104: Electrical energy consumption as a function of urban variables

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Abstract

This paper analyzes the electrical energy consumption of households as a function of urban variables, by modelling the urban thermal environment with Artificial Neural Networks (ANN). The study area was a residential neighbourhood. Urban features of reference points were determined by the following characteristics: urban heat island, sky view factor, and users' income level. For each of these reference points, urban air temperatures at the pedestrian level were collected with data-loggers. At the same time, rural temperatures made available by the city meteorological station site were registered. In addition, the user's profiles were identified by means of a questionnaire applied to the households. Their electrical energy consumption data were also collected from the power supply company. Models applying Artificial Neural Networks were then developed for the most important periods of UHI intensity. The results show that low values of sky view factor and high urban heat islands, when observed in high income zones, are associated with the largest electrical energy consumption patterns.

Keywords: energy consumption, sky view factors, artificial neural networks

1. Introduction

Urban heat island (UHI) is one of the main consequences of densely occupied urban areas for the climate. On the other hand, the rise of urban temperatures has a significant impact on the electricity demand. Buildings are the largest consumer of energy in cities. [1] shows that heat-island effect in warm to hot climates raises the energy use for cooling in summer.

Many other aspects also influence the energy demand of buildings, like human behaviour and living standards. Domestic electrical energy use is one of the growing energy demands in the world. According to [2], among different sectors concerning buildings, the largest consumer is the domestic sector. The same author states that in this sector, heating consumes almost 75% of the energy, warming water consumes 10%, and the remaining 15% are related to household appliances.

In Brazil, the amount of energy consumed by buildings corresponds to 46% of the national consumption [3].

Even so, there are still few studies integrating urban environment, climate parameters and energy use. The work of [1], [2] and [4] are remarkable references in this area.

These facts bring up questions about the extent of the influence of urban variables on the building energy demand, in a way that planners could extract useful information for performing their activities. Limiting the study to the range of electricity consumption in the domestic sector, this paper emphasizes the integrated role of UHI, sky view factors (SVF) and households' incomes on building energy demand.

SVF is a parameter established in urban climatology to represent an estimation of the visible area of the sky from an Earth viewpoint. It is a geometric ratio that expresses the fraction of the visible sky from an observer's standpoint. It is also defined as the ratio between the total amount of radiation received from a plane surface and that received from the whole radiant environment. It is, thus, a dimensionless parameterization of the quantity of visible sky at a location. The SVF is one of the causes of urban heat islands and represents a tool for determining urban geometry. It also indirectly indicates urban density. The work of [5] emphasizes the potential of manipulating urban geometry to control urban environment.

Due to the complex relationships involved, the methodology proposed in this work uses Artificial Neural Networks (ANN) for modelling the phenomenon. The ANN is an information processing that has the ability to learn tasks based on a set of data, and working in a similar way the human brain does. It is an adaptive system that deals with no linear-problems and changes its structure by learning from examples. This mathematical model has the ability to extract complex patterns and trends, allowing further predictions of new situations. In the field of energy consumption this technique was applied by some authors, such as [6], [7] and [8].

By modelling the urban thermal environment with ANN, this paper analyzes the electrical energy consumption of households as a function of urban variables in a residential neighbourhood. First, the methodology applied is presented, followed by some results, analysis and discussions.

2. Methodology

A specific residential area in the city of Bauru, Brazil, was selected for the development of the study. Bauru is a medium sized city with around 340.000 inhabitants. The city is situated in the state of São Paulo, in the area comprised by the geographical coordinates 22º15' and 22º24' South latitude, 48º57' and 49º08' West longitude, and between 500 and 630 meters of altitude.

In this area forty points were taken as urban reference points, so that air temperatures at the pedestrian level could be collected. For that purpose, a data logger was programmed and installed to register the hourly temperatures of selected summer days. The equipment was installed two meters above the ground, i.e., at the pedestrian level of the urban canyons. The days of measurement corresponded to typical days of that season, with low wind speed (less than 2 m/s) and clear sky. The thermal data collection campaign carried out considered each one of the forty field survey points. Fig. 1 shows an overview of the study area, in which the forty points of reference are indicated.

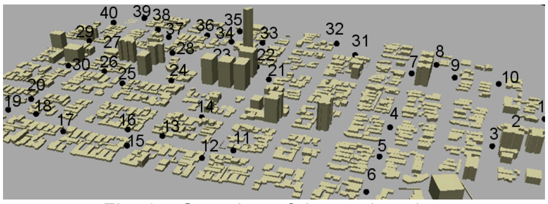

Fig. 1 – Overview of the study point

At the same time, rural temperatures made available by the city meteorological station were registered. These data allowed the hourly comparison of urban and rural temperatures indicating the UHI intensity and development.

