Prediction of Household Energy Consumption in a Toronto High-Rise Multi-Unit Residential Building Using Artificial Neural Networking

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Abstract

This paper uses the Artificial Neural Network (ANN) modeling technique to predict household energy consumption in a Toronto multi-unit residential building (MURB). The Quick Propagation learning algorithm was used to develop the network with 151 iterations. The ANN results obtained a R^2 of 0.89 for all phases. The model found that middle-aged occupants (between 31 and 45 years old) consume less than the other age groups. In terms of gender, it was found that males consumed more energy than females. Lastly, higher income households consume less energy than those of lower income.

Keywords: Multi-unit residential building (MURB), artificial neural networking (ANN), demographics.

Résumé

Cet article utilise la technique de modélisation par réseau de neurones artificiels pour prédire la consommation énergétique d'un habitat résidentiel a logement multiple (HLM) dans la ville de Toronto. L'algorithme « Quick Propagation » a été utilisé pour développer le réseau avec 151 itérations. Il a été trouvé un R2 de 0.89 comprenant toutes les phases. . Le modèle a décelé que les occupants d'âge moyen (entre 31 et 45 ans) consomment moins d'énergie que les autres. Pour ce qui est du genre, les hommes consomment plus d'énergie que les femmes. Pour finir, les occupants avec un haut salaire consomment moins d'énergie que ceux ayant un bas salaire.
Mots clés: Habitat à logement multiple (HLM), réseau de neurones artificiels, démographiques.

1. Introduction

There has been a significant amount of studies on household energy consumption, particularly in the matter of residential building design and materials [1]. Energy behaviour and usage, however, is relatively a new topic [1]. Household energy consumption is an important issue, especially in Canada, where 17% of Canada's total energy use is due to the residential sector. Household energy consumption is the function of structure and energy intensity of a home [2]. Energy intensity is affected by behaviour, age and type of appliance, demographics and more [1]. Determining all factors contributing to one's household energy consumption, however, is complex. Household energy consumption involves elements of technical, economic, social and psycho-social origin [3]. Understanding and evaluating occupant's present household energy use and behaviour, therefore, is significant in order to develop energy reduction strategies such as tenant engagement and education. Artificial neural networking technique is an effective evaluation tool in determining casual relationships between a large number of parameters [4]. In this case, neural networking may have the capabilities to develop a model in order to predict household energy consumption based on multiple parameters such as demographics. Currently, there has been no research done investigating household energy use in a Toronto high-rise MURB using neural networking (at an apartment unit level). In this study, the main objective is to fill this void.

The concept of ANN was first introduced by McCulloch and Pitts in 1943 with their McCulloch-Pitts model. The ANN approach is inspired by networks of biological neurons, containing multiple layers of computing nodes [5]. The McCulloch-Pitts model (Figure 1) resembles a biological neuron. The concept of the model shows that a neuron receives a weighted sum of inputs. These weighted sum of inputs are then connected and outputs a value [6].

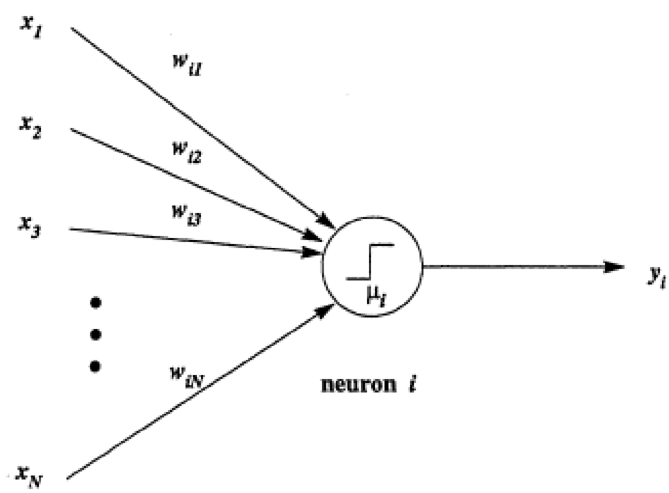

Figure 1: Illustration of McCullock-Pitts Neuron [6]

ANN has the ability to discover internal relationships between data. It also has the ability to classify nonlinear relationships with incomplete and small datasets. Because of this, ANN has become a huge interest in all fields of study and has matured over the past 40 years [5]. To date, ANN is used for many applications from national green energy use analysis [7], public awareness campaign assessments [8], depression symptom analysis [9], perceptions on building quality [10], energy dependency projections [11], and the list goes on.

