural network (Figure 10) judged them differently. The ratio of those 60 years or older was most important, followed by the ratio of employment-seekers, and, finally, the one that helped the model the least in its estimation was the number of persons per household (Figure 11).

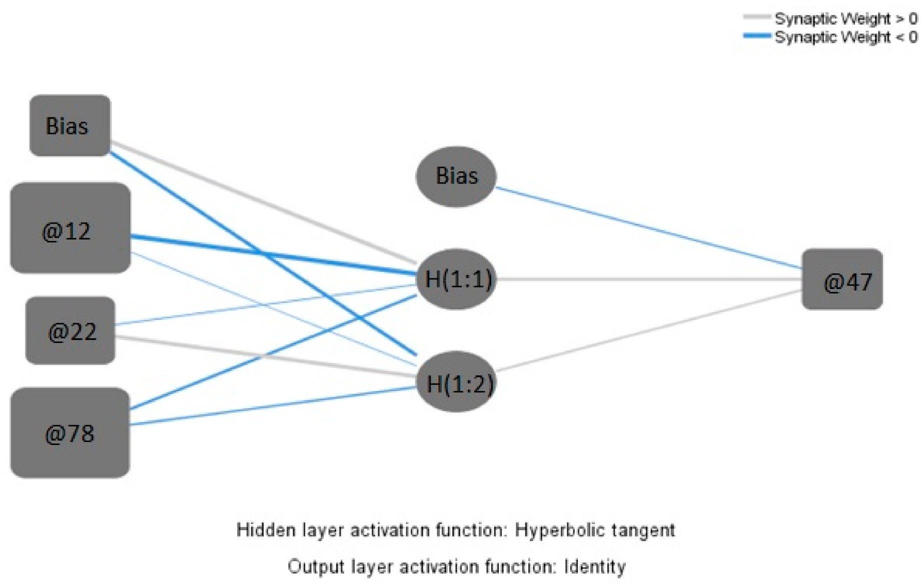

Figure 10. The artificial neural network–perceptron graphic model.

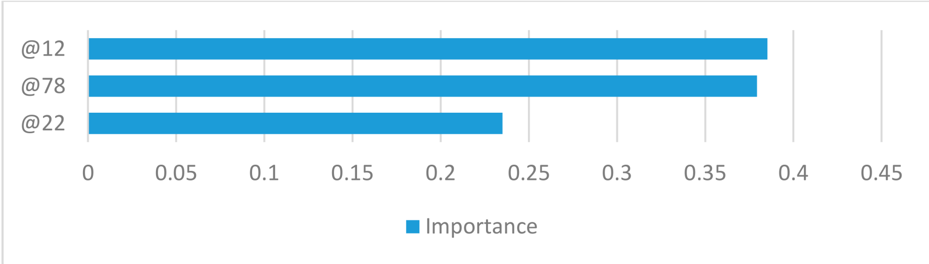

Figure 11. The orders of importance given by the artificial neural network. Legend: (22) = the number of people per household (person/household), (78) = the ratio of employmentseekers (%), (12) the ratio of those 60 years and older within the permanent population (%), (47) = The amount of electricity provided to households (1000 kWh/household) (n = 46).

After this, we used both our models, the regression equation and the artificial neural networking model, to we estimate the values of the 16 deleted cities using strictly independent parameters (Figure 12).

