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Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks

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Abstract

Two methods are currently used to model residential energy consumption at the national or regional level: the engineering method and the conditional demand analysis method. Another potentially feasible method to model residential energy consumption is the neural network (NN) method. Using the NN method, it is possible to determine causal relationships amongst a large number of parameters, such as occur in the energy consumption patterns in the residential sector. A review of the published literature indicates that the NN method has not been used or tested for housing-sector energy consumption modeling. A NN based energy consumption model is being developed for the Canadian residential sector. This paper presents the NN methodology used in developing the appliances, lighting, and space-cooling component of the model, the accuracy of its predictions, and some sample results. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Residential energy consumption modeling; Appliance, lighting, and space-cooling energy; Neural networks modeling

1. Introduction

Energy use has been a matter of policy concern since the 1970s. After the oil crises in 1973 and 1979, governments intensively promoted energy conservation.

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Nomenclature

A/C	air conditioning
ALC	appliance, lighting and space cooling
ANN	artificial neural network
C	thermal capacitance
CANN	cascaded artificial neural network
CDA	conditional demand analysis
CDD	cooling degree days
CV	coefficient of variation
DHW	domestic hot water
EM	engineering model
GHG	greenhouse gas
HDD	heating degree days
N	number of patterns
NN	neural network
R	thermal resistance
R^2	correlation coefficient
RMSE	root-mean-square error
SHEU	Survey of Household Energy Use
SNNS	Stuttgart neural network simulator
SSE	sum of square errors
$\bar{t}$	mean of the target values
t_i	target value of the ith pattern
x	value of the input/output unit
$x_{\max}$	maximum of the scaled input/output unit
$x_{\min}$	minimum value of the scaled input/output unit
x_n	value of the scaled input/output unit
y_i	predicted value of the ith pattern
μ	mean of the input/output unit
σ	standard deviation of the input/output unit

Then in the 1980s, the primary focus shifted to air pollution caused by combustion of fossil fuels. In recent years, energy use and associated GHG emissions, and their potential effects on global climate change have been of world-wide concern.

Improving the end-use energy efficiency is one of the most effective ways to reduce energy consumption and associated GHG emissions, especially for Canada. In 1999, the total energy consumption in Canada was about 7875 PJ, making Canada one of the highest per capita energy consumers in the world [1]. Mostly, owing to its northerly location and the prevalence of single-family housing, close to 20% of this total, i.e. about 1335 PJ, was for residential use, while the associated GHG emissions were 69.9 Mt, representing 15% of secondary energy related emissions. Thus, one of the effective means of reducing GHG emissions is reducing the end-use energy consumption in the residential sector.

To reduce the end-use energy consumption and GHG emissions from the residential sector, a large number of options need to be considered. These include improving the energy efficiency of houses through improving envelope characteristics; replacing existing heating equipment, household appliances and lighting with higher efficiency ones; and switching to less carbon-intensive fuels for space and domestic hot water heating. Energy-efficiency improvements have complex interrelated effects on the end-use energy consumptions of houses and the associated GHG emissions [2–4]. For example, improving the efficiency of lighting reduces the heat gain from lights, increasing the space-heating energy consumption. Owing to such interrelations, detailed computer models are necessary to evaluate the effect of various energy-efficiency improvement options on residential end-use energy consumption and associated emissions.

Recently, two methods have been used to model residential end-use energy consumption: the engineering method (EM) [4–7] and the CDA method [8–12].

The EM involves developing a housing database representative of the national housing stock and estimating the energy consumption of the houses in the database using a building energy simulation program. Thus, this method requires a database representative of the housing stock with detailed house-description data, as well as extensive user expertise and lengthy input data preparation time. A difficulty with this method is the inclusion of consumer behavior and other socio-economic variables that have a significant effect on the residential energy use. However, because of the high level of detail and flexibility provided by EM based models, they can be used to evaluate the impact of a wide range of scenarios for energy conservation on residential energy consumption and GHG emissions [5].

CDA is a regression-based method. Compared to the EM based models, the CDA based models are easier to develop and use, and do not require as detailed data. However, since these are regression-based models, the number of dwellings in the database needs to be larger, and the models do not provide much detail and flexibility. As a result, they have limited capability to assess the impact of energy conservation scenarios. It is, however, possible to include socio-economic parameters in the model if such data are available in the database. On the other hand, in most CDA models, multi-collinearity problems often makes it difficult to isolate the energy use of highly saturated appliances, such as the refrigerator [12].

In this paper, the NN method is proposed to model the residential end-use energy consumption because NNs are highly suitable for determining causal relationships amongst a large number of parameters such as seen in the energy consumption patterns in the residential sector. So far, the ALC component of the model for the Canadian residential sector is completed. This paper presents the NN methodology used in developing the model, the accuracy of the predictions of the NN model for the ALC energy consumption, and some sample results.

2. Energy modeling for the building sector using neural networks

In the area of residential energy modeling, the application of NN has been mainly limited to utility load forecasting. There are several hundred papers in the literature on the application of NN for utility load forecasting. These clearly show the superior capability of NN models over conventional methods, such as time series and regression. Park et al. [13] were the first group of researchers to use NN for load forecasting. They used a 3-layer NN to forecast the electrical load in the Seattle/Tacoma area, 1 and 24 h ahead of time. Using past and current ambient temperatures and electrical loads, their NN model could forecast the future load with an absolute error of about 1–2% for 1 h, and 4% for 24 h ahead forecasts. For 24-hour load forecasting, Peng et al. [14] employed an improved NN that used an alternate formulation of the problem in which the input is mapped to the output by both linear and non-linear terms, an improved method for selecting training cases, and a better normalization scheme. Consequently, the absolute errors in their 24-h forecasts were less than 3% for each day of the week, with some days less than 2%.