Many urban features of the forty points were determined, including street orientation, sky view factors (SVF) and percentage of non-built areas. This neighbourhood presents only two street's orientations: one is the urban canyon orientation along the NE-SO axis and the other one along the NO-SE axis.

In addition, the inhabitants of the neighbourhood were asked to answer a questionnaire about household characteristics, such as income and electrical energy consumption. These data were then associated with the forty points of reference.

For determining the SVF of these points the tool applied was the 3DSkyView extension [9], an algorithm incorporated into ArcView GIS.

All data were submitted as output and input variables developing Artificial Neural Network (ANN) models. Consisting of an interconnected cells (artificial neurons) and process information, this kind of modelling simulates the behaviour of human brain neurons, based on real input and real output data. The networks are trained with the actual data for "learning" the relationships patterns among input and output variables. Once these patterns are learned, the network model is able to estimate new output values when looking at different input values.

In the case studied the output variable is the monthly average consumption of electrical energy, while the input is represented by the other variables determined for the reference points, e.g., income, SVF, number of house appliances (heating and freezers), number of bedrooms, percentage of non-built area, urban heat island intensity, etc. The application of the ANN also allows an evaluation of the influence of urban variables on the electrical energy consumption.

This could then shed light to the influence of each variable on the electricity consumption. The software EasyNN, developed by Stephen Wolstenholme, was applied for that purpose [10].

Models for the most relevant periods of UHI development were kept under evaluation. The models are basically established in three periods of the day: morning, afternoon, and evening. They were evaluated according to the relative error generated and also by the Determination Coefficient (R^2) encountered when comparing real and estimated data.

For each model, three sets of data were prepared for learning, validating and testing the network. In the preparation of each data set, the real data were divided randomly in three groups: 50 % of data for the phase of training (when the network "learns" the patterns), 25 % for the phase of validation (when the variables weights are evaluated and adjusted iteratively) and 25 % for the phase of test (when the model simulates new values for comparison with actual values that have never been "seen" by the network).

The best models can be used to simulate the electricity consumption. Moreover, they can be used to evaluate the impact of each variable on the output.

3. Results and Analysis

The monthly average electrical energy consumption found for the households in the area is distributed as follows:

- 31 % of the houses consume about 100 to 200 kWh/month;
- 24% range from 200 to 300 kWh/month;
- 13% have a consumption varying between 300 and 400 kWh/month.

The average values of income per month, here converted from Brazilian Reais to US dollars, are:

- 36% range from \$150 to \$1500;
- 44% range from \$1500 to \$3000;
- 16% range from \$3000 to \$6000;
- 3% range from \$6000 to \$9000;
- 1% range from \$9000 to \$12000.

Based on the air temperatures registered, the average thermal differences between the study neighbourhood and the rural area were calculated. They were then divided into ranges of thermal differences in order to compare their behaviour with the electrical energy consumption. The results of this operation are graphically represented in Fig. 2.

As shown in Fig. 2, the urban heat island revealed a close relationship to the energy consumed in the neighbourhood studied. These data shows the tendency of increasing the energy consumption with the elevation of heat island intensity.

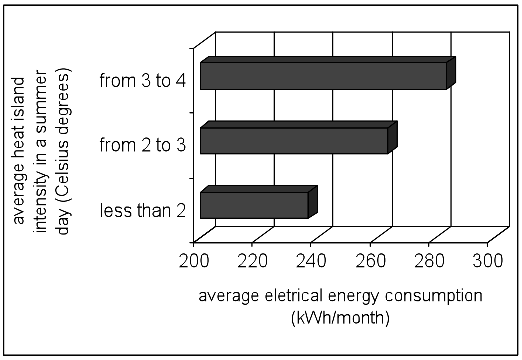

Fig 2. Actual electrical energy consumption and UHI intensity in a summer day

Afterwards, all other variables of the houses and appliances collected with the questionnaire were joined to compose the input data for the development of the ANN models.

Amongst the variables studied, those having the highest influence on the models are listed from Tables 1 to 3. Their relative importance in each model is discriminated in the right column of the tables.

Table 1: Relative importance of selected variables in the morning model.

Variables	Relative importance (%)
Number of heaters	16
Household income	11
Relative humidity	10
Number of freezers	9
SVF	8

Table 2: Relative importance of selected variables in the afternoon model.

Variables	Relative importance (%)
Household income	14
Number of heaters	13
Number of bedrooms	13
SVF	12
% non-built áreas	11

Table 3: Relative importance of selected variables in the evening model.

Variables	Relative importance (%)
Household income	13
Number of heaters	12
Number of bedrooms	11
Number of households	9
UHI	8

According to their relative importance in the models, the variables "household income" and "number of heaters" are the most significant aspects related to the electrical energy consumption. Regardless the period of the day, these variables are responsible for more than 11% of the amount of electrical energy consumed.

The other variables, however changing their position within the models, also assumed central importance in the study. The values of their relative importance are very similar to each other, ranging from 8% to 11%. It is yet remarkable that some of these are urban parameters such as SVF and non-built areas, which were mainly relevant for the diurnal period.

In order to analyze the behaviour of some variables in the models, simulations were carried out. For this purpose, the variable being tested had its value ranging from the minimum to the maximum ones, while the others were kept at their average values. From Fig. 3 to 5 there are examples of these tests. Fig. 3 shows that the higher the household income, the higher the energy consumption. There was no difference in this tendency among the models studied. The influence of the number of heaters can be observed in Fig. 4. Consumption goes up as a consequence of the increment on the number of heating appliances, but slight differences occurred among the models, according to the period of the day. While in the morning model and in the afternoon model the highest energy consumption due to the number of heaters corresponded to NE-SW orientation, the evening model tended to equalize the consumption of both orientations.

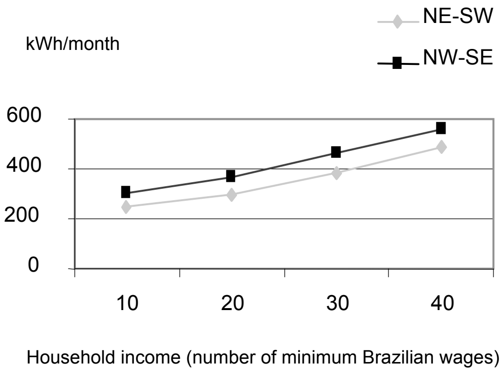

Fig 3. Electrical energy consumption and household income simulated by applying the evening model. Household incomes are expressed by the number of minimum Brazilian wage, which was equivalent to US$ 250.

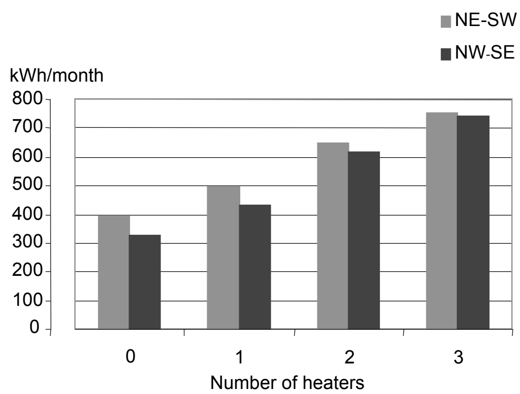

Fig 4. Electrical energy consumption and the number of heaters, simulated by applying the morning model

Increment on energy consumption was also a consequence of other variables. For instance, each time the number of bedrooms was doubled, there was an increase of 45% in the electrical energy consumption. In contrast, doubling the number of freezers corresponded to an increase of 10% in the electrical energy consumption.

On the other hand, the influence of urban parameters such as SVF and percentage of non-built area follow different trends (Fig. 5 and 6). For both models in which the SVF was one of the main variables, the higher the SVF, the lower the electrical energy consumption. Moreover, for the percentage of non-built area, there was a considerable reduction when changing its range from 60 to 70%. After achieving this level, the increase on the percentage of non-built areas did not modify the consumption. On the contrary, it remained stable.

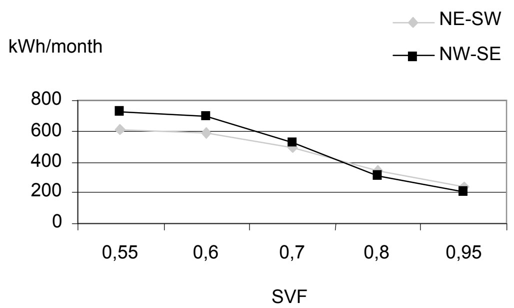

Fig 5. Electrical energy consumption and SVF, simulated by applying the afternoon model

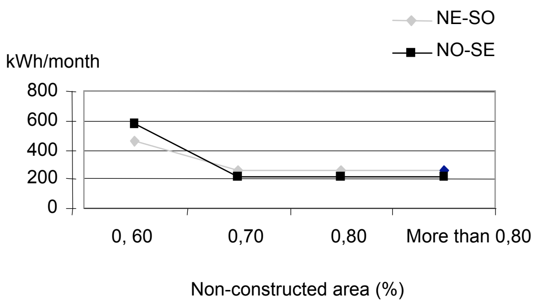

Fig 6. Electrical energy consumption and percentage of non-built area, simulated by applying the afternoon. model

Thermal variables, such as relative humidity and UHI intensity, were also classified amongst the five most important variables. The former is noticed in the morning model and the latter in the evening model. A growth of 10% in the relative humidity represented an increasing rate of energy consumption of 15% for the NW-SE orientation, while the same growth for the NE-SW orientation generated no significant increment. For the UHI, a 75% increase in its intensity in the evening model produced an increase of 25% in the electrical energy consumption, as seen in Fig. 7.

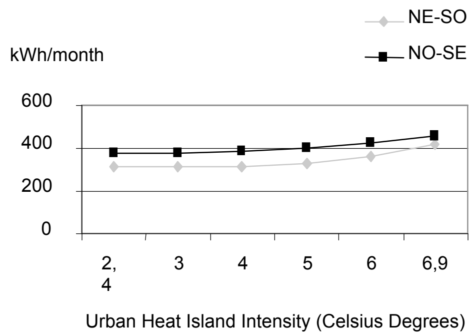

Fig 7. Electrical energy consumption and UHI intensity, simulated by applying the evening model

4. Discussions

According to [2] the biggest consumer in cities is the domestic sector. This is a result of heating and cooling, dense construction and a large number of home appliances. Many of the results here achieved highlight these relationships.

In a way, the strong relationship found between energy consumption and household incomes was somehow predictable, but its almost constant increasing rate is remarkable. It is the same for both orientations studied and it reflects the indirect effects of the number of appliances on the electricity consumption. There is a natural tendency of a larger number of appliances associated to higher incomes. That could be the reason for finding out that a growth of four times in the household income causes the consumption of twice the amount of electricity.

About the direct consequence of the elevation in the number of appliances, the duplication on the number of heaters almost doubled the amount of electricity consumed. From this point of view, the number of freezers had a much lower influence in electricity consumption than heaters, but still its effects are noticeable.

Although all this results are very important to get a profile of actual electrical energy consumption in this neighbourhood, the most important point of this discussion are focused upon the urban building variables, e.g. SVF and percentage of non-built areas.

SVF determines the daylight availability inside buildings, as well as it affects radiation exchanges. So the electricity consumed in these buildings is also a consequence of the SVF. For city planning purposes, it would be then important to check in a foreseeable future which the best configuration minimizing the energy consumption is. Here it was clearly shown a growth of 2% on the electricity consumption when the SVF changed from 55% to 95%. The larger the sky visibility is, the lower is the electrical energy consumption. But that is yet not possible to generalize, because there was a slight difference among orientations. About this matter there are other studies of [11] which have pointed out that SVF influence depends in fact on the building orientation.

Complementary, the studies revealed that the non-built area greatest influence on reducing the electricity use remained on a specific range. This suggests that the worst situation occurs when the urban tissue reaches levels of density lower than 70% of non-built area. Though, there was no sample of places with less than 60% of the non-built area in the studied neighbourhood.

Finally, the elevation of urban temperatures integrated with all the abovementioned facts, illustrates the issue of planning with the environment. [1] has already shown that increased urban temperatures have a direct effect on energy consumption. And this statement is here reassured with the fact that the higher the UHI intensity registered, the higher the electricity consumed.

5. Conclusion

There are in fact many urban variables that affect energy consumption that should be better understood in order to help planners and dwellers in saving energy.

The models allowed the analysis of the influence of urban variables on the electrical energy consumption of households. The results show that low values of sky view factor and high urban heat islands, when observed in high income zones, are associated with the largest electrical energy consumption patterns.

The most important variables influencing the electrical energy consumption, together with their average level of importance in the models were: the number of heaters with 13,6%, household income with 12.6%, the number of bedrooms with 12.0%, and the sky view factor with 10.0%.

In addition, it is also important to remark that during the evening period, when the largest development of the urban heat islands occurs, the highest electrical energy consumption tended to concentrate in houses located in the streets oriented along the axis NW-SE.

Further studies must be conducted in order to deeply investigate the issues that were here arisen.

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