1.1. Artificial Neural Networking Modeling Approach

This study uses a common ANN model approach called multi-layer perceptron (MLP). MLP consists of an input layer, one or more hidden layers, and an output layer [12]. Each layer consists of neurons that are interconnected with each other and are assigned with various weights. The output neuron is established by the input layer passing through hidden layer. Each neuron receives signals from the neurons of the previous layer. Figure 2 presents a neural networks structure [12].

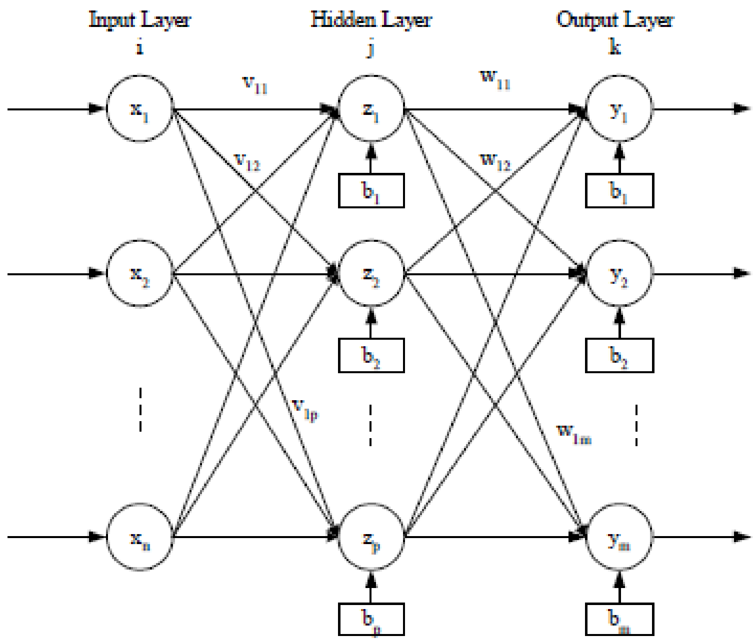

Figure 2: MLP neural network structure with one hidden layer [12]

There are seven major components of an artificial neural network [13]. These components apply for all layers of the neural network - input layer, hidden layers, and output layer.

1. Weighting factors and weights: Neurons interact with many inputs at the same time. Some inputs have greater significance than others, thus, these inputs receive a greater weight than other inputs. These weighted inputs have a great effect on the output.
2. Summation function: The sum of all the weighted inputs and results in a single number.
3. Transfer function: This function is an algorithmic process that transfers the results from the summation function or the weighted sum of the inputs to a working output.
4. Scaling and limiting: After the processing element's transfer function, the results may be scaled or limited.
5. Output function: The output reflects on the many neurons in the network, where each neuron is consists of the many interactions between weighted inputs.
6. Error function and back-propagated value: The error function calculates the difference between the current output (from the model) to the desired output. In order to reduce the network's error, the error function transforms the output error to match the network's architecture. In some cases, the error is modified by squaring the error, cubing the error, or some use the error directly. Afterwards, the neuron's error is then typically propagated into the learning function.
7. Learning function: This function is also referred to as the adaption function, which modifies the weights of the input connections in order to achieve a desired result. Examples of learning functions are back propagation algorithms, enhanced back propagation, and Quickprop.

1.2. Objectives of the Study

The main objective of this study is to develop a model that represents occupant's household energy use in a Toronto high-rise MURB. This model will be used to evaluate the impact of demographic factors (age, gender, and income) on household energy consumption in a Toronto high-rise multi-unit residential building (MURB).

2. Methodology

2.1. Sources of Data

Three sources of data were used for the development of the input units of the ANN models: the survey data of household energy use in the Toronto high-rise MURB [14], the energy consumption of each unit and the weather conditions [15]. The source of data for the output unit of the models was the monthly energy consumption per unit.

Surveys were sent out to household's mailboxes. Three methods were used to collect the surveys; 1.) A drop box was available in the main lobby; 2.) Interview assisted surveys - five interview sessions were held in the main lobby during evenings; and 3.) Online survey. The survey was based on a mail out survey that included 51 questions. The survey database contains detailed information on space heating/cooling equipment, small household appliances and electronics and their use, environment comfort as perceived by occupants and socio-economic characteristics of the occupants [14].

With the permission of the Property Manager of the Toronto MURB, the research project obtained the complete monthly energy consumption for the 136 units in the Toronto MURB from October 2010 to September 2012. This energy consumption is the amount of electric draw from each apartment unit in a month (kWh/month).

The weather conditions data were obtained from National Climate Data and Information Archive [15]. The weather data obtained includes the monthly mean temperature (℃), the monthly total of precipitation (mm), the mean direction (10's deg) of gust, and the mean speed of gust (km/h).

2.2. ANN Model

The ANN model developed in this study consists of one network. This network is able to predict household's energy consumption per month. The methodology of the network is shown through Sections 2.2.1. to 2.2.6.

<u>2.2.1. Development of the Network Dataset</u>

A total of 48 surveys were completed, therefore, corresponding energy metering data were extracted. The monthly energy metering data consisted of a total of 24 months of energy consumption. This calculates to a total of 1,152 cases. In addition, the weather conditions include a total of 24 months of data from 2010 to 2012.

<u>2.2.2. ANN Software</u>

Once the dataset was constructed, the ANN software was to train, validate, and test in order to develop the model. The entire dataset was partitioned randomly. Data were partitioned in the following way: 750 records to Training set (65.1%), 218 records to Validation set (18.92%), 184 records to Test set (15.97%). The training dataset is used to develop the model. The validation and testing dataset is used to strengthen the performance of the model by introducing a dataset that the model has not used to develop the model.

The ANN software used was Alyuda NeuroIntelligence Version 2.1 [16]. This software has a friendly user interface and a number of options for the different stages of the analysis.

2.2.3. Development of Input and Output Units

The input units of the network include:

- Date - Month / Year
- Orientation (e.g., East or West)
- Demographic (e.g., age, gender, income)
- Toronto weather data [15]
- Appliances and usage (e.g., computer, television, stove)
- Appliance energy consumption behaviour (e.g., whether they turn off their television when not in use or not at home)

There are a total of 34 inputs units. The output of the network is the monthly energy consumption data for each household.

2.2.4. Network Architecture

To design the network, it is necessary to specify the network architecture (number of hidden layers and neurons in each layer) and the network properties (activation functions). For this study, an architecture search was launched with two (2) hidden layers and with different activation functions. An architecture search is a process determining the number of layers the neural networks needs along side with the activation function for the layer and network error function. An activation function is a mathematical function (e.g., logistic, linear, or tangent) that a network unit uses to produces an output referring to its input value [16].

Table 1 shows the results. The best retained network architecture is [34-85-54-1].

2.2.5. Training of the Network

The following algorithms supported by NeuroIntelligence were applied to the analysis of the data:

- Quick Propagation (QP),
- Conjugate Gradient Descent (CGD),
- Quasi-Newton (Q-N),
- Limited Memory Quasi-Newton (LMQ-N),
- Levenberg-Marquardt (L-M),
- Online Back Propagation (OBP),
- Batch Back Propagation (BBP).

The termination criterion (when to stop training) used was the increase of the network error or the number of iterations (1,000 iterations). The algorithms that resulted with negative correlation coefficients were Quasi-Newton (Q-N), Levenberg-Marquardt (L-M), and Batch Back Propagation (BBP). They were not used for further network training.

2.2.6. Testing of the Network

The performance of each network model was assessed numerically using both the coefficient of determination (R^2) and the validation error. The testing was conducted for all data sets: training, validation, and testing. If the coefficient did not reach the minimum values accepted (for validation and testing $R^2>0.75$, for all $R^2>0.85$) then the network was re-trained by choosing a different algorithm or by adjusting the weights.

Table 2 shows the performance of the ANN model. The best network activated for the query is the first one with a number of iterations equal to 151 and a $R^2=0.895$. The number of weights signify the number of interactions between the inputs.

Table 1. Architecture search

Hidden layer activation function	Output activation function	Architecture	Number of weight	R^2
Logistic	Logistic	[34-85-54-1]	7674	0.993
Tangent	Logistic	[34-70-39-1]	5259	0.992
Tangent	Logistic	[34-68-1]	2449	0.974
Logistic	Logistic	[34-73-1]	2629	0.974
Logistic	Tangent	[34-77-1]	2773	0.961
Logistic	Linear	[34-72-1]	2593	0.935
Linear	Logistic	[34-8-1]	289	0.593

Table 2. Performance of the ANN model

Number of iterations	Training algorithm	Coefficient of determination (R^2)			
		Training	Validation	Testing	All
151	QP	0.857	0.942	0.937	0.895
415	LMQ-N	0.873	0.762	0.784	0.835
173	CGD	0.817	0.608	0.689	0.756
1000	OBP	0.778	0.568	0.678	0.756

3. Results

The ANN software allows querying every case in the dataset. This query dataset was compared to the actual energy consumption. Every month was summed and the percentage of error found is 0.37%. This shows that the model was able to predict energy consumption effective since the percentage of error between the predicted and actual was less than 1%.

3.1. Overview

In this section, impacts of various scenarios on household demographics were assessed. The analysis was conducted by using the ANN model developed in Section 2. The model was used to compare different monthly energy consumption profile scenarios for each of the following: gender, age, and income. The Alyuda NeuroIntelligence Version 2.1 allows us to compare monthly energy consumptions by querying the model. This is done by selecting a set of characteristics from the inputs provided, then an energy consumption (kWh) is given.

In order to measure the effects of demographics, a selected set of household energy behaviour inputs were fixed, while the demographics were changed. This means that the energy behaviour inputs did not matter as long as it was selected consistently throughout the query. This enabled a comparison between age groups, for example, and monthly consumption trends from October 2010 to September 2012. All data was manually entered to develop monthly demographical trends for the selected set of household behaviours.

The selected set of household energy behaviour was randomly determined from the survey results. The selected set of household behaviours are defined by the following characteristics: apartment unit located on the East side of the building, male, between the ages of 46 to 60 years old, grew up in Africa, living in the Toronto MURB between 5 to 7 years, single-family household, spends 9 to 13 hours per day in their apartment unit (includes sleeping), household income between $15,000 and $29,999 per year, and appliance ownership, type.

3.2. Demographics

3.2.1. Gender

Figure 3 the energy consumption comparison between males and females obtained from ANN model. On average, males used more energy than females did during winter (December, January, and February). The mean difference is approximately 5 kWh/month above the female's consumption of 199 kWh/month during the winter season. During the summer season, however, males and females tend to have equivalent energy consumption patterns.

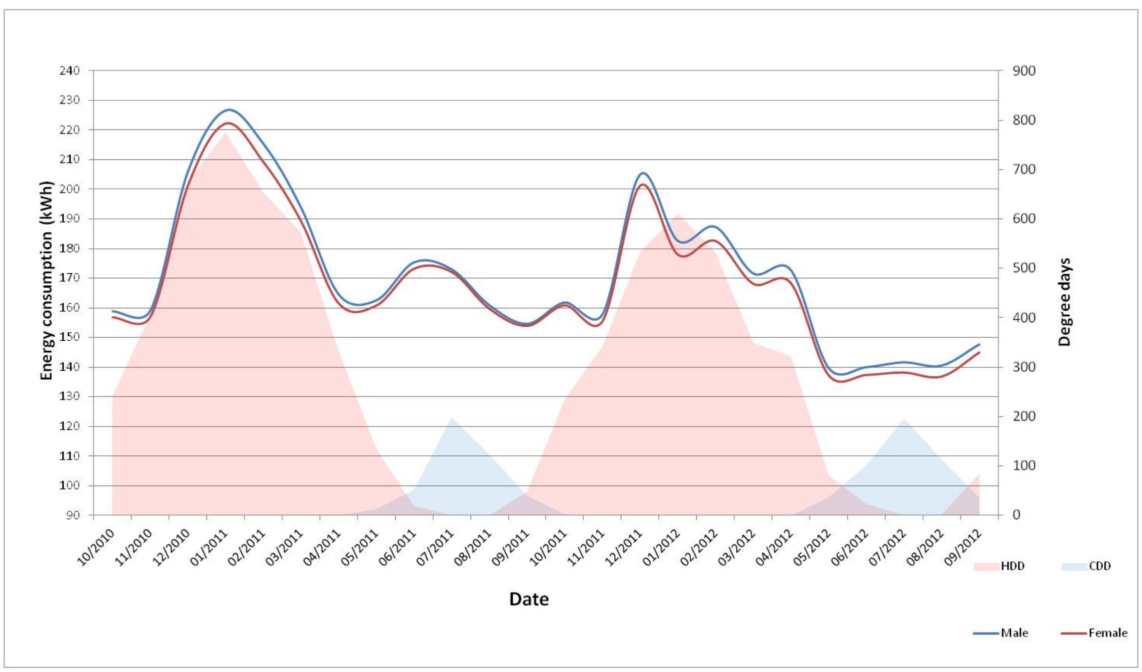

Figure 3: Gender - Comparison of energy consumption between male and female surveyed respondents in the Toronto high-rise MURB