Kiartzis et al. [15] also used a 3-layer NN with 24 output neurons, one for each hour of the day (i.e. their model could forecast the next 24-h load profile 1 h at a time). With a NN made up of 63 input, 70 hidden and 24 output neurons, the yearly average absolute error of their forecasts was 2.66%. Chen et al. [16] included humidity in their NN in addition to ambient temperature to account for the effect of humidity on the air-conditioning component of the load at three types of sub-stations (residential, commercial, and industrial). They used a functional link network algorithm (a combination of the time series and the back propagation algorithms) to train the network due to its higher convergence speed and accuracy. The load forecasting errors were 1.93, 2 and 2.87% for residential, commercial and industrial substations, respectively.

AlFuhaid et al. [17] used a CANN to forecast half-hourly loads for the next 24 h. The CANN approach captured the sensitivity of the non-linear influence of temperature and humidity on the load. They used a 3-layer ANN (16 input, 3 output, 8 hidden neurons) as the lower ANN, and a 4-layer ANN (107 input, 48 output, 70 hidden neurons) as the cascaded ANN. The use of the cascaded ANN approach as opposed to standard ANN reduced the absolute error from 3.4 to 2.7%.

NN models were used to predict energy consumption of individual buildings since they have a high potential to model non-linear processes such as building energy loads [18]. NN applications specific to building energy analysis were pioneered by the Joint Center for Energy Management at the University of Colorado, Boulder, about a decade ago. It is reported by Krarti et al. [19] that Kreider and Wang [20] were the first to apply a NN model to predict the energy consumption of a building. The electricity consumption of a commercial building was predicted, and the results showed that the predictions of the NN model were accurate. The authors indicated that NN was easier to use than classical regression methods since it learns from fact patterns, and there was no requirement for an a priori statistical analysis. In a later study by the authors, the NN results were compared with statistical results for the same commercial building data [21]. The regression method attempted to fit all the data globally, but the accuracy at some specific points was not acceptable. The NN prediction was accurate with a correlation coefficient (R^2) of 0.946 for those points where the regression method completely missed.

Anstett and Kreider [22] used a NN to predict energy use (steam, natural gas, electricity and water) in a complex institutional building. They used various network configurations, starting with a simple configuration with no hidden layers, moving progressively to more complex configurations with two or three hidden layers. They used the month, day of the month and day of the week, outdoor (high, low and average) temperatures as input parameters, and evaluated several different training algorithms. The predictive quality of the NNs was found to be good.

In order to evaluate many of the analytical methods and to assess new methods not widely used in building data studies, an open competition was held in 1993 to identify the most accurate method for making hourly energy-use predictions based on a limited amount of measured data [23]. More than 150 contestants requested the building data. The results of the top six models were presented in the study of Kreider and Haberl [23]. Excellent predictions were achieved by NNs in all six models, with a coefficient of variation value ranging from of 10.46 to 16.58%. The aspect of the competition was that NNs of various designs and training methods obtained more accurate values than the traditional statistical methods.

Kreider et al. [24] used a NN to predict the energy consumption of a complex building without knowledge of the various energies for the immediate past. In this case, the forecasting problem was more difficult because the forecast was several months into the future rather than a few hours. Using dry-bulb temperature, humidity ratio, horizontal solar flux, wind speed, hour of the day, and weekday/weekend binary flag as inputs and recurrent (feedback) NNs (with one or two hidden layers and five or nine neurons, respectively), they predicted future heating and cooling loads. They also used the NN method to estimate the building's equivalent thermal resistance (R) and building equivalent thermal capacitance (C) from time series data on energy consumption. The assumption was that the energy consumption data contain, or implicitly represent, the characteristics of the building and its usage. Their NN was able to estimate both the R and the C with less than 1% errors.

Besides predicting building energy consumption, NNs were also used to predict energy savings from building retrofits [25,26]. Cohen and Krarti [25] developed a NN model from the monitored building end-use data available for a given period of time before the retrofit was implemented. Using the pre-retrofit NN model, the future building energy use without the retrofit was predicted. The energy savings were calculated from the difference between the actual post-retrofit measured data and the energy use prediction from the pre-retrofit NN model. In general, the NN model predicted savings within 10%.

Another NN approach to determine energy savings from building retrofits was proposed by Dodier and Henze [26]. They used one NN for each end-use energy variable to be predicted for the estimation of energy savings of a commercial building. All NNs had two hidden layers of 25 neurons each and the input variables for the NNs were selected by Wald's test [27]. The results of the end-use estimates obtained an average coefficient of variation value of 16.91%.

3. Modeling of residential sector energy consumption using neural networks

As the review of the literature presented above indicates, NNs have not been used to model national or regional residential energy consumption. In this paper, a new NN model that was developed to model the ALC end-use energy consumption in the Canadian residential sector is presented. This model is one of three new NN models that are being developed to model the residential energy consumption in Canada. The three models are:

- NN model for ALC end-use energy consumption,
- NN model for space heating end-use energy consumption,
- NN model for DHW heating end-use energy consumption.

So far, the ALC NN model is completed. The approach used in the development of the ALC NN is shown in Fig. 1. The Stuttgart Neural Network Simulator (SNNS) V4.2 software [28] was used in the development of the NN model.

4. Sources of data

Two sources of data were used for the development of the ALC network data set and the input units used in the ALC NN model: the data from the 1993 Survey of Household Energy Use (SHEU) database [29] and the 1993 heating and cooling degree-day data for the cities in which the households in the ALC network data set are located [30].

The 1993 SHEU database contains detailed information on house construction, space heating/cooling and DHW heating equipment, household appliances and some socio-economic characteristics of the occupants for 8767 households in Canada. Electricity billing data for a complete year for 2050 households in the 1993 SHEU database are also available. Out of these 2050 households, 988 do not own electric space and DHW heating equipment; therefore, the electricity consumption of these houses is only for space cooling, appliance and lighting. The ALC network was developed using the data from these 988 households.

5. Development of input and output units

The objective of the ALC model is to predict the ALC energy consumption of a household based on a number of parameters. For the model to predict the ALC energy consumption accurately, the input parameters chosen for the model must be of relevance to the ALC energy consumption. The input units used in the ALC model are described below.

5.1. Input units for appliances

In order to reflect the contribution of the appliance energy consumption to the total household energy consumption, input units reflecting ownership, size and

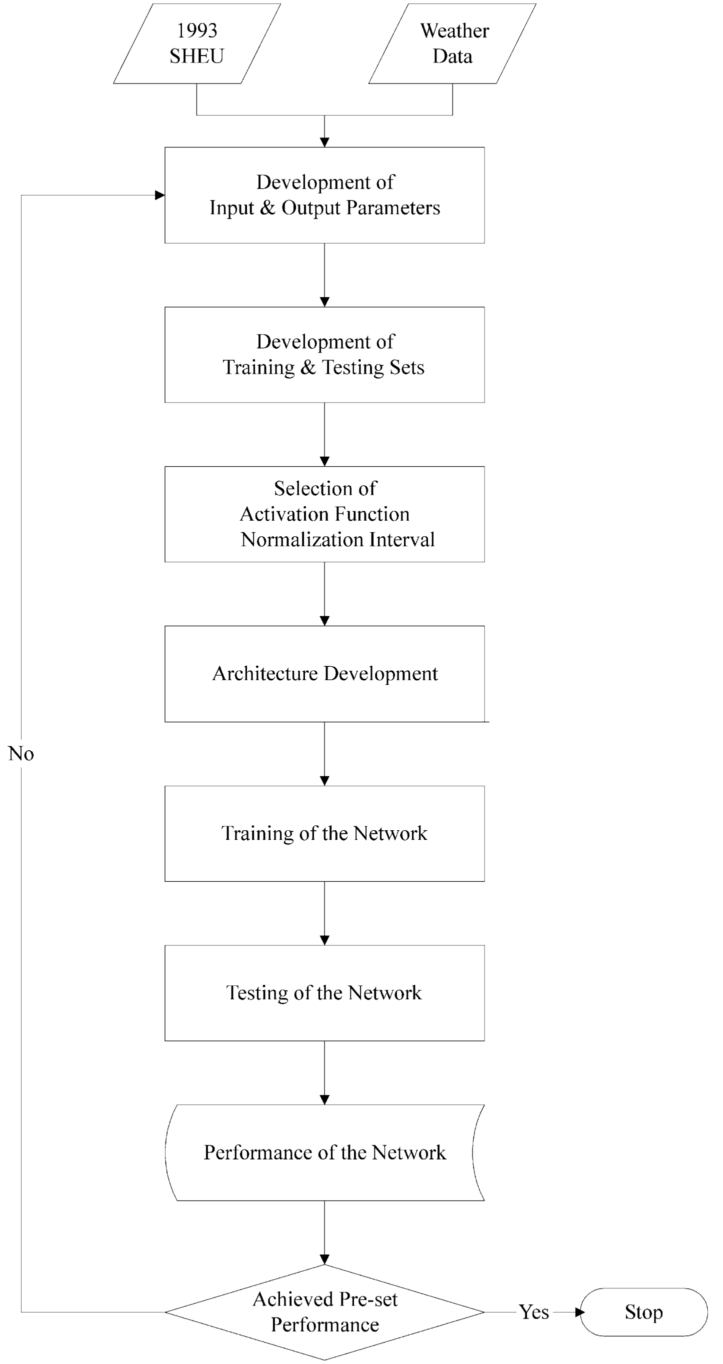


Fig. 1. The approach used in the development of the ALC NN model.

usage information were included in the ALC network. The 1993 SHEU database contains information on 40 appliances, and all 40 are included in the ALC network.

A review of the ALC data set indicated that households own only one of some appliances (e.g. clothes washer) and more than one of others (e.g. color TV). To indicate the ownership of the appliances that a household owns, only one of, binary variables 0 and 1 were used as input units. Thus, the variable 1 was used if the household owns the appliance, and 0 was used if it does not. For appliances that the household owns more than one of, the number of units of the appliance that the household owns was used as the input unit.

The ALC data set also contains information on the size of the main and second refrigerators and freezers, and the average weekly usage of dishwashers, clothes washers, and clothes dryers in terms of the number of loads. Since energy consumption of a household appliance is a function of its properties and usage pattern, the input units chosen for the main and second refrigerators and freezers reflect their size, and the input units for dishwashers, clothes washers, and clothes dryers reflect their usage. The input units used in the ALC network for appliances are given in Table 1.

5.2. Input unit for air conditioners

There are 275 households with central A/C and 84 with window A/C units in the ALC network data set. The information on A/C equipment is limited to the capacity and annual usage of central and window A/C equipment. Since not all of the households reported the capacity of their A/C units, it is not possible to include capacity as an input unit in the ALC network.

The information in the ALC network data set on the annual usage of the central and window A/C units is in the form of:

- never
- only a few days
- less than half of the summer
- about half of the summer
- most of the summer

The number of hours A/C usage was estimated by assuming that the response "about half of the summer" corresponds to 750 h/year.[1] The number of hours of usage for each of the other four categories was estimated based on this value as follows:

- never: 0 h/year
- only a few days: $0.25\times750=187.5$ h/year
- less than half of the summer $=0.5\times750=375$ h/year
- about half of the summer $=750$ h/yr
- most of the summer $=1.5\times750=1{,}125$ h/year

[1] 750 h/year is calculated as follows: summer months: May–August (123 days); A/C operation: during daytime (12 h/day); "Half of the summer": $1/2\times123$ days$\times12$ h/day $=738$–750

Table 1
The input units used in the ALC network

Input unit	range
Boiler pump	0–1
Central electronic air-filter	0–1
Central electronic dehumidifier	0–1
Central electronic humidifier	0–1
Central vacuum-cleaner	0–1
Central ventilation system	0–1
Electrical cooking appliance	0–1
Furnace fan	0–1
Heat-recovery ventilation system	0–1
Jacuzzi	0–1
Kitchen exhaust-fan	0–1
Microwave	0–1
Sauna	0–1
Sump pump	0–1
Water cooler	0–1
Water softener	0–1
Portable dehumidifier	0–2
Black-and-white TV	0–3
CD player	0–3
Portable electric-heater	0–3
Portable humidifier	0–3
Bathroom exhaust-fan	0–4
Computer	0–4
Interior car warmer	0–4
VCR	0–4
Water bed	0–4
Stereo	0–6
Car block heater	0–7
Ceiling fan	0–7
Color TV	0–7
Electric blanket	0–7
Fish tank	0–8
Portable fan	0–8
Clothes dryer	0–15 loads/week
Clothes washer	0–15 loads/week
Dishwasher	0–15 loads/week
Main refrigerator	0–625 L
Second refrigerator	0–625 L
Main freezer	0–710 L
Second freezer	0–710 L
Central A/C	0–1125 h/year
Window A/C	0–1125 h/year
HDD	2930–6128 (°C-day)
CDD	3.7–405 (°C-day)
Halogen lights	0–18
Fluorescent lights	0–46
Incandescent lights	0–106
Total heated area	51.2–753 m^2

(*continued on next page*)

Table 1 (*continued*)

Input unit	range
Income ($10,000/year)	10–85
Dwelling type	
1 if single-detached; 0 if single-attached	0–1
Dwelling ownership: 1 if owner; 0 if renter	0–1
Size of area of residence	
1 if population is less than 15,000	
2 if population is between 15,000 and 100,000	
3 if population is 100,000 or over	1–3
Employed adult ratio	
Number of employed adults / number of adults	0–1
Number of children	0–6
Number of adults	1–8

Based on the available information in the data set, only the annual usage of A/C equipment was used to reflect the contribution of the A/C units to the total household energy consumption. The input units that are used to represent the energy consumption of central and window A/C units are given in Table 1.

5.3. Input unit for weather effects

The outside temperature has an important effect on space heating and cooling energy consumptions. Therefore, the number of cooling degree-days (CDD) is used as an input unit to reflect the energy consumption for cooling, whereas the number of HDD is used as an input unit to reflect the temperature effect on the usage of portable electric heaters, as seen in Table 1.

5.4. Other input units

In order to reflect the effect of lighting energy consumption, the total numbers of halogen, fluorescent, and incandescent lights that households own are used as input units. Other input units included in the data set are the total heated area, the household income, the dwelling type, the dwelling ownership information, the size of residence area information, number of children, the number of adults, and the ratio of employed adults in the household. With the inclusion of these, the number of input units in the data set is 55. The complete list of input units is given in Table 1.

5.5. Output unit

The annual electricity consumption for appliances, lighting, and space cooling is the output unit for the ALC network. Thus, the annual electricity consumption values obtained from the billing data for the 988 houses are used as the output unit of the ALC network. The electricity consumption covers the calendar year of 1993, and the consumption is given in kWh.

6. Network development

6.1. Development of the training and testing sets

The ALC network data set was divided into two subsets. One of these subsets was used for training (training set) and the other was used for testing (testing set) of the network. The training set contains 741 households and the testing set contains 247 households. The households in each sub-set were chosen randomly.

6.2. Selection of the activation function and scaling interval

In this work, identity, logistic, and hyperbolic tangent functions were tested as the activation functions for the hidden and output layers. These are the most commonly used activation functions for the networks trained by back-propagation [31].

The training and testing data sets were scaled into the following intervals:

- [0.1–0.9]
- [−0.5 –0.5]
- [0.0–1.0]
- [−1.0–1.0]
- [−0.9–0.9]

The following equations were used to scale the data for each interval:

For the [0.1–0.9] interval:

$$x_n = 0.8\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) + 0.1 \tag{1}$$

For the [−0.5–0.5] interval:

$$x_n = 1.0\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) - 0.5 \tag{2}$$

For the [0.0–1.0] interval:

$$x_n = \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) \tag{3}$$

For the [−1.0–1.0] interval:

$$x_n = 2.0\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) - 1.0 \tag{4}$$

For the [−0.9–0.9] interval:

$$x_n = 1.8\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) - 0.9 \tag{5}$$

where,

x = value of the input/output unit
x_n = value of the scaled input/output unit
$x_{\min}$ = minimum value of the input/output unit
$x_{\max}$ = maximum value of the input/output unit

Another method used for scaling is the normalization of the input/output units by subtracting the mean and dividing by the standard deviation, i.e.

$$x_n = \frac{x - \mu}{\sigma} \tag{6}$$

where,

μ = mean of the input/output unit
σ = standard deviation of the input/output unit

Two approaches were used with respect to scaling:

(i) All of the data in the data set were scaled into the intervals given above.
(ii) Only continuous data in the data set were scaled into the intervals given above, and the discrete [0,1] data were left "as is", without scaling.

With the five scaling intervals to be compared, a total of 11 data sets were therefore generated.

1. All data scaled to the [0.1–0.9] interval,
2. Only continuous data scaled to the [0.1–0.9] interval,
3. All data scaled to the [−0.5 to 0.5] interval,
4. Only continuous data scaled to the [−0.5–0.5] interval,
5. Only continuous data scaled to the [0.0–1.0] interval, since discrete data are already in the [0,1] range,
6. All data scaled to the [−1.0–1.0] interval,
7. Only continuous data scaled to the [−1.0–1.0] interval,
8. All data scaled to the [−0.9–0.9] interval,
9. Only continuous data scaled to the [−0.9–0.9] interval,
10. All data normalized,
11. Only continuous data normalized,

The identity, logistic, and hyperbolic tangent activation functions were used to develop eight networks with the configurations shown in Table 2.

Table 2
Network configurations tested

Network name	Hidden layer activation function	Output layer activation function
Network-A	Logistic	Logistic
Network-B	Logistic	Hyperbolic tangent
Network-C	Logistic	Identity
Network-D	Hyperbolic tangent	Logistic
Network-E	Hyperbolic tangent	Hyperbolic tangent
Network-F	Hyperbolic tangent	Identity
Network-G	Identity	Logistic
Network-H	Identity	Hyperbolic tangent

Each of the eight configurations given in Table 2 was tested for each of the eleven data sets to determine the combination that provided the best prediction performance for a total of 88 networks (i.e. 11 scaling intervals$\times$8 network configurations). The testing was done using a network with 55 input, 25 hidden, and 1 output units (55:25:1) trained by a standard back-propagation learning algorithm with a learning rate of 0.02. Training was halted when the testing set sum of square of errors (SSE) value stopped decreasing and started to increase, which is an indication of overtraining. The prediction performances of the networks were assessed using the SSE, R^2, root-mean-square error (RMSE), and coefficient of variation (CV) values. The formulae used to calculate these are given in the Appendix.

The prediction performance and the number of cycles for each of the eight configurations that produced the best prediction performance for each of the eleven data sets are given in Table 3. As can be seen in Table 3, normalization of the data did not produce good predictions, while the prediction performances of all other scaling and activation function combinations were very good with an R^2 of 0.875 or better (except one). The network with best prediction performance (R^2 of 0.895) used data scaled to the interval [−0.5–0.5], the logistic function for the hidden layer, and the identity function for the output layer. Thus, in the rest of the network development,

Table 3
Comparison of scaling intervals and activation functions

Scaling interval	Applied to	Network configuration	R^2	Cycles
0.1–0.9	All data	Network G: identity + logistic	0.876	318
0.1–0.9	Only continuous	Network G: identity + logistic	0.875	1093
−0.5–0.5	All data	Network C: logistic + identity	0.895	160
−0.5 to 0.5	Only continuous	Network C: logistic + identity	0.888	174
0.0–1.0	All data	Network G: identity + logistic	0.724	202
−1.0→ + 1.0	All data	Network C: logistic + identity	0.888	49
−1.0→ + 1.0	Only continuous	Network C: logistic + identity	0.890	79
−0.9→ + 0.9	All data	Network C: logistic + identity	0.889	55
−0.9→ + 0.9	Only continuous	Network C: logistic + identity	0.892	90
Normalization	all data set	Network A: logistic + logistic	0.215	156
Normalization	Only continuous	Network A: logistic + logistic	0.221	87

the logistic function was used as the activation function for the hidden layer, the identity function was used as the activation function for the output layer, and all data in the data set were scaled to the interval [−0.5–0.5].

6.3. Selection of the network architecture

Since there are 55 input data units and one output data unit, the network has 55 input units and 1 output unit. In order to determine the combination of the number of hidden layer units and the learning algorithm that produces the best prediction performance, networks with the number of hidden layer units ranging from unity to 30 were trained with the following five learning algorithms available in the SNNS software:

- quickprop
- resilient propagation,
- enhanced back-propagation,
- back-propagation with weight decay,
- standard back-propagation.

Thus, a total of 150 networks (5 learning algorithms×30 network configurations = 150) were tested. The parameters of the learning algorithms used in the analysis are given in Table 4. Training was halted when the testing set SSE value stopped decreasing and started to increase—an indication of over-training. The prediction performance in terms of SSE, R^2, RMSE, and *CV* of the networks with the lowest testing set SSE values amongst the 30 networks for each of the five learning algorithms is presented in Table 5.

As can be seen from Table 5, the network trained with the Quickprop learning algorithm with 27 hidden layer units results in the lowest testing set SSE, RMSE, and *CV*, and highest R^2, indicating that this network has the highest prediction performance amongst the networks tested.

As can be seen from Table 5, all learning algorithms produced very good predictions with the lowest R^2 being 0.903. The network trained with the Quickprop learning algorithm with 27 hidden layer units resulted in the highest R^2 (0.908) indicating that this network has the highest prediction performance amongst the networks tested.

Table 4
Parameters of the learning algorithms used

Learning algorithm	Parameters[a]
Standard back-propagation	η: 0.010
Enhanced back-propagation	η: 0.010, μ: 0.001, c: 0.04
Back-propagation with weight decay	η: 0.010, d: 0.000001
Quickprop	η: 0.0015, μ: 2.10, ν: 0.000015
Resilient propagation	β: 1.10, ϕ_{initial}: 0.00075, $\phi_{\max}$: 30

[a] The definitions for the parameters of the learning algorithms are given in the Appendix.

Table 5
The performance of the network trained using five different learning algorithms

Network	Learning algorithm	Number of hidden units	SSE	R^2	RMSE	CV	Number of cycles
55:27:1	Quickprop	27	3.015	0.908	0.110	2.099	182
55:02:1	Resilient propagation	2	3.084	0.906	0.112	2.123	90
55:02:1	Enhanced back-propagation	2	3.131	0.905	0.113	2.139	833
55:02:1	Back-propagation weight decay	2	3.152	0.904	0.113	2.147	850
55:02:1	Standard back-propagation	2	3.208	0.903	0.114	2.165	1280

To explore the potential of improving the prediction performance, different network architectures with a total of 27 hidden layer units in one, two or three layers were trained with the Quickprop learning algorithm. The configuration with three hidden layers, each having nine units, achieved a slightly higher prediction performance with an R^2 value of 0.909.

6.4. Network selected to model the ALC energy consumption in the Canadian residential sector

Based on the results presented above, the following network was chosen to model the ALC energy consumption in the Canadian residential sector:

- data scaling interval: $[-0.5 \rightarrow +0.5]$
- activation function for the hidden layer: logistic function
- activation function for the output layer: identity function
- hidden layers: three hidden layers, each with nine units
- learning algorithm: quickprop

7. Comparison of the prediction performances of the NN and engineering models

The engineering model [4,6,7] was used to predict the ALC energy consumption of the 247 houses in the testing data set. The prediction performance of the 55:09:09:09:1 network and the engineering model based on their predictions for the 247 houses in the testing data set is given in Table 6. As seen from Table 6, the engineering model has lower R^2 and higher CV values than the NN model, so indicating that the NN model is superior in predicting the ALC energy consumption.

The estimates from the NN model and the engineering model are plotted along with the actual consumption data for the 247 households in the testing set in Fig. 2. As can be seen, the NN model was not able to predict accurately the consumption of some of the households with high electricity consumptions, such as households 44, 76, 138, 148, and 220. When the input units of these households were examined, it was found that they have an average number of appliances with average sizes and usage, but unusually high electricity consumption. This indicates that there are other

Table 6
Prediction performances of the NN model and the engineering model

Model	R^2	CV
Engineering model	0.780	3.463
NN model [55:09:09:09:1]	0.909	2.094

factors affecting the electricity consumption than those represented by the input units in the model. On the other hand, the NN Model was able to predict the electricity consumption of household number 146 with an accuracy of 6%. This household has a high electricity consumption (18,998 kWh/year) and appliances of large sizes and high usage. This indicates that under normal circumstances the NN model is capable of predicting the appliance energy consumption with reasonable accuracy.

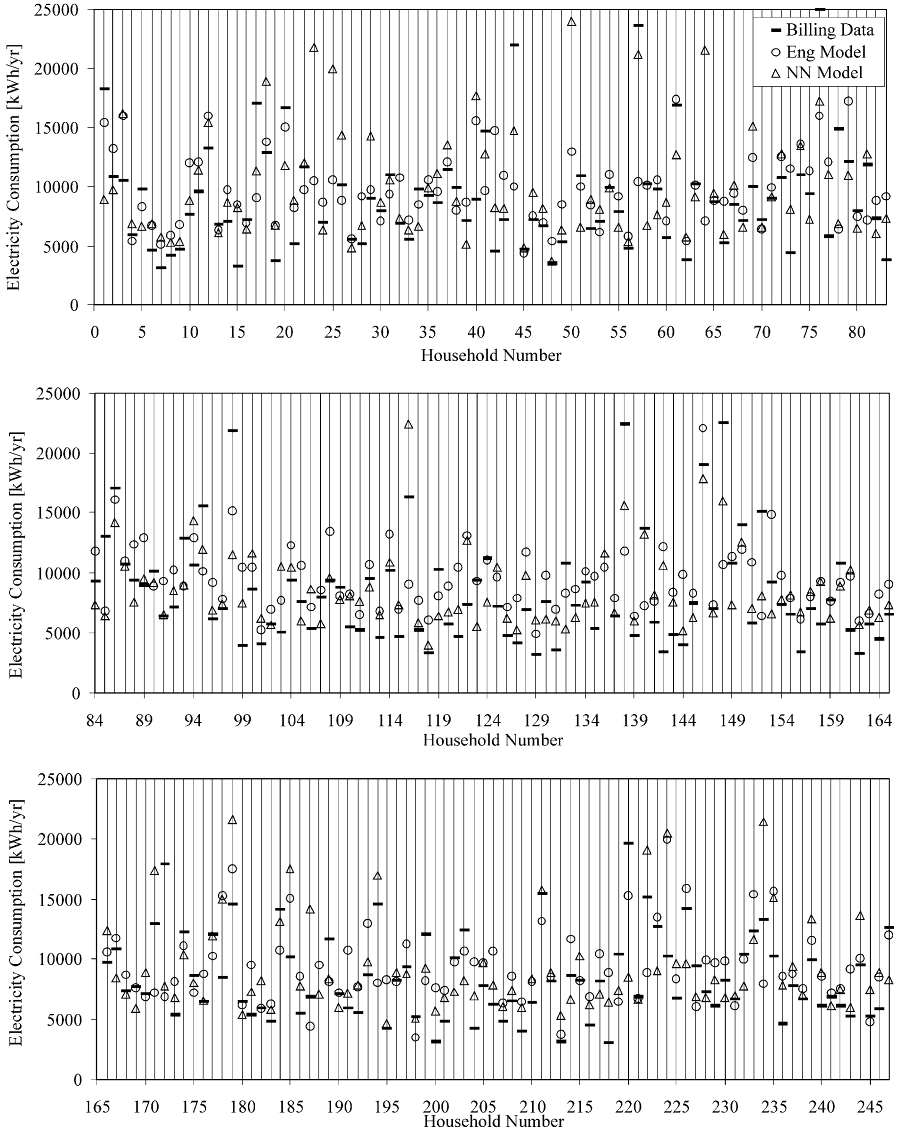
8. Prediction of the ALC energy consumption in the Canadian residential sector using the NN model—sample results

8.1. Average household ALC energy consumption in Canada

As stated earlier, the 1993 SHEU database has 8767 houses, and 988 of them were used to develop the ALC NN model. These 988 houses were not included in the dataset used in predicting the various components of ALC electricity consumption. The "prediction data-set" therefore included the remaining 7779 houses, and the ALC NN model was used to predict the ALC electricity consumption of these houses. Since the 1993 SHEU database is representative of the Canadian housing stock, it is possible to extrapolate the predicted electricity consumption of the households in the 1993 SHEU database to the entire Canadian housing stock using weighting factors [29].

The ALC electricity consumption of each of the 7779 houses in the prediction data-set was predicted using the ALC NN model (55:09:09:09:1), and the results were extrapolated to the entire Canadian housing stock. It was found that the average ALC electricity consumption in the Canadian housing stock is about 8790 kWh per year. This is about 2% less than that estimated by the engineering model.

The average ALC electricity consumption estimates for all Canadian households categorized according to the type of fuel used for space heating are shown in Table 7. These estimates indicate that electricity and wood heated houses have lower ALC energy consumptions than the houses using natural-gas, oil, or propane for space heating. This is due to the fact that a large proportion of the natural-gas, oil, and propane heated houses have either furnace fans or boiler pumps that increase their electricity consumption. Thus, it can be concluded that the NN model is capable of capturing the increase in the electricity consumption by furnace fans and boiler pumps.



Note: There are six households whose actual electricity consumption values do not fit on the graph. The household numbers and electricity consumptions of these households are as follows: No. 23: 27,238 kWh/yr; No. 25: 28,856 kWh/yr; No. 50: 25,630 kWh/yr No. 64: 37,797 kWh/yr; No. 136:38,246 kWh/yr; No. 188: 27,568kWh/yr

Fig. 2. The actual and predicted electricity consumptions by the NN model and the engineering model of the 247 households in the testing set.

Table 7
Weighted average ALC electricity consumptions of the houses in the prediction data-set based on the space-heating fuel type

Space-heating fuel type	Number of houses in the 1993 SHEU database	Corresponding number of households in Canada	Weighted average ALC Electricity consumption (kWh/year)
Electricity	2460	2,176,352	7984
Natural gas	2296	2,555,326	9918
Oil	1985	978,897	8179
Propane	91	65,478	8669
Wood	947	453,686	7655
Total	7779	6,229,739	8790

8.2. Predicting the electricity consumptions of some appliances

It is possible to estimate the annual average electricity consumptions of individual appliances in the input unit data set using the ALC NN model. For this purpose, a separate data-set, consisting of the data for households that contain the given appliance, is formed. The NN model is used to predict the annual average ALC electricity consumption of the households in the data set. Then, the input unit for the appliance in question is removed from the data set, and the NN model is used to predict the annual average ALC electricity consumption of the modified data-set. The difference between the two average predictions gives the annual average electricity consumption of the given appliance.

This approach was used to predict the annual average electricity consumption of various appliances. It was found that the NN model fails to estimate the energy consumption of appliances with high saturation values (e.g. the main refrigerator). However, the model was able to predict reasonably the average electricity consumptions of several major appliances as discussed below.

There are 720 houses with central A/C units in the set of 7779 houses. The average annual electricity consumption of A/C units predicted by the NN model is 832 kWh.

Using a statistical approach to incorporate usage characteristics into the estimates of the engineering model, Aydinalp et al. [32] estimated the central A/C electricity consumption as 865 kWh/year, which is slightly higher than the NN model's estimate of 832 kWh/year. On the other hand, the A/C annual electricity consumption estimates, obtained by several other researchers using the CDA approach, are about 60–100% higher than that of the NN Model. The CDA model, developed by Lafrange and Perron [11] using Hydro Quebec data, estimated the central A/C consumption as 1662 kWh/year and the CDA model developed by Kellas [33] using Manitoba Hydro data estimated the central A/C consumption as 1360 kWh/year. However, these two estimates were obtained considering the central A/C unit ownership and assuming a constant number of hours of central A/C usage for all the households with central A/C units. The estimates from the NN model and from the statistical model [32] were developed considering the number of hours each household used the central A/C unit during summer. Thus, the NN model estimate, as well as the statistical model estimate, are more reasonable than the ones from the CDA models.

There are 1444 houses with a second refrigerator in the set of 7779 houses. The average annual electricity consumption of a second refrigerator, predicted by the NN model, is 755 kWh.

The CDA model developed by Kellas [33] using Manitoba Hydro data estimated second refrigerator consumption as 815 kWh/year. The size of the refrigerator is one of the factors effecting its energy consumption. The average sizes for the main and second refrigerators in the 1993 SHEU database are 460 and 375 L, respectively. Since, second refrigerators are smaller than the main refrigerators, their energy consumption is expected to be lower than that of the main ones. Using the published annual electricity consumption estimate of about 1330 kWh/year for the main refrigerator [34], it can be expected that the electricity consumption by the second refrigerator would be lower than 1330 kWh/year. Therefore, the second refrigerator electricity consumption estimates of the NN Model and the CDA model developed by Kellas [33] are reasonable.

There are 4147 houses in the set of 7779 houses with a furnace fan or a boiler pump. The average annual electricity consumption of a furnace fan or a boiler pump predicted by the NN model is 770 kWh.

The engineering model [4,6,7] estimated the furnace fan/boiler pump energy consumption as 476 kWh/year. The CDA model developed by Kellas [33] using Manitoba Hydro data estimated the furnace fan energy consumption as 799 kWh/year. If the power of the motor of an average furnace fan is assumed to be 0.5 HP (372.85 W) and if it runs for about 9 h/day for 210 days in 1 year ($9\times210=1890$ h), then the annual energy consumption would be about 705 kWh (372.85 W$\times$1890 h$=$704,686.5 Wh$\approx$705 kWh/year). Thus, even with conservative assumptions, the annual furnace fan energy consumption is about 705 kWh. Thus, the NN model estimate, as well as the CDA model estimate, are reasonable.

9. Effects of the socio-economic factors on the ALC energy consumption

The input data set of the ALC NN model contains information on the socio-economic factors of the households including the household income, dwelling type and ownership, size of area of residence, and number of children and adults. The effects of these socioeconomic factors on the ALC energy consumption were examined using the NN model. The results are plotted in Fig. 3.

As is seen from Fig. 3, the ALC electricity-consumption of the households varies as follows:

- ALC electricity consumption of the household increases as the income of the household increases. It is interesting to note that, at low income levels, the slope of the curve becomes less, indicating that the elasticity of the ALC energy consumption with respect to income reduces. In other words, as income decreases the ALC energy consumption reaches a minimum and stays constant.

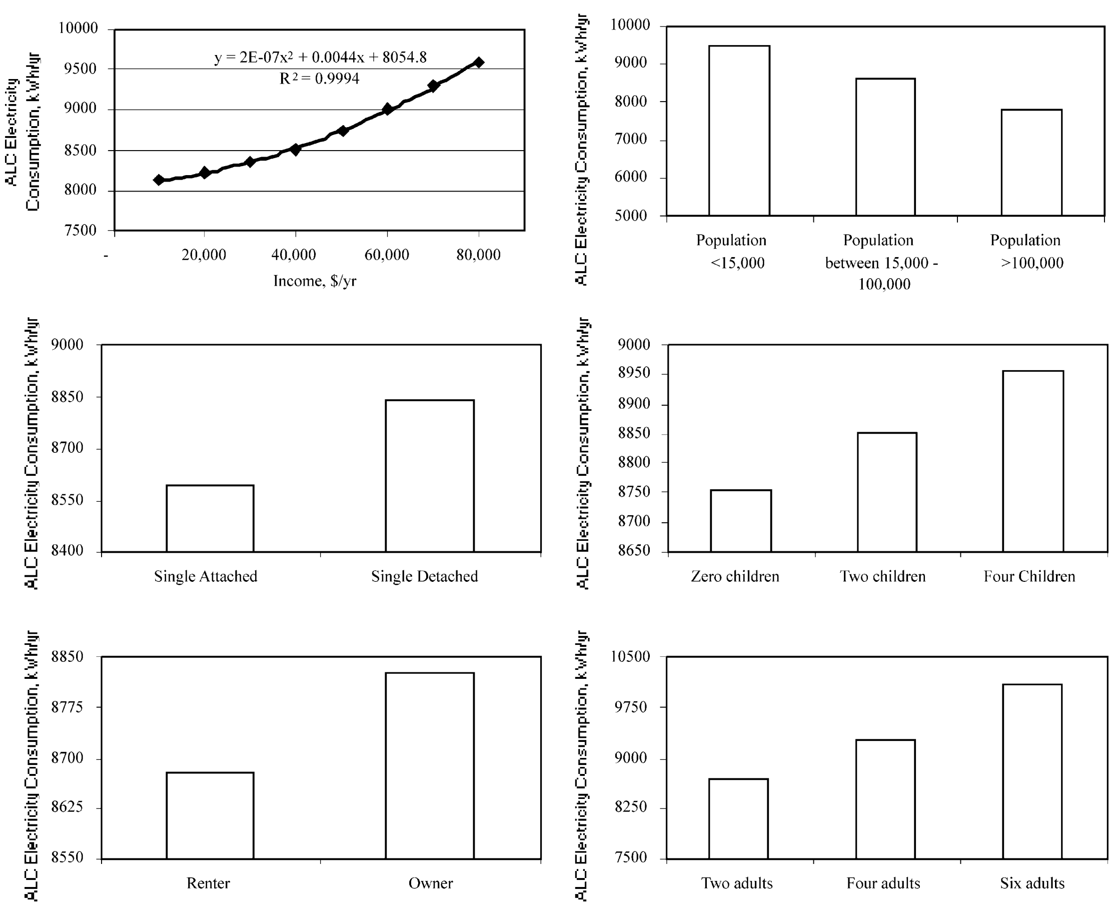


Fig. 3. ALC electricity consumption versus socio-economic factors.

- ALC electricity consumption of a single detached household is higher than that of a single attached household.
- ALC electricity consumption of an owner-occupied household is higher than that of a rented occupied household.
- ALC electricity consumption of a household decreases as the population of the area increases.
- ALC electricity consumption of a household increases as the number of children and adults living there increases.

10. Conclusion

The NN model developed to estimate the ALC energy-consumption achieved a high prediction performance ($R^2 = 0.909$) that is significantly better than that of the engineering model. It was also found that the ALC NN model is capable of predicting the energy consumptions of households with unusually high or low energy-consumptions provided that the input units of these households were representative of the households' energy consumptions.

The ALC NN model was able to estimate the electricity consumptions of furnace fans/boiler pumps using natural gas or oil, and propane-heated households, as well as the electricity consumptions of central A/C, second refrigerator, and furnace fan/boiler pumps. On the other hand, the ALC NN model failed to give rational estimates for appliances used to a high degree of saturation, e.g. a main refrigerator. This is to be expected because it is not possible for the NN algorithm to isolate the energy consumption when the saturation is very high (i.e. approximately 100%).

The effects of the socio-economic factors on the ALC energy-consumption were also examined using the ALC NN model, and it was found that the model results are as expected.

It can be concluded from these results that the NN model can be used to model accurately the ALC energy consumptions in the residential sector.

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Appendix. Measures used to judge the performances of networks

Name	Symbol	Formula
Sum of square errors	SSE	$\sum_{i=1}^{N}(y_i - t_i)^2$
Multiple correlation coefficient	R^2	$1 - \frac{\sum_{i=1}^{N}(y_i - t_i)^2}{\sum_{i=1}^{N} t_i^2}$
Root-mean-square error	RMSE	$\sqrt{\frac{\sum_{i=1}^{N}(y_i - t_i)^2}{N}}$
Coefficient of variation	CV	$\frac{\frac{\sqrt{\sum_{i=1}^{N}(y_i - t_i)^2}}{N}}{\bar{t}} \times 100$

where;

y_i = predicted value of the ith pattern;
t_i = target value of the ith pattern
N = number of patterns;
$\bar{t}$ = mean of the target values.

Parameters of the learning algorithms

Detailed information on the learning algorithms used in this work can be found in SNNS [28].

- Standard back-propagation
  - o η: learning parameter
- Enhanced back-propagation
  - o η: learning parameter
  - o μ: momentum term
  - o c: flat-spot elimination value
- Back propagation with weight decay
  - o η: learning parameter
  - o d: weight decay term
- Quickprop
  - o η: learning parameter
  - o μ: maximum growth parameter
  - o ν: weight decay term to shrink the weights

- Resilient propagation
  - o β: weight-decay determines the relationship between the output error and the reduction in the size of the weights
  - o $\phi_{initial}$: starting values for all update-values
  - o ϕ_{max}: the upper limit for the update values

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