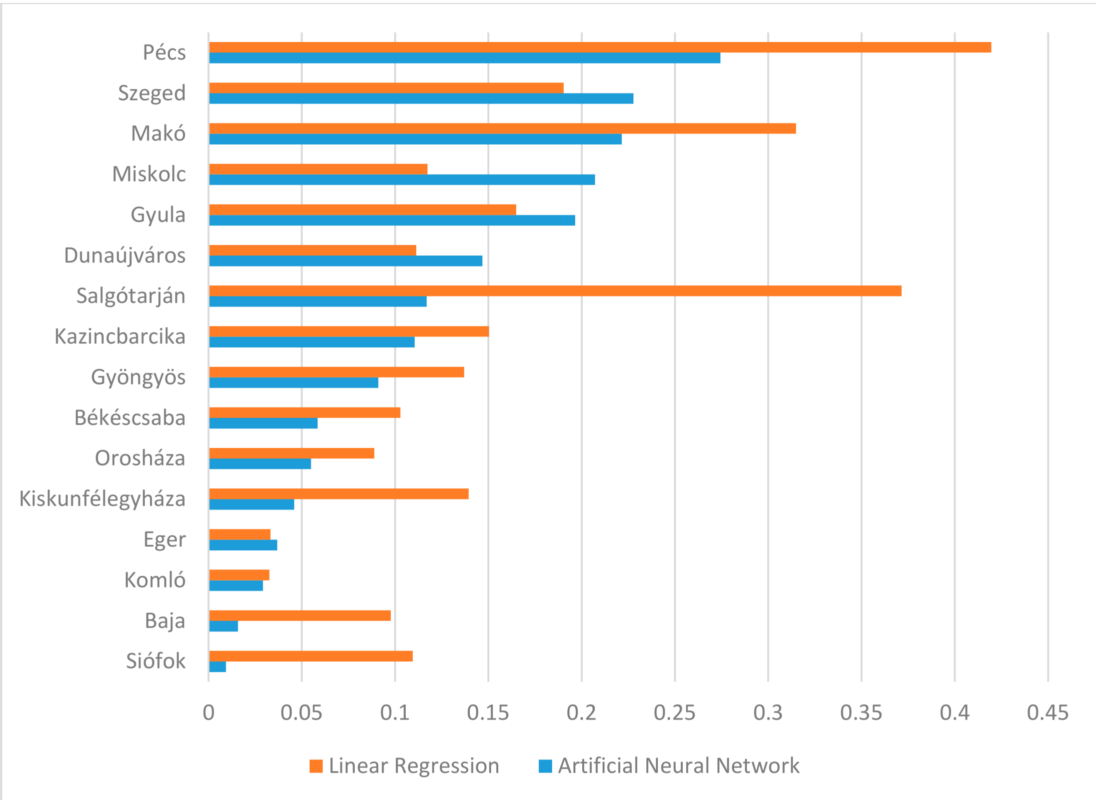

Figure 12. The difference between the true and estimated values, in absolute value.

The original value, which we previously deleted from the database, we used to determine the accuracy of the estimated results.

In total, we can say that overestimation was typical of the regression procedure, while underestimation was the attribute of artificial neural networking in the case of our model. The average of the regression's estimation mistakes was 161.3 kilowatt hours, while its standard deviation was 112.3 kilowatt hours. In contrast, the error average of artificial neural networking was considerably lower, at a total of 115.2 kilowatt hours, with a standard deviation of 86.4 kilowatt hours, which is much lower than that of regression. In the case of cities like Salgótarján or Pécs, when discussing what caused the outstanding regression overestimation, or, with Siófok and Baja, why the neural networks were able to make such extraordinarily accurate estimates of consumption, while in Miskolc it substantially overestimated that consumption, is best left for examination in methodology studies.

Regression analysis is a common and much-used technique for this type of analysis. However, the artificial neural network analysis was not specifically developed for the analysis of economic and statistical data. The study was written with the aim of testing this type of ANN application.

4.2. The Interpretation of Results for CO_2

Taking Hungary's electrical energy production trends into consideration (the produced electrical energy, the ratio of energy import, and the power plant reports of aggregate CO_2 emissions), the output for 1 kilowatt hour is 0.35 kg. From an energy consumption perspective, taking the losses suffered in the network into consideration, the value rises to 0.375 kg [90–93]. All things considered, when the number of persons per household rises by one member, based on the amount of consumed power, the carbon dioxide coming from that consumption rises to 273.374 kg in one year. This value, based on the estimate, is a minimum of 25.125 in cities with lower consumption, but can be as much as 529.25 kg in cities close to the capital, with a 95% probability.

In cities where a large portion of society is elderly and the ratio of those 60 years or older within the resident populace rises by 1%, the pollutants expelled from urban households' average energy consumption may decrease by 22.8745 kg.

The rate of unemployment within the resident population is a key factor. When the ratio of unemployed persons within the resident community rises by 1%, the energy requirement per household also decreases by, from a carbon dioxide pollution perspective, is 41.25 kg per year.

5. Discussion and Conclusions

The results show that the artificial neural network gave more accurate results than the linear regression. There are additional latent variables that can further refine the results. Incorporating these variables into the analysis can also improve the learning processes and predictive estimating skills of the artificial neural network. Exploring this requires further research.

Sadly, the statistical data found in Hungary become harder to obtain the more we decrease the data's territorial aggregation. This raises the problem that some factors, like the number of wooded streets, the average age, and the level of renovation, energy structure, and energy classification of structures, have no available data. However, it is surmisable that these factors significantly influence household energy usage. Furthermore, the time series analysis of mid-year data may prove interesting, as we can establish different trends in the inner structure and attributes of each cities' consumption from these. It is also worthwhile to, at this time, include factors from the natural environment in the analysis, since the number of daylight hours, the summer and winter temperature and the number of windy days all have a significant impact on household energy usage. For example, the spatial density of homes and the material they are made from can affect summer energy consumption, and the greenhouse effect typical of cities can shed light on the climate control use habits. This could provide an explanation for the increased energy usage.

At present, it is apparent that most pollutant emissions come from our cities, the handling of which demands the development of and application of appropriate strategies and technologies. For all this, however, we must recognize the inner factors and structure of these processes. We must understand what kind of effect the features of a settlement have on a city's energy usage.

It has been shown from our analysis, as regards Hungarian cities, that the ratio of elderly people, the number of employment seekers and the number of persons per household significantly determine the energy demands of the household sector of a settlement. In contrast, the settlement's geographical coverage and population density have no influence on the energy intensity. Factors such as location within the country can be a defining factor to a certain extent; however, this is settlement-specific.

Regarding the CO_2 emissions from energy consumption, we identified unemployment as a key factor which reduces a household's energy consumption, and thus its pollutant emission. This effect is also controlled by the ratio of persons over 65, although only in a minor way. On the contrary, the number of persons per household is seen as having a stimulant rather a suppressant effect, meaning considerably larger amounts of direct pollution, the closer the city is to the capital.

We hope that, from the 2021 census data, we will be able to paint a more precise picture of this topic, since we would also be able to obtain a better look at the number, age, and technical classification of electronic items used in the home. Until then, we shall strive to continue developing our models and search for more determinant variables, so that we might increase our model's explanatory power and practical usefulness.

Proof of Theorem 1. The closer a town is to the capital, the higher the energy consumption per household. □

We identified one cluster in which every member is a settlement found in Pest. In this area, the number of persons under one roof is also considerably higher than the national average. This results in significantly higher energy consumption, which also indirectly leads to high carbon emissions.

Proof of Theorem 2. Changes to the age structure of society influences energy consumption. □

When the ratio of people 60 or over with in a city rises by 1%, the urban household average energy consumption decreases by 61 kilowatt hours, meaning that the pollutants expelled from urban households' average energy consumption may decrease by 22.8745 kg.

The research area of our paper was greatly influenced by the availability of statistical data. This approach might also be worth executing at the micro-level, but this requires extensive data collection. If the methods we applied were used to analyze larger samples, the accuracy of the results can increase significantly. The method is presumably applicable at the macro-level as well, in which case the estimation accuracy of the model may improve as the number of explanatory variables included in the analysis increases. The artificial neural network can also be used in a number of similar areas [86,87], such as the estimation of wastewater discharge, waste generation, and similar environmental emissions [37,65].

The primary task of urban development is to find concentrated cohorts where this phenomenon can be detected. Once these clusters are identified, appropriate measures can be taken to optimize electricity consumption within the city. The results may also be useful for operators and developers of electricity networks. This method can also be used to study the consumption patterns of additional consumer segments (e.g., the deployment of an electronic car charging network). The results could also be used in urban development planning and provide a basis for the direction for urban development. A primary task in urban planning is to find concentrated cohorts where this phenomenon can be detected. Once these clusters are identified, appropriate measures can be taken to optimize electricity consumption within the city.

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Appendix A

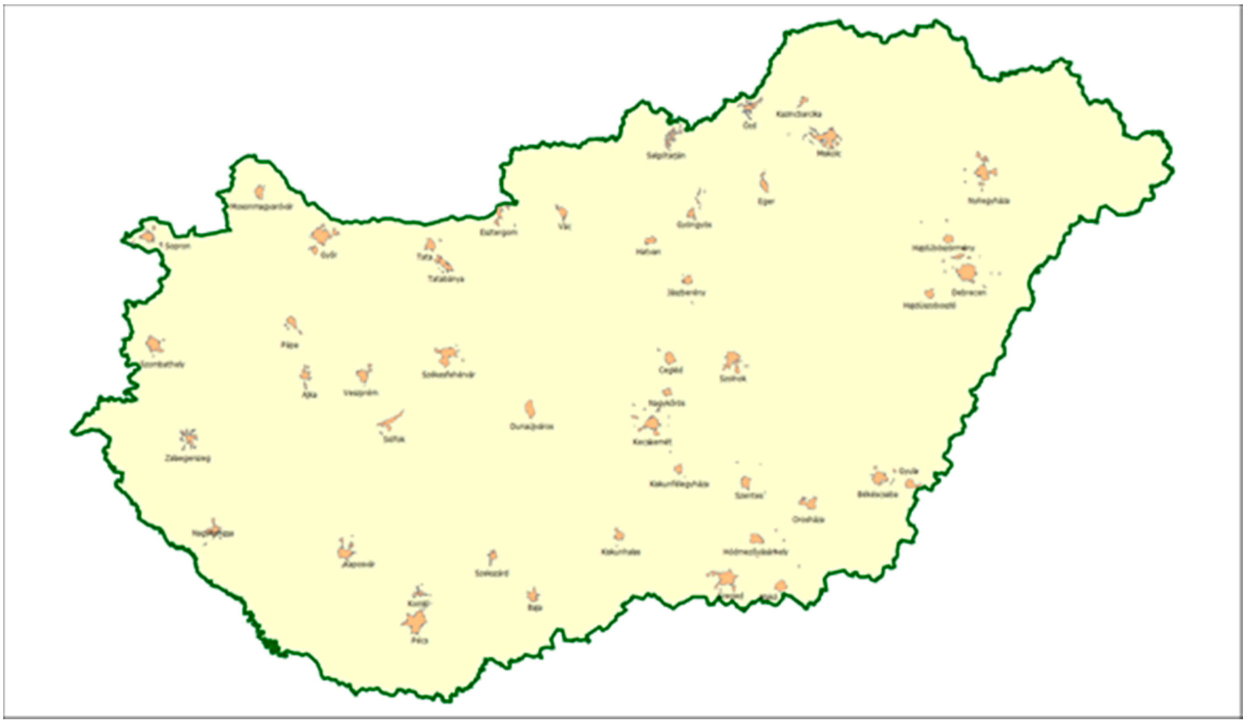

Figure A1. Location of cities.

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