Another energy consumption relationship found was that the monthly energy consumption runs parallel to the heating degree days (HDD) and cooling degree days (CDD). Heating degree day is the heating degree-days for a given day are the number of degrees Celsius that the mean temperature is below 18℃. If the temperature is equal to or greater than 18℃, then the number will be zero [15]. Cooling degree day is the cooling degree-days for a given day are the number of degrees Celsius that the mean temperature is above 18℃. If the temperature is equal to or less than 18℃, then the number will be zero [15].

3.2.2. Age

Since females were found to consume less energy than males during the winter season, two different results were extracted using the ANN model. First, a comparison between different male age groups were analyzed. Figure 4 shows that middle-aged male people (31 to 45 years old) use less energy than other male age groups - approximately 26 kWh/month. Second, different female age groups were compared.

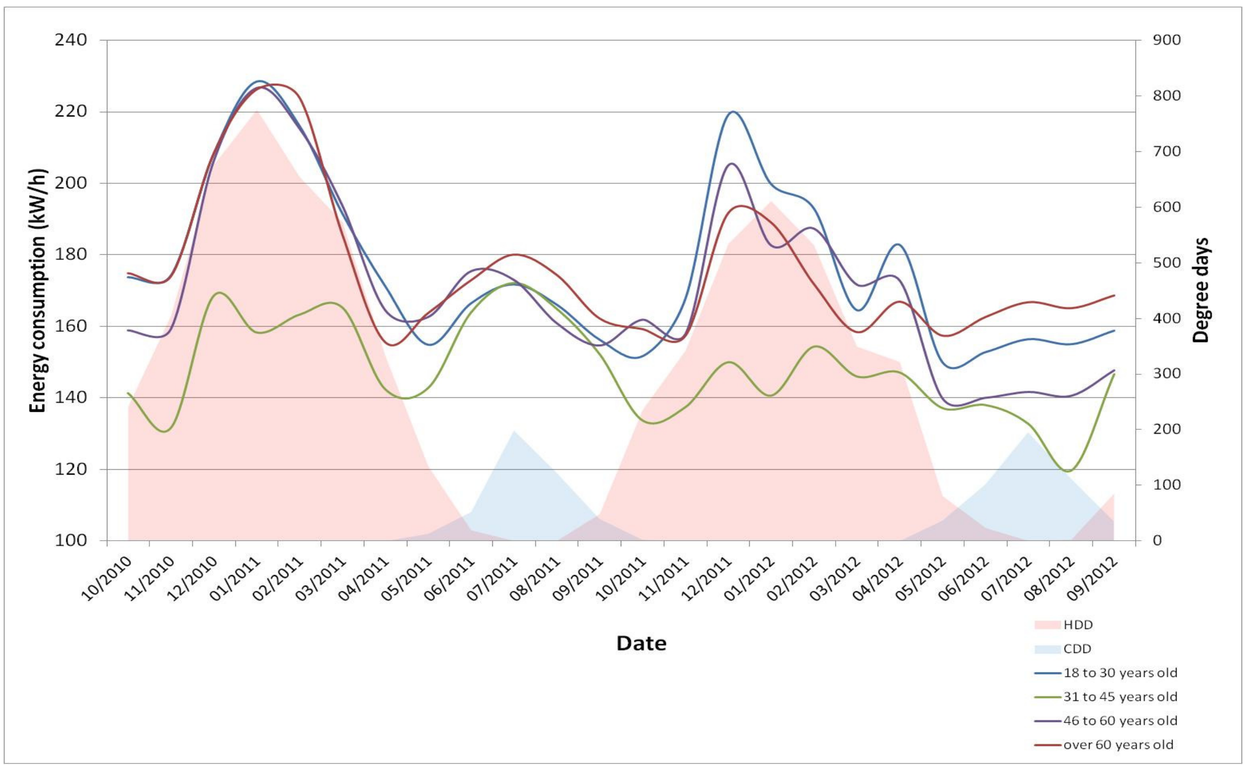

Figure 4: Male Age Groups - Comparison of energy consumption between different male age groups

Similarly, Figure 5 shows that middle-aged females (31 to 45 years) use less energy than the other age groups - approximately 26.71 kWh/month compared to the average female. Figure 5 also illustrates that during the winter seasons, females over the age of 60 years use more energy than the average females did- approximately 10.96 kWh/month.

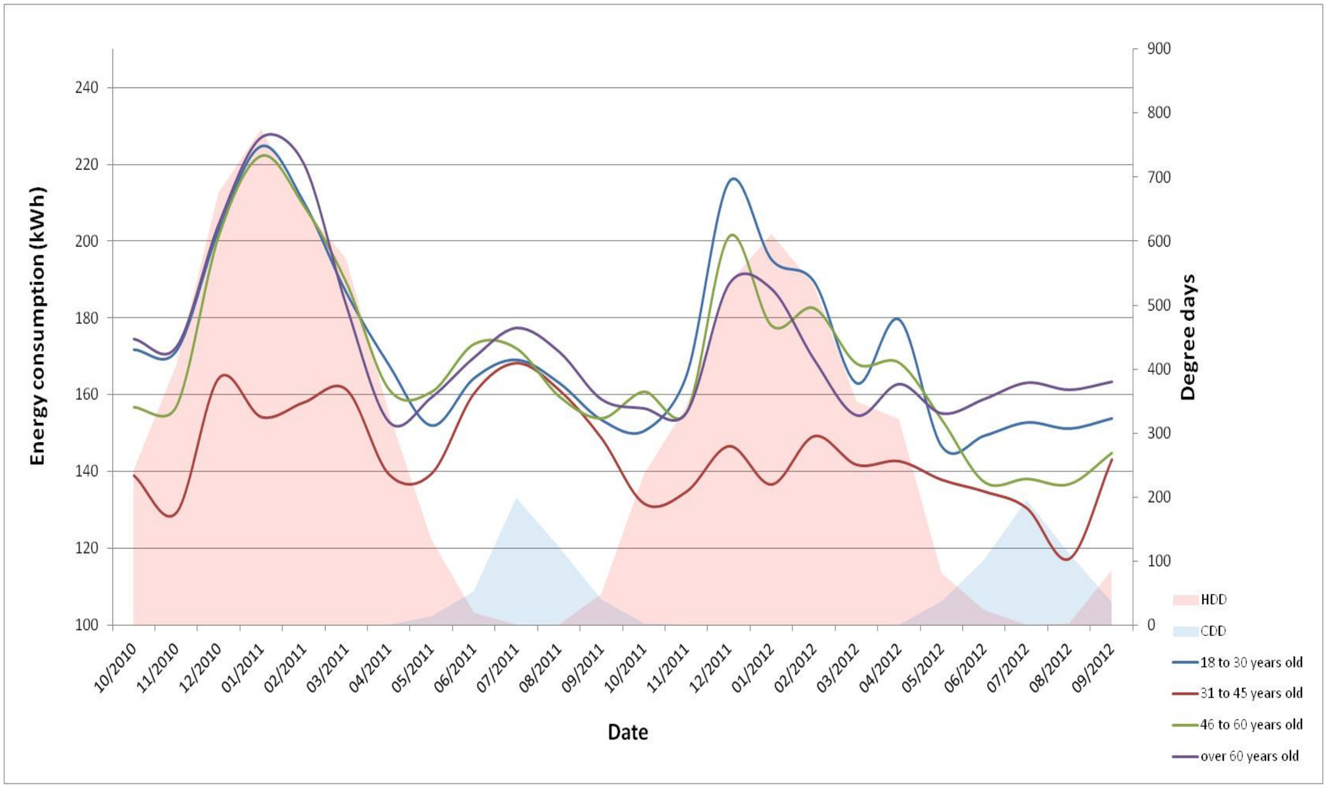

Figure 5: Female Age Groups - Comparison of energy consumption between different female age groups

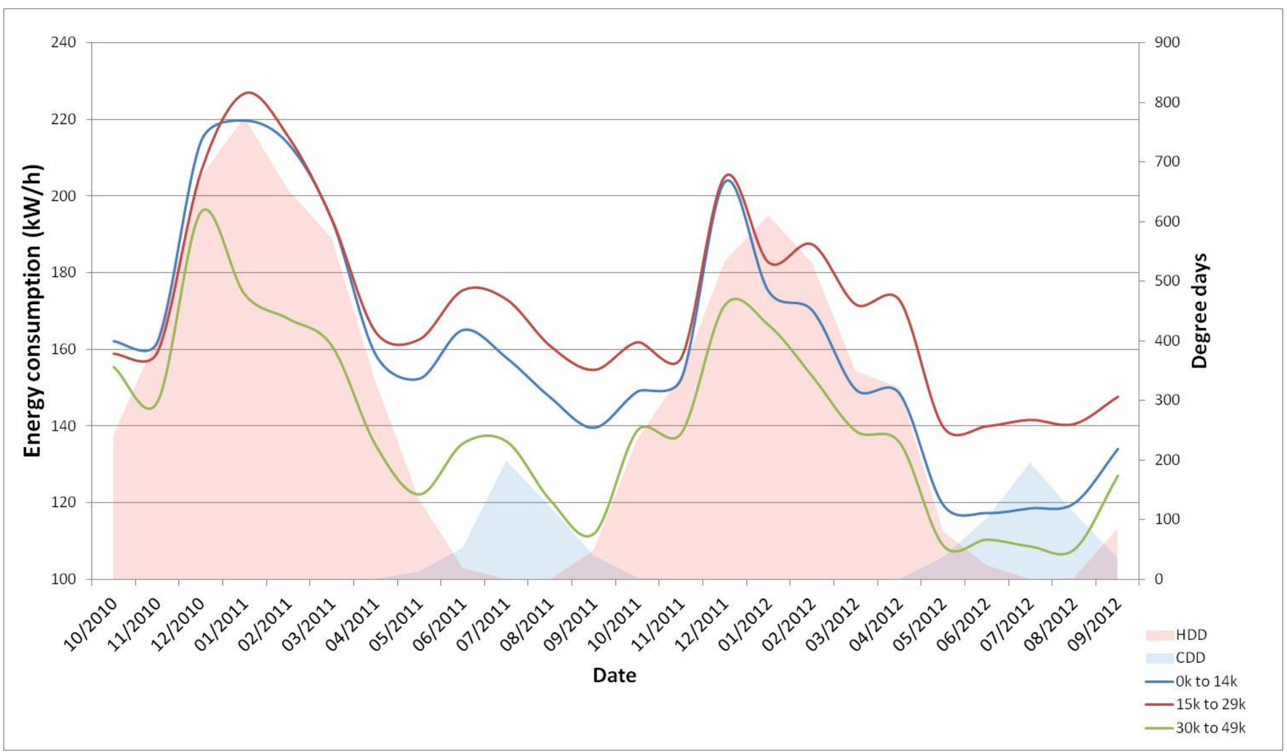

Figure 6: Income - Comparison of energy consumption between different incomes

It is also interesting to note that overall females between the ages 31 to 45 years old consume, on average, 145 kWh/month; whereas, males between the ages of 31 to 45 years old consume more than females between that age bracket (on average, 148 kWh/month).

3.2.3. Income

Figure 6 shows that households with the highest income ($30,000 to $49,999) consume about 18% less energy than the other income groups. The mean difference is approximately 25 kWh/month below the average of 165 kWh/month (on average) during the 24 months.

4. Conclusions

In this study, the Artificial Neural Network approach was used to develop a model that can predict household monthly energy consumption within a Toronto high-rise multi-unit residential building. The network's correlation coefficient was very high with a R^2 of 0.89 for all phases - training, validation, and testing. The model was able to evaluate the effect of household's demographics on monthly energy consumption - gender, age, and income. Results showed that females consume more energy than males during the winter season. Middle-aged males and females consume approximately 26kWh/month less energy than all other age groups. Lastly, it was found that wealthier households consume less energy, especially during the months of fall and spring compared to other households.

Based on multiple variables, the neural networking approach can predict one's household energy consumption effectively. It has also demonstrated its ability to evaluate the effects of human factors such as gender, income, and age. It is recommended to further investigate the effects of human factors and energy behaviour using neural networking as this topic is relatively new.

5. Acknowledgements

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7. Biography

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