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Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks

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Abstract

Two methods have been used to model residential end-use energy consumption at the national or regional level: the engineering method and the conditional demand-analysis method. It was recently shown that the neural network (NN) method is capable of accurately modeling the behaviours of the appliances, lighting, and space-cooling energy consumption in the residential sector. As a continuation of the work on the use of the NN method for modeling residential end-use energy-consumption, two NN based energy-consumption models were developed to estimate the space and domestic hot-water heating energy consumptions in the Canadian residential sector. This paper presents the NN methodology used in developing the models, the accuracy of the predictions, and some sample results.

Keywords: Residential energy-consumption modeling; Space-heating energy; Domestic hot-water heating energy; Neural-network modeling

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Nomenclature

Abbreviations and parameters

ALC	appliance, lighting, and cooling
CDA	conditional demand analysis
CV	coefficient of variation
DHW	domestic hot-water
EM	engineering model
GHG	green-house gas
HDD	heating degree-days
MDT	mean daily temperature
NN	neural network
R^2	correlation coefficient
SH	space heating
SHEU	survey of household energy-use
SNNS	Stuttgart neural-network simulator
SSE	sum of square of errors
c	flat spot elimination value
β	resilient propagation algorithm weight decay term
η	learning parameter
ν	quickprop weight-decay term
μ	momentum term
ρ	maximum growth parameter
ϕ	resilient propagation algorithm update value

1. Introduction

Having ratified the Kyoto Protocol in 2002, Canada is committed to reduce its green-house gas (GHG) emissions to 6% below the 1990 level by 2010. This means Canada will have to emit 26% less than what it would have emitted without the Protocol. To meet this commitment, Canada has to evaluate and exploit every feasible measure to reduce energy consumption and GHG emissions, while maintaining its economic growth and standard of living. Other countries that have ratified the Protocol are in a similar situation as Canada.

Residential energy consumption is a significant component of the national energy consumption in most of the developed countries. In Canada for example, close to 20% of the national energy consumption is for residential use. Consequently, improving the end-use energy efficiency in the residential sector presents an effective approach to reduce energy consumption and associated GHG emissions.

As was discussed in detail elsewhere [1], to reduce the end-use energy consumption and GHG emissions from the residential sector, a large number of options need to be considered. Since energy efficiency improvements have complex interrelated effects

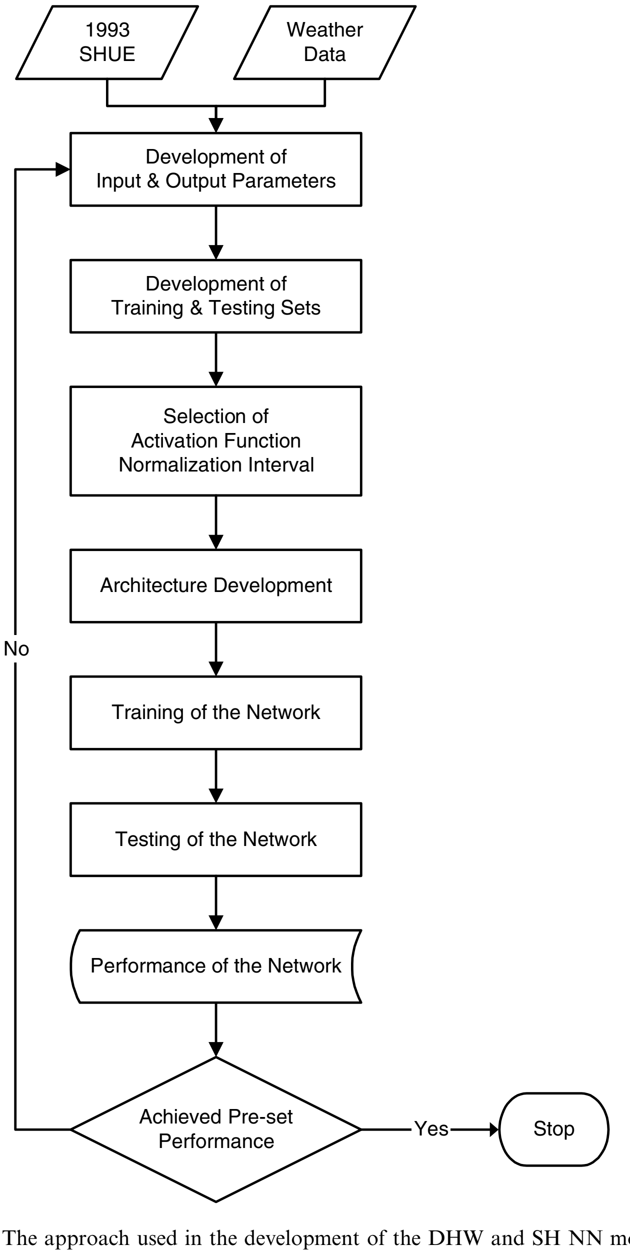

Fig. 1. The approach used in the development of the DHW and SH NN models.

on the end-use energy consumption of houses and the associated GHG emissions, detailed computer models are necessary to evaluate the effect of various energy-efficiency improvement options on residential end-use energy consumption and associated emissions. It was recently shown that, in addition to the engineering method

(EM) and the conditional demand analysis (CDA) method, the neural network (NN) method is capable of accurately modeling the appliances, lighting, and space-cooling energy-consumption in the residential sector [1].

In this paper, two new NN method based end-use energy-consumption models are presented. One of these models predicts the space heating (SH) energy-consumption, and the other predicts the domestic hot-water (DHW) heating energy-consumption in the Canadian residential sector. This paper presents the NN methodology used in developing the models, the accuracy of the predictions of the NN models, and some sample results. An extensive review of the literature on the use of NN method for modeling energy-consumption in the building sector was presented earlier [2].

The approach used in the development of the NN models is shown in Fig. 1. The Stuttgart Neural Network Simulator (SNNS) V4.2 software [2] was used in the development of both NN models.

2. Data sources

Two sources of data were used for the development of the input units of the NN models: the data from the 1993 survey of household energy use (SHEU) database [3], and the weather and ground-temperature data for 1993 [4]. The source of data for the output unit of the models was the actual energy-billing data obtained from fuel suppliers and utility companies for a set of households from the 1993 SHEU.

The 1993 SHEU database is the most comprehensive energy related database for the Canadian residential sector. The data were collected by conducting a mail-out survey that included 376 questions. The database is representative of the Canadian housing stock, and includes detailed information on house construction, space heating/cooling and DHW heating equipment, household appliances, and socio-economic characteristics of 8767 households from all provinces of Canada. The actual energy-billing data exist for 2749 households of the 1993 SHEU database. The weather and ground-temperature data for the cities, where the 2749 households are located, were obtained from Environment Canada [4]. The weather data obtained include the local mean daily temperatures (MDTs) of the households for the year 1993. The MDTs were used to calculate the heating degree-days (HDD) for the locations. [1]

A detailed review of energy-billing data of the 2749 households indicated that 563 households could be included in the DHW heating network dataset, and 1228 in the SH network dataset [5]. Of the 563 households in the DHW heating network dataset, 388 had electrical and 175 had natural-gas DHW heating systems, whereas of the 1228 households in the SH network dataset, 396 had electrical, 755 had natural-gas, and 77 had oil SH systems.

[1] A base value of 18 °C is taken for the HDD calculations. If the MDT is lower than 18 °C, the day is said to be a heating day, and will have (18 – MDT) heating degree-days. The annual HDD values for each city are calculated by summing the daily HDD values.

For households with electrical DHW heating-systems in the database, the annual DHW electricity-consumption was calculated by deducting from the total annual energy billing data, the appliances, lighting, and space cooling (ALC) electricity-consumptions estimated using the ALC NN model [1]. Although this approach introduces an error in the DHW electricity-consumption data used in developing the DHW NN model, it was used because disaggregated DHW electricity-consumption data do not exist. Due to a lack of disaggregated energy-consumption data, the annual SH electricity consumption of households with electrical space and DHW heating systems, and the annual SH natural gas-consumption of households with natural-gas space and DHW heating-systems were also calculated using a similar approach. Details of the analyses conducted to develop the DHW and SH network datasets are given elsewhere [5].

3. Input and output units

Since the purpose of the DHW and SH NN models is to predict the DHW and SH energy-consumptions of a household based on a number of parameters, the input units chosen for the models must be of relevance to energy-consumption. The input units used in the models are described below.

3.1. DHW network input and output units

The input units of the DHW network dataset were developed using the information available in the 1993 SHEU database on DHW heating system and equipment properties, DHW consumption patterns, and socio-economic characteristics of the households. This information includes:

- the fuel types and energy sources used,
- number of water heaters,
- age of the system,
- size of the water tank,
- ownership information (single user or shared),
- insulation of hot water tank and hot water pipes.

Based on Canadian experience [6], an end-use energy-conversion efficiency of 0.824 was used for electric DHW heating systems, and an efficiency of 0.554 was used for natural gas DHW heating systems. Binary variables zero and unity were used as input units to indicate the presence and absence of insulation around the hot water tank and hot-water pipes, as well as to denote shared and single user DHW heating systems by more than one dwelling.

In addition to the DHW heating system and equipment properties, household income, dwelling type, dwelling ownership, size of residence area, as well as the number of household occupants, low-flow showerheads, aerators, and weekly clothes washer and dishwasher loads were included as input units. The size of area of residence was included in the input data set to reflect the socio-economic differences between urban and rural populations. To reflect the effect of city water temperature on DHW heating-energy consumption, the average annual ground temperature for the location was used as an input unit. Summary information on all input units used in the DHW heating network is given in Table 1.

The annual DHW heating energy-consumption is the output unit of the DHW network. Thus, the annual electricity and natural-gas consumption values obtained from the energy billing data for the 563 households were used to train the DHW network, and to test its predictions. The electricity and natural-gas consumption data cover the calendar year of 1993, and were converted to GJ.

3.2. Space-heating network input and output units

SH energy consumption of a dwelling can be determined by conducting an energy balance between heat losses and heat gains as follows:

$$\text{SH energy consumption} = \sum \text{heat losses} - \sum \text{heat gains} \tag{1}$$

where,

$$\sum \text{heat losses} = \text{heat losses due to transmission through the building envelope} + \text{heat loss due to infiltration and ventilation}$$

Table 1
DHW NN model input units

	Input unit	Range
DHW heating system and equipment properties	End-use efficiency of the system	0.554–0.824
	Age of the system [years]	0.5–18
	Size of the water tanks [l]	130–280
	Number water heaters	1–2
	Shared with other dwellings	0–1
	Insulation around the water tank	0–1
	Insulation around hot water pipes	0–1
DHW consumption patterns	Number of children	0–5
	Number of adults	1–8
	Clothes washer [loads/week]	0–15
	Dishwasher [loads/week]	0–15
	Number of low-flow shower heads	0–3
	Number of aerators	0–4
Weather effects	Ground temperature [°C]	5–12
Socio-economic characteristics of the households	Income [$1,000/yr]	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

$$\sum \text{heat gains} = \text{internal heat gain from people, lighting, and appliances} \\ + \text{solar heat gain}$$

In addition to the building-envelope's thermal characteristics, tightness and area, the magnitudes of the heat losses and gains depend on the outdoor weather conditions, solar radiation, occupant behavior, and electric appliances and lighting. The input units were selected from the available data in the 1993 SHEU database to represent the relevant characteristics of households. The input units used in the SH network are given in Table 2.

Since the 1993 SHEU database does not contain sufficient information on the building envelope's thermal characteristics, the vintage of the envelope components was used as proxy for the envelope's thermal characteristics. [2] Thus, as shown in Table 2, a total of six age-categories were used to reflect the level of thermal insulation in the building envelope:

Category 1: before 1941,
Category 2: 1941–1960,
Category 3: 1961–1977,
Category 4: 1978–1982,
Category 5: 1983–1988,
Category 6: 1989 and later.

While the wall, roof and floor areas were calculated using the available information in the 1993 SHEU database and the assumptions used in other similar studies [7–9], the number of doors and windows were used as input units representing the heat loss through these components since no information is available on the thermal resistance, area, or direction of windows or doors.

In the 1993 SHEU database, dwellings are classified into four categories: single detached, double, row or terrace, and duplex. In this work, double, row or terrace, and duplex dwellings are combined into one category called "single attached". As shown in Table 2, binary variables zero and unity are used as input units for the dwelling type.

In the 1993 SHEU database, the efficiency ratings of oil and natural-gas fuelled SH equipment are reported in three categories: standard (50–65%), medium (75–80%), and high (90% or higher) efficiency. Using the average values of the responses in the 1993 SHEU database, the HOT2000 default values [6], and engineering judgment, the SH equipment efficiency values given in Table 3 were chosen. The end-use efficiency of the SH systems that use electricity were set to 100%.

The 1993 SHEU database contains information on the average indoor temperature during daytime (6 a.m.–6 p.m.), evening (6 p.m.–10 p.m.), and overnight (10 p.m.–6 a.m.). The average daily indoor temperature was calculated using these

[2] The relationship between the vintage of the dwellings and the overall heat-transfer coefficient of each envelope component was studied by Farahbakhsh [7] and Farahbakhsh et al. [8,9]. It was found that the thermal resistance increased as the age of the dwelling decreased.

Table 2
SH NN model input units

	Input unit	Range
Dwelling characteristics	Dwelling type: 1 if single-detached; 0 if single-attached	0–1
	Number of doors	1–11
	Number of triple-glazed windows	0–30
	Number of double-glazed windows	0–48
	Number of single-glazed windows	0–24
	Wall area [m^2]	71–733
	Floor area [m^2]	17–265
	Basement wall-area [m^2]	0–163
	Basement floor-area [m^2]	0–265
	Roof area [m^2]	17–265
	Dwelling age category	1–6
	Wall-age category	1–6
	Roof-age category	1–6
	Basement wall-age category	0–6
	Basement floor-age category	0–6
	Percentage of the basement heated [%]	0–100
	Heated garage: 1 if heated; 0 if not heated	0–1
SH system and equipment properties	End-use efficiency of the SH equipment [%]	65–100
	Presence of heat-recovery ventilation system	0–1
	Presence of programmable thermostats	0–1
Indoor and outdoor temperatures	Average indoor temperature [°C]	16–24
	Heating degree-days [°C-day]	2930–6541
Socio-economic characteristics of the households	Income [$1,000/yr]	10–85
	Dwelling ownership: 1 if owner; 0 if renter	0–1
	Number of children	0–6
	Number of adults	1–6
	Daytime occupancy	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

Table 3
SH equipment efficiency values used for each efficiency rating and fuel type

	Standard (%)	Medium (%)	High (%)
Natural gas	70	78	94
Oil	65	75	93

values, and was used as an input unit as shown in Table 2. The HDD was used as an input unit to represent the outdoor conditions during the heating season.

To reflect the impact of socio-economic characteristics of a dwelling on its energy consumption, household income, type of dwelling ownership (owned or rented), number of children and adults, daytime occupancy (yes or no), and the size of the area of residence were used as input units (Table 2).

The annual energy consumption for SH is the output unit for the SH network. Thus, the annual SH electricity, natural-gas, and oil consumption values obtained from the energy-billing data for the 1228 households were used to train the SH network, and to test its predictions. The SH consumption data of the households covers the calendar year of 1993, and were all converted to GJ.

4. Development of networks

4.1. Training and testing datasets

The DHW and SH network datasets were 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 sets were randomly assigned 75% of all households in the datasets (422 households for the DHW and 921 households for the SH training sets). The remaining 25% of the households were assigned to the testing sets.

4.2. Selection of activation functions and scaling intervals

As was done in the development of the ALC network [1], identity, logic, and hyperbolic tangent functions were tested as the activation functions for the hidden and output layers of both the DHW and SH networks. These are the most commonly used activation-functions for networks trained by a back-propagation learning algorithm [10]. The same scaling intervals and equations used for the ALC training and testing data sets [1] were used, resulting in eleven datasets. Each of the eight configurations given in Table 4 was tested for each of the eleven datasets that were scaled to different intervals. Thus, a total of 88 networks were tested ($= 11$ scaling intervals $\times$ 8 network configurations) to identify the scaling intervals and the activation functions that produced the best prediction performance. For the DHW network, a network with 18 input, 10 hidden, and one output units (18:10:1) trained by a standard back-propagation learning algorithm [11] with a learning

Table 4
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

rate of 0.02 was used to compare the various scaling intervals and activation functions with respect to their prediction performances. For the SH network, a network with 28 input, two hidden and one output units (28:2:1) was used. The training of the network was halted when the testing set sum of squared errors (SSE) value stopped decreasing and started to increase, which is an indication of over-training.

As seen in Table 5, normalization of the data did not produce good predictions for the DHW network, which was also seen during the development of the ALC network [1]. The other scaling and activation function combinations resulted in predictions with a correlation coefficient (R^2 of 0.863) higher than 0.59. The network with the best prediction performance (R^2) used the dataset with only continuous data scaled to the interval [0.1–0.9], and the logistic function for the hidden and output layers. Thus, in the rest of the DHW network development, the logistic function was used as the activation function for the hidden and output layers, and only continuous data in the sets were scaled to the interval [0.1–0.9].

The results for the SH network were similar. It was found that the network with the best prediction performance (R^2 of 0.906) used the data scaled to the interval [0.1–0.9], the identity function for the hidden layers, and the logistic function for the output layers. Thus, in the rest of the SH network development, the identity function was used as the activation function for the hidden layers, the logistic function was used as the activation function for the output layer, and all data in the dataset were scaled to the interval [0.1–0.9].

4.3. Development of the architecture of networks

There are 18 input data units and one output data unit in the DHW NN, and 28 input data units and one output data unit in the SH NN. In order to find the number of hidden layer units resulting in the best prediction performance, networks with the number of hidden layer units ranging from unity to 40 were trained with standard back-propagation [11], enhanced back-propagation [12], Quickprop [11] and resilient propagation [13] algorithms. Thus, a total of 160 networks were tested for each of

Table 5
Comparison of scaling intervals and activation functions for DHW network

Scaling interval	Applied to	Network configuration	R^2	Cycles
$0.1 \rightarrow 0.9$	All data	Network-A: Logistic + Logistic	0.862	438
$0.1 \rightarrow 0.9$	Only continuous	Network-A: Logistic + Logistic	0.863	442
$-0.5 \rightarrow 0.5$	All data	Network-B: Logistic + TanH	0.595	57
$-0.5 \rightarrow 0.5$	Only continuous	Network-B: Logistic + TanH	0.593	69
$0.0 \rightarrow 1.0$	All data	Network-A: Logistic + Logistic	0.766	315
$-1.0 \rightarrow 1.0$	All data	Network-H: Identity + TanH	0.608	191
$-1.0 \rightarrow 1.0$	Only continuous	Network-H: Identity + TanH	0.607	186
$-0.9 \rightarrow 0.9$	All data	Network-H: Identity + TanH	0.607	258
$-0.9 \rightarrow 0.9$	Only continuous	Network-H: Identity + TanH	0.607	244
Normalized	All dataset	Network-D: TanH + Logistic	0.179	16
Normalized	Only continuous	Network-B: Logistic + TanH	0.175	54

DHW and SH networks (i.e. four learning algorithms $\times$ 40 network configurations $=$ 160 networks). A wide range of values was tested for the parameters of the learning algorithms, and the values that resulted in the highest prediction performance for each NN model are given in Table 6.

The prediction performance indicators of the DHW and SH networks with the lowest testing set SSE values are presented in Table 7. As seen from this table, the learning algorithms produced good predictions for both DHW heating (R^2 of $0.869 \rightarrow 0.871$) and SH energy consumption (R^2 of $0.907 \rightarrow 0.908$). The DHW network trained with the resilient propagation learning algorithm with 29 hidden layer units resulted in the lowest testing set SSE, RMS, and coefficient of variation (CV), and highest R^2, indicating that this network has the highest prediction performance amongst the DHW networks tested. For SH energy consumption, the network trained with the resilient propagation learning algorithm with two hidden layer units resulted in the highest prediction performance.

To determine the DHW network architecture that produced the best prediction performance, different network architectures with a total of 29 hidden layer units in one, two and three layers were trained with the resilient propagation learning algorithm. As seen in Table 8, the most suitable network to predict the DHW heating energy consumption in Canadian single-family households has one hidden layer with

Table 6
Parameters of the learning algorithms used in the DHW and SH NN models*

Learning algorithm	Parameters used in the DHW NN model	Parameters used in the SH NN model
Standard backprop.	η: 0.025	η: 0.0075
Enhanced backprop.	η: 0.015, μ: 0.1, c: 0.1	η: 0.0075, μ: 0.0005, c: 0.005
Quickprop	η: 0.005, ρ: 1.5, v: 0.0005	η: 0.001, ρ: 2.0, v: 0.00001
Resilient prop.	β: 1.7, ϕ_{initial}: 0.02, $\phi_{\max}$: 30	β: 1.1, ϕ_{initial}: 0.06, $\phi_{\max}$: 10

* The definitions for the parameters of the learning algorithms are given in Aydinalp [5].

Table 7
Performances of the DHW and SH NN models trained using four different learning-algorithms

	Network	Learning algorithm	Number of hidden units	SSE	R^2	RMS	CV
DHW NN model	18:29:1	Resilient prop.	29	2.518	0.871	0.134	3.337
	18:29:1	Quickprop	29	2.521	0.871	0.134	3.340
	18:29:1	Enhanced backprop.	29	2.549	0.869	0.134	3.358
	18:29:1	Standard backprop.	29	2.551	0.869	0.135	3.360
SH NN model	28:2:1	Resilient prop.	2	5.400	0.908	0.133	1.871
	28:28:1	Quickprop	28	5.433	0.908	0.133	1.877
	28:1:1	Standard backprop.	1	5.508	0.907	0.134	1.890
	28:1:1	Enhanced backprop.	1	5.508	0.907	0.134	1.890

Table 8
Performances of the DHW NN models with various architectures

Network	Number of hidden layer units			SSE	R^2	RMS	CV
	Layer 1	Layer 2	Layer 3				
18:29:1	29			2.518	0.871	0.134	3.337
18:29:29:1	29	29		2.645	0.864	0.137	3.421
18:29:29:29:1	29	29	29	2.687	0.862	0.138	3.448
18:14:15:1	14	15		2.635	0.865	0.137	3.415
18:15:14:1	15	14		2.614	0.866	0.136	3.401
18:10:19:1	10	19		2.676	0.863	0.138	3.441
18:19:10:1	19	10		2.605	0.867	0.136	3.395
18:9:10:10:1	9	10	10	2.650	0.864	0.137	3.424
18:10:9:10:1	10	9	10	2.585	0.868	0.135	3.382
18:10:10:9:1	10	10	9	2.665	0.864	0.137	3.433

Table 9
Performances of the SH NN models with various architectures

Network	Number of hidden layer units			SSE	R^2	RMS	CV
	Layer 1	Layer 2	Layer 3				
28:2:1	2			5.400	0.908	0.133	1.871
28:2:2:1	2	2		5.482	0.907	0.134	1.885
28:2:2:2:1	2	2	2	5.481	0.907	0.134	1.885
28:1:1:1	1	1		5.492	0.907	0.134	1.887

29 units (18:29:1). The best results are obtained using the resilient propagation learning algorithm, with the logistic function for the hidden and output layers, and the dataset scaled to the interval [0.1–0.9]. The values of the weights and biases of the (18:29:1) DHW NN model are given in Aydinalp [5].

The same approach was used to determine the SH network architecture that produces the best prediction performance. Thus, different network architectures with a total of two hidden layer units in one, two and three layers were trained with the resilient propagation learning algorithm. The prediction performances of these networks are given in Table 9. None of these configurations resulted in better prediction performances than the network with two hidden units in one hidden layer. Thus, the network with one hidden layer with two units (28:2:1) trained with the resilient propagation learning algorithm, and using an identity function for the hidden layer, the logistic function for the output layer, and a dataset scaled to the interval $[0.1 \rightarrow 0.9]$ was found to be the most suitable network architecture to predict the SH energy consumption in Canadian single-family households. The values of the weights and biases of the (28:2:1) SH NN model are given in Aydinalp [5].

5. Comparison of the NN and engineering models

The prediction performances of the NN and the engineering models was assessed by comparing the estimates of the models with actual energy-consumption data from the 141 households in the DHW and 307 households in the SH NN testing datasets. The results are presented in Table 10. As it can be seen, both models are capable of predicting the SH and DHW energy consumption with reasonable accuracy (i.e. R^2 better than 0.77). The engineering model has lower R^2 and higher CV values than the NN models, which shows that the NN models have a better prediction performance than the engineering model.

The SH energy-consumption estimates of the engineering and NN models are plotted along with the actual energy-consumption data for the 307 households in the SH NN testing dataset in Figs. 2 and 3. As seen in these figures, both the NN and the engineering models were unable to accurately predict the SH energy-consumption of most of the households with consumption values lower than 30 GJ/yr. When the input data for these households were analyzed, it was found that based on the values of the input units, these households could not be expected to have such low SH energy-consumption values. Most of these households are single-detached, located in areas with HDD values higher than 4500 °C-day, and have average wall areas. This shows that there are other factors affecting the SH energy-consumption than those reported in the 1993 SHEU database and represented by the input units in the model (such as long vacations in winter months) that would result in the lower SH energy

Table 10
Prediction performances of the NN and engineering models

		R^2	CV
DHW model	NN	0.871	3.337
	Engineering	0.828	3.898
SH model	NN	0.908	1.871
	Engineering	0.778	2.877

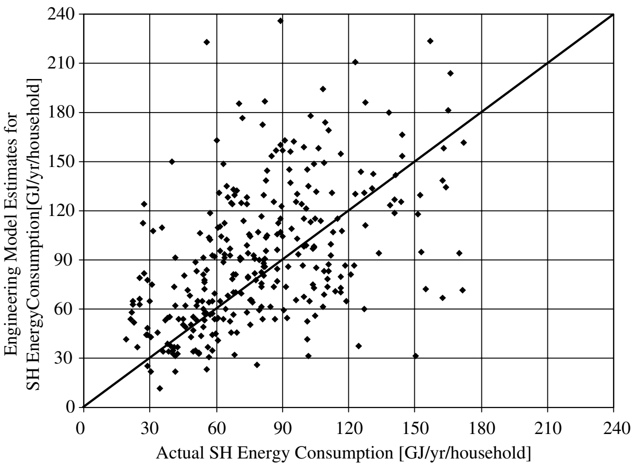

Fig. 2. Actual billing data and engineering model estimates for SH energy consumptions of the households in the SH NN testing dataset.

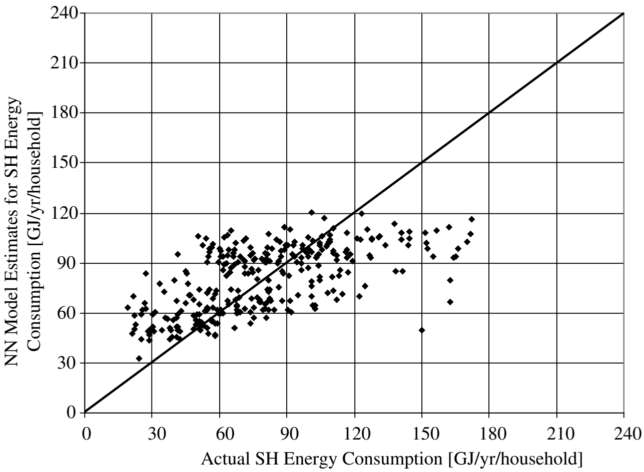

Fig. 3. Actual billing data and NN model estimates for SH energy consumptions of the households in the SH NN testing dataset.

consumption of the households. In addition, it was found that these households use electricity for SH. As stated in Section 2, the amount of electricity consumed in these households for SH was calculated by subtracting the ALC and DHW-heating electricity-consumption predicted by the ALC and DHW NN models from the total billed electricity consumption. Therefore, the annual SH electricity-consumptions of these households contain the cumulative errors from the ALC and DHW NN models. A review of the DHW energy-consumption estimates presents a similar pattern. These results are presented elsewhere [5].

The NN and engineering models were also used to predict the SH and DHW energy consumptions of the 1993 SHEU households that were not used in the development of the NN model. The average SH and DHW energy-consumption estimates, and the average percent deviations are given in Table 11. As seen in this table, the averages of the NN and engineering model estimates are close to each other.

Further comparisons of the estimates of the NN and engineering models were conducted based on dwelling type, size and age, as well as the type of fuel used. The results of these comparisons, which are presented elsewhere [5], indicate that the NN and engineering model estimates are generally in good agreement.

Table 11
Weighted average DHW heating and SH energy-consumptions estimated by the NN and engineering models and average percentage deviations

	Weighted average DHW heating/SH energy consumption [GJ/yr/household]		Average deviation [%]
DHW model	NN	26	–
	Engineering	25	−4.5
SH model	NN	80	–
	Engineering	77	−3.4

6. Household energy-consumption in Canada

The household energy-consumption of the households in the 1993 SHEU database were computed using the engineering model and by combining the ALC [1], DHW heating, and SH energy-consumption estimates of the NN models. Since the 1993 SHEU database is representative of the Canadian housing stock, the weighted average household energy-consumption estimates of the NN and engineering models represent the weighted average household energy-consumption of the housing stock. The NN model estimate of 139 GJ/year/household is 3.7% higher than the 134 GJ/year/household estimate by Natural Resources Canada [14], and 3% higher than the engineering model estimate.

The average household energy-consumption in each province was also calculated using the estimates of the NN and engineering models. The results presented in Fig. 4 indicate that the estimates of the two models are in agreement. The average household energy-consumption in Quebec is found to be the lowest, whereas Alberta and Saskatchewan have the highest household energy-consumptions. Since SH energy-consumption accounts for about 60% of the total household energy-consumption, factors such as climate, end-use efficiency, and fuel type of the SH equipment have significant effects on the total household energy-consumption. Consequently, the trend seen in Fig. 4 is mainly due to the fact that, in the 1993 SHEU database, 79% of the households in Quebec, and, respectively, 1% and 5% of the households in Alberta and Saskatchewan, have electrical SH equipment that have 100% end-use efficiency. In addition, 66% and 69% of the households in Alberta and Saskatchewan, respectively, have standard (50–65%) efficiency natural-gas, oil, or propane-fueled SH equipment. Along with the cold winters of Alberta and Saskatchewan, these factors explain the high household energy-consumption trends in these two provinces.

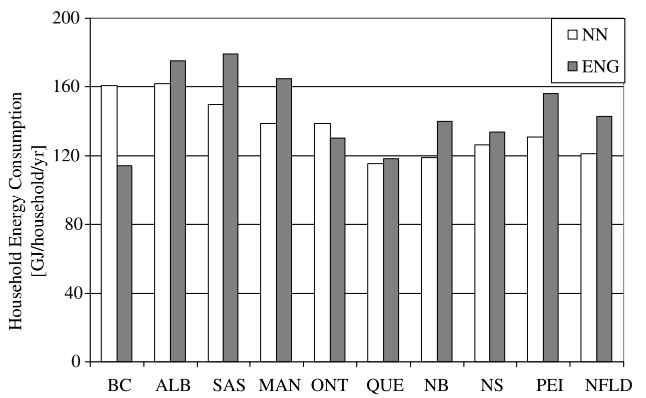

Fig. 4. Provincial household energy-consumption predictions by the NN and engineering models.

7. Assessment of socio-economic factors

Since it is possible to incorporate socio-economic factors, such as household income, dwelling ownership, size of area of residence, dwelling type and ownership, and number of children and adults, into the dataset of a NN model, it is possible to estimate the effects of such factors on the residential energy-consumption. On the other hand, to include such factors into the engineering model, detailed occupancy and preference profiles are required, but which are not available in the 1993 SHEU database, or elsewhere in the open literature.

As described in Section 2, data on a number of socio-economic factors available in the 1993 SHEU database were incorporated into the NN model data-set to study the effect of socio-economic factors on SH and DHW energy-consumptions. Some of the results obtained using the NN model are presented in Fig. 5, while more detailed

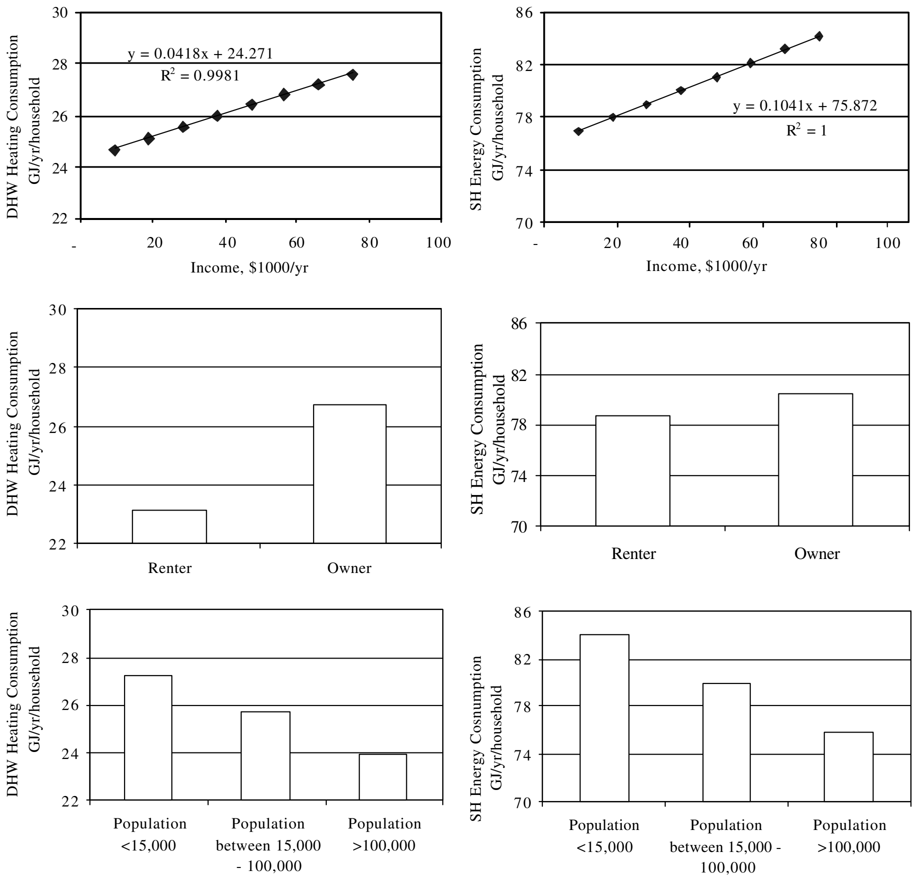

Fig. 5. Effects of socio-economic factors on the DHW heating and SH energy-consumptions of the households estimated by the NN model.

results are presented elsewhere [5]. As seen from Fig. 5, SH and DHW energy-consumption estimates are affected by socio-economic factors as follows:

7.1. Household income

Both SH and DHW energy-consumption values increase linearly as income increases. This is due to the fact that households with higher income levels have larger dwellings and use more DHW. As the household income increases, SH energy-consumption increases linearly with a slope of 0.1014 GJ/year/household per $1000/year income, while DHW heating energy-consumption increases with a slope of 0.0418 GJ/year/household per $1000/year income. The slope of the DHW curve is 2.5 times less than the slope of the SH curve, indicating that for each dollar increase in household income, the expenditure for SH energy-consumption increases 2.5 times more than the expenditure for DHW heating energy-consumption.

7.2. Dwelling ownership

Both SH and DHW heating energy-consumption values of an owner-occupied household are higher than that of a renter-occupied household. In Canada, the majority of the owner-occupied dwellings are single detached, larger and have more occupants. Thus, the SH and DHW energy-consumption values of owner-occupied dwellings are higher than that of renter-occupied ones.

7.3. Size of area of residence

Both DHW heating and SH energy-consumption values decrease as the population of the area increases. In Canada, almost all of the households located in areas with populations less than 15,000 are single detached. Since the energy consumption of single detached-dwellings is higher than single attached ones [1], energy consumption of the households located in rural areas is higher than those located in urban areas.

8. Assessment of energy-conservation measures

Due to the limited number of variables that could be included in the NN models, the SH energy-conservation measures evaluated using the NN model included window glazing upgrades, SH equipment efficiency upgrades, and lowering the overnight temperature. For the same reason, only two DHW energy-conservation measures could be evaluated: insulating hot-water pipes and increasing the efficiency of DHW heating systems. The energy-savings predictions of the NN models were compared with those from other studies [5].

The estimated energy savings due to upgrading SH equipment efficiency was found to be in good agreement with the estimates from other studies. For example, the reduction in SH energy consumption due to upgrading medium-efficiency SH equipment to high efficiency was estimated to be 22%, which is close to the engineering model estimate of 18%. Similarly, in agreement with the engineering model estimate of 4.3 GJ/yr/household, the savings due to upgrading double-glazed windows to triple-glazed was estimated to be 3.6 GJ/yr/household. Also, the energy-savings estimate of 4% due to lowering overnight temperature by 6 °C is close to the value reported by the US Department of Energy [15]. However, the savings with single-glazed window upgrades were underestimated in comparison to those from the engineering model and other studies. This is largely because of the inability of the NN model to capture the effect of upgrading single-glazed windows from a dataset of only 129 households with such windows.

The savings in DHW energy-consumption due to increasing the end-use efficiency of natural gas/propane fuelled DHW heating-systems was estimated to be 3.9 GJ/yr/household, which is in good agreement with the engineering model estimate. However, the energy savings due to the addition of insulation around hot-water pipes was overestimated, also due to the low number of households with hot-water pipe insulation in the NN DHW training dataset.

These results show that NN models have limited ability to estimate the impacts of energy-saving measures, mainly due to the limited availability of pertinent data in the dataset used to develop the models. Also, NN models cannot evaluate the impact of an energy-saving scenario on other energy end-uses (such as impact of using high-efficiency lighting on SH energy consumption), since each end-use is predicted separately in a NN model. Thus, compared to NN models, the engineering model, which estimates energy consumption using thermodynamic and heat-transfer principles, has a significantly higher level of flexibility in evaluating energy-conservation measures.

9. Conclusion

Following an earlier paper [1], this paper continued to investigate the use of the NN method for modeling residential end-use energy-consumptions at the national and regional levels. In this work, end-use energy-consumption models were developed to model the SH and DHW energy-consumptions in the Canadian residential sector using the NN method and the extensive data available in the 1993 SHEU database [3]. Both models achieved a very high prediction performance ($R^2 = 0.91$ and 0.87, respectively for SH and DHW models), i.e. significantly better than the prediction performance of the engineering model developed using the same database [7–9]. These results are similar to the prediction performance of the NN ALC model ($R^2 = 0.91$) that was developed earlier [1], and indicate that NN method can confidently be used to develop models to estimate the energy consumption in the residential sector.

The SH and DHW NN models were also able to isolate the effects of several socio-economic factors on end-use energy consumption, including household income, dwelling type and ownership, number of children and adults, and size of the area of residence. This capability represents a clear advantage of the NN models over the engineering model, since none of the socio-economic factors could be evaluated by the engineering model.

In terms of estimating the impacts of the energy-savings scenarios, the NN models were found to be limited in their scope due to the limited number of variables that could be included in the model, and the vulnerability of the NN models to data limitations. The accuracy of the predictions was found to depend on the quantity of the information in the training dataset: as long as the households that undertook the energy-saving measures were well represented in the training dataset, the prediction accuracy was high. If however the households that undertook the energy-saving measure were not well represented in the training dataset, the accuracy was low. Also, since NN models predict each end-use separately, they are unable to predict the impact of an energy-saving measure on other energy end-uses. The engineering model, on the other hand, which estimates the energy consumption using thermodynamics and heat-transfer principles, has a significantly higher level of flexibility in evaluating energy-conservation measures, including the effects of energy conservation measures on end-uses other than that directly affected by the measure.

In conclusion, the findings of this work indicate that the NN method can confidently be used to develop models to estimate the energy consumption in the residential sector. While NN models have distinct advantages in predicting the energy consumption and the impact of socio-economic factors on energy consumption, they are not flexible in evaluating the impact of energy conservation measures.

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