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Modelling of residential energy consumption at the national level

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SUMMARY

Three methods are currently used to model residential energy consumption at the national level: the engineering method (EM), the conditional demand analysis (CDA) method, and the neural network (NN) method. While the use of the first two methods has been established over the past decade for residential energy modelling, the use of NN method is still in the development and verification phase.

The EM involves developing a housing database representative of the national housing stock and estimating the energy consumption of the dwellings in the database using a building energy simulation program. CDA is a regression-based method in which the regression attributes consumption to end-uses on the basis of the total household energy consumption. The NN method models the residential energy consumption as a neural network, which is an information-processing model inspired by the way the densely interconnected, parallel structure of the brain processes information.

In this paper, the three methods are briefly described and a comparative assessment of the three methods is presented. Copyright © 2003 John Wiley & Sons, Ltd.

KEY WORDS: energy; modelling; residential energy consumption

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

Improving the end-use energy efficiency is one of the most effective ways to reduce energy consumption in the residential sector and associated pollutant emissions. To identify strategies that would improve the energy efficiency in the residential sector in an economically and environmentally feasible manner, a large number of scenarios need to be considered. Such scenarios include improving envelope characteristics, replacing existing standard efficiency

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heating equipment, household appliances and lighting with higher efficiency units, 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 consumption of houses and the associated pollutant emissions. 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 scenarios on residential end-use energy consumption and associated emissions. Such models would help policy makers and analysts in government agencies, energy suppliers and utilities to evaluate the impact of a wide range of energy efficiency measures and strategies on the energy consumption and emissions in the residential sector.

Recently, two methods have been commonly used to model residential end-use energy consumption: the engineering method (EM) and the conditional demand analysis (CDA) method. 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 simulation program (Ugursal and Fung, 1996, 1998; Farahbakhsh *et al*., 1998). Thus, this approach requires a database representative of the housing stock with detailed house description data. Some of the difficulties associated with the use of the EM-based models are the inclusion of consumer behaviour and other socioeconomic variables that have a significant effect on the residential energy use, as well as the extensive data and expertise required to develop and use such models. The most important advantage of the EM-based models is their capability to evaluate a wide range of energy efficiency upgrade scenarios.

CDA, on the other hand, is a regression-based method in which the regression attributes consumption to end-uses on the basis of the total household energy consumption (Parti and Parti, 1980; Aigner *et al*., 1984; Fiebeg *et al*., 1991; Lafrance and Perron, 1994; Hsiao *et al*., 1995). Since CDA does not involve modelling of the energy consumption of each house, it does not require as detailed data on the characteristics of the houses as the EM does. However, its results are sometimes unreliable due to multicollinearity problems that make it difficult to isolate the energy use of the highly saturated appliances, such as the space heating equipment and the refrigerator. Also, the model requires data from several thousand households due to the large number of independent variables needed in the regression equations. Unlike the EM-based models however, the CDA models do not have the flexibility of evaluating a wide range of energy efficiency upgrade scenarios, but they can handle socioeconomic factors if they are included in the model formulation.

In the area of energy modeling, the application of NN has, until recently, been mainly limited to utility load forecasting (Park *et al*., 1991; Peng *et al*., 1992; Kiartzis *et al*., 1995; Chen *et al*., 1996; AlFuaid *et al*., 1997), and predicting the energy consumption of individual buildings (Kreider and Wang, 1991, 1992; Anstett and Kreider, 1993; Kawashima, 1994; Kreider and Haberl, 1994) as well as the energy savings from building retrofits (Cohen and Krarti, 1995; Dodier and Henze, 1996; Krarti *et al*., 1998). Currently however, a NN-based energy consumption model is being developed for the Canadian residential sector. So far, the appliances, lighting and space cooling (ALC) component of the model is completed. The methodology used in developing the NN model and the accuracy of its predictions are discussed in this paper. Also, the EM and CDA models are briefly described and a comparative assessment of the three methods is presented.

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MODELLING OF RESIDENTIAL ENERGY CONSUMPTION

Engineering method (EM)

To model the energy consumption in the residential sector using the EM, a database of dwellings that is representative of the residential sector is needed. In a representative database, each dwelling represents a certain number of dwellings in the residential sector, i.e.

$$\text{NDRS} = \sum_{i=1}^{n} M_i \tag{1}$$

where, NDRS is the number of dwellings in the residential sector, M_i the multiplier for dwelling i in the database and n the number of dwellings in the database.

Thus, if the annual energy consumption of each dwelling in the database can be estimated, the total annual energy consumption of the residential sector can be calculated from

$$\text{AERS} = \sum_{i=1}^{n} \text{AED}_i M_i \tag{2}$$

where, AERS is the annual energy consumption by the residential sector and AED_i the annual energy consumption of dwelling i.

The EM involves the estimation of the annual energy consumption of each dwelling in the database using a building energy simulation program, and then extrapolating the energy consumption of the dwellings in the database to the entire residential sector using Equation (2). Therefore, the available information on each dwelling in the database must be sufficiently detailed to develop an input data file to use it with a building energy simulation program.

One of the most comprehensive EM-based residential end-use energy consumption model is the Canadian residential energy end-use model (CREEM) (Ugursal and Fung, 1996, 1998; Farahbakhsh *et al*., 1998); therefore, the use of the EM will be explained here with reference to CREEM.

CREEM is a versatile end-use energy model of the Canadian housing stock. It contains 8767 house files and it uses the HOT2000 building energy simulation program, developed specifically for houses, as its simulation engine (NRCan, 1996). It can evaluate the impact of a wide variety of potential energy saving measures on the residential end-use energy consumption and the associated carbon dioxide emissions. To develop CREEM, data from the 1993 Survey of Household Energy Use (SHEU) (Statistics Canada, 1993) was used as the core of the model. SHEU contains detailed information on 8767 houses that represent the Canadian housing stock. However, the information in the SHEU database was not sufficient to develop the input files for the HOT2000 program. Therefore, 16 house archetypes were developed using the data from other databases on the Canadian housing stock (Scanada, 1992; NRCan, 1994, 1996; Ugursal and Fung, 1996) and minor contributions from other sources. The archetypes are based on vintage (pre-1941, 1941–1960, 1961–1977, 1978 and later) and regional location (Western Canada, Prairies, Central Canada, Atlantic Canada), and they provide typical house characteristics for each archetype house. The information from the SHEU database was augmented with archetype descriptions, and a HOT2000 input file was developed for each one of the 8767 houses in the SHEU database.

HOT2000 simulations were run using weather files for the location of each house. The weather files represent long term ($\sim$30 year) averages of weather data obtained by Environment

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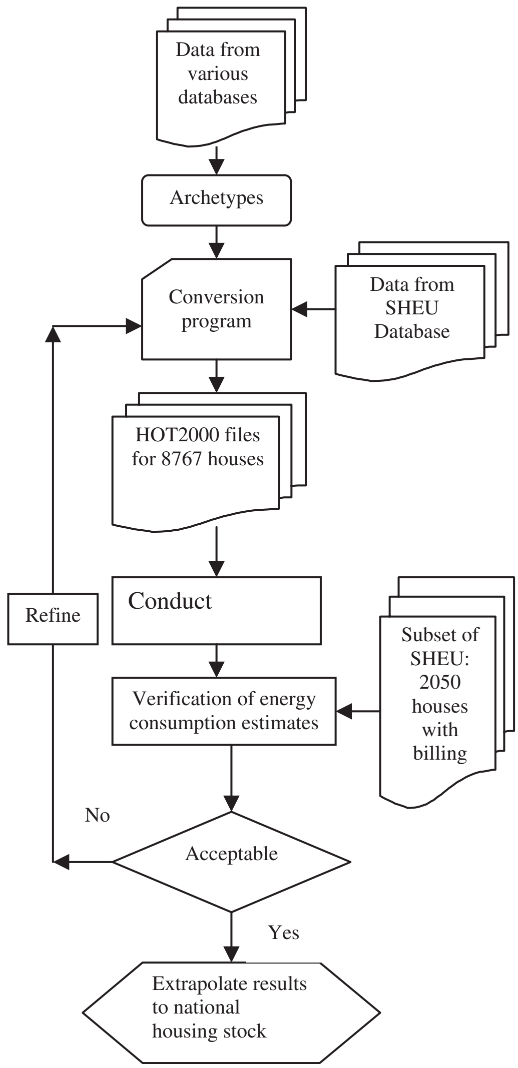

Figure 1. The structure of CREEM.

Canada. Thus, the simulation results are estimates of the 'typical' or 'average' energy consumption that can be expected in an 'average' year. The structure of CREEM is shown in Figure 1.

Actual energy billing data obtained from fuel suppliers and utility companies for a complete year are available for 2050 of the 8767 houses in the SHEU database. These billing data were used to verify the accuracy of the annual unit energy consumption (UEC) estimates obtained from the simulations of the 2050 house files. To do this, the UEC estimates were compared with the actual billing data, and some systemic errors in the input files were identified from these comparisons. After several cycles of simulation and input file improvement, an acceptable level

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of agreement was achieved between the actual billing data and the HOT2000 estimates. The refinements identified from the verification process were applied to the rest of the 8767 house files as necessary to improve the accuracy of the simulation results. Thus, the refined 8767 HOT2000 house files that are representative of the Canadian housing stock constitute CREEM.

The impact of any energy saving measure can be estimated by modifying the 8767 input files to reflect the measure, and conducting a HOT2000 simulation on CREEM. The difference in the energy consumption of the houses in their original state and with the modifications reflects the energy savings potential of the measure.

Conditional demand analysis method

Four kinds of data are generally used to develop a CDA model: household energy consumption, generally in the form of billing records; information on the household appliance holdings and economic/demographic features, obtained from appliance saturation surveys; weather data; and information on market conditions (e.g. energy prices). The CDA method is based on the premise that the energy consumption of any household can be expressed as a summation of the energy consumed by each one of the appliances present in the household (here the term 'appliance' is used in the most general way, including the space and domestic hot water (DHW) heating as well as space cooling equipment). Thus, the energy consumption of a household is directly related with the appliance stock present in the dwelling, the specific features of these appliances, dwelling characteristics, utilization patterns of the appliances (such as thermostat settings on water/space heaters), and behavioural patterns relating to the use of appliances. The basic CDA model can therefore be represented in algebraic form as (EPRI, 1989).

$$\mathrm{HEC}_{it} = \sum_{j=1}^{m} \mathrm{UEC}_{ijt} S_{ij} \tag{3}$$

where HEC_{it} is the end-use energy consumption by household i in period t, UEC_{ijt} the end-use energy consumption by appliance j in period t, S_{ij} the binary indicator of household i's ownership of appliance j and m the number of types of appliances in household i.

To develop a CDA model, the data on household energy consumption (HEC_{it}) can be obtained from utility billing records and appliance stock (S_{ij}) information can be obtained through an appliance saturation survey.

The end-use energy consumption depends upon a variety of factors and this relationship can be formalized as

$$\mathrm{UEC}_{ijt} = f_j\left(\mathrm{AF}_{ij}, \mathrm{STRUC}_i, \mathrm{UP}_{ijt}, e_{ijt}\right) \tag{4}$$

where AF_{ij} is the features of household i's appliance j, STRUC_i the relevant structural features of household i, UP_{ijt} the utilization patterns relating to appliance j and e_{ijt} the random error term for the end-use.

The effect of weather conditions (WC_{it}), market conditions (MC_{it}), and household's economic and demographic characteristics (EDC_i) on the end-use energy utilization pattern can be shown as

$$\mathrm{UP}_{ijt} = g_j(\mathrm{WC}_{it}, \mathrm{MC}_{it}, \mathrm{EDC}_i) \tag{5}$$

Substituting Equations (5) and (4) into Equation (3), and noting that the individual error terms are additive within their respective UEC functions, the household energy consumption equation

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can be written as

$$\mathrm{HEC}_{it} = \sum_{j=1}^{j} F_j(X) S_{it} + e_{it} \tag{6}$$

where $X = \mathrm{AF}_{ij}$, STRUC_i, WC_{it}, MC_{it}, EDC_i and $e_{it} = \sum_{j=1}^{1} e_{ij} S_{ij}$.

The CDA model can be estimated statistically by standard multivariate regression analysis using data on household energy consumption, appliance saturation, and other variables given in Equation (6). Once the CDA model is estimated statistically, it can be used to estimate the UEC of individual households, as well as a designated group of households. In these cases, the time-dependent variables like weather and market conditions are replaced by their average values for the period of estimation. Besides estimating the end-use energy consumption of households, CDA can be used to estimate income and price elasticities (Parti and Parti, 1980), and the hourly load of major household appliances through the day (Aigner *et al*., 1984; Fiebig *et al*., 1991; Hsiao *et al*., 1995).

In most CDA models multicollinearity problem arises, which is caused by high correlation across appliance ownership dummy variables, limiting the capability of the regression to distinguish the impacts of these variables. Thus, the influence of some individual appliances on the total end-use energy consumption becomes difficult to separate. Mostly, appliances with high saturation cause multicollinearity problems. Moreover, it is not uncommon for CDA models to yield unrealistic negative appliance consumption estimates because of the high degree of multicollinearity. The problem of multicollinearity is a gap between the information requirements of the model and the information provided by the sample data. The way to reduce this gap is to expand the information content of the data, reduce the requirements of the model, or both. Therefore, prior information in the form of data obtained from engineering estimates (Caves *et al*., 1987; Train, 1992) or direct metering of specific appliances (Fiebig *et al*., 1991; Hsiao *et al*., 1995) is used to reduce the data requirements.

The overall fit of the CDA model depends on the model specification and data quality. In general, the multiple correlation coefficient (R^2) values of these models range from 0.55 (Aigner *et al*., 1984) to 0.75 (Kellas, 1993). These values might seem low, but explaining the cross-sectional behaviour of individual households is a difficult process since energy consumption is affected by many other factors that cannot be readily identified or quantified (tastes, habits, special circumstances), and consequently, cannot be incorporated into the model. Similarly, it is not possible to incorporate all of the house characteristics (e.g. wall, roof, window, etc. areas, insulation values, infiltration, solar heat gains, climatic factors, etc.) into the regression model due to the limitations in data availability. Thus, although it is theoretically possible to develop CDA models that would include parameters defining detailed house characteristics, this is difficult to accomplish in practice because of the prohibitively large data requirements to carry out the regression. Consequently, it is not possible to assess the impacts of energy conservation measures (such as increasing building envelope insulation and appliance efficiencies) using a CDA model.

Neural network method

A NN, also commonly referred to as an artificial neural network (ANN), is an information-processing model inspired by the way the densely interconnected, parallel structure of the brain processes information. In other words, NNs are simplified mathematical models of biological

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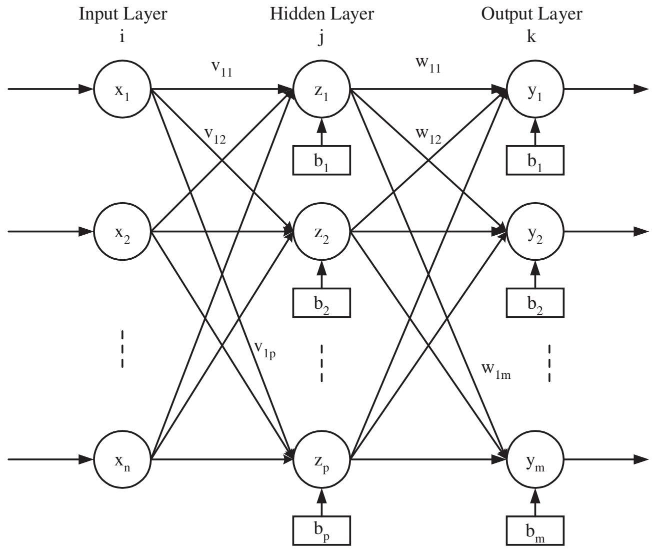

Figure 2. Architecture of a MLP with one hidden layer.

neural networks. The key element of the NN is the novel structure of the information-processing system. It is composed of a large number of highly interconnected processing elements that are analogous to neurons, and tied together with weighted connections that are analogous to synapses.

NNs are capable of finding internal representations of interrelations within raw data. They are considered to be intuitive because they learn by example rather than by following programmed rules. This characteristic, together with the relative simplicity of building and training NNs, encouraged their application to the task of prediction. Because of their inherent non-linearity, NNs are able to identify the complex interactions between independent variables without the need for complex functional models to describe the relationships between dependent and independent variables.

A widely used NN architecture called the multi-layer perceptron (MLP) NN is shown in Figure 2. The MLP type NN consists of one input layer, one or more hidden layers and one output layer. Each layer employs several neurons and each neuron in a layer is connected to the neurons in the adjacent layer with different weights.

Signals flow into the input layer, pass through the hidden layer(s), and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer. The incoming signals are multiplied by the weights and summed up with the bias contribution, i.e.

$$\mathrm{net}_j = \sum_{i=1}^{n} x_i v_{ij} + b_j \tag{7}$$

where net_j = is the total input of the hidden layer neuron j, x_i the input to the hidden layer neuron j from input layer neuron i, v_{ij} the weight between the input layer neuron i and hidden

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layer neuron j, b_j the bias value of the hidden layer neuron j and n the number of neurons in the input layer.

The output of a neuron is determined by applying an activation function to this summation with the bias contribution. Thus, the NN calculates its outputs using the calculation architecture defined by the structure of the network, the activation function used, and the inputs provided to it. If the computed outputs do not match the known (i.e. target) values, NN model is in error. Then a portion of this error is propagated backward through the network. This error is used to adjust the weight and bias of each neuron throughout the network so the next iteration error will be less for the same units. The procedure is applied repetitively for each set of inputs until the total error is less than a specified level. At this point, the net remembers the patterns for which it was trained, and is able to recognize similar patterns in new sets of data. Once training is completed, predictions from a new set of data may be done using the already trained network. During the training process, the neural network develops the capability of recognizing different patterns and capturing relevant relationships in the new data set. There are a number of learning algorithms used in the development of NNs such as standard backpropagation (Rumelhart and McClelland, 1988), enhanced backpropagation (Anstett and Kreider, 1993), Backpropagation with Weight Decay (Werbos, 1988), Quickprop (Fausett, 1994) and resilient propagation (Riedmiller and Braun, 1993). In developing a NN model, the available data set is divided into two sets, one to be used for training of the network (70–80% of the data), and the rest for testing the performance.

The NN that is being developed to model the end-use energy consumption in the Canadian housing stock consists of three separate networks: (i) domestic hot water (DHW) heating energy consumption network, (ii) space heating (SH) energy consumption network, (iii) appliance, lighting, and space cooling (ALC) energy consumption network. The steps used in the development of the networks are as shown in Figure 3. The input units of the networks describe:

- construction details and usage characteristics of the houses,
- specifications and usage of space heating and cooling equipment, appliances and lighting,
- socioeconomic characteristics of the occupants,
- weather characteristics.

The number and choice of input units will be different for each network, and the units will be selected based on their contribution on the prediction performance of the end-use network. The actual energy consumption data for each house will be used as the output (target) unit of the networks. Various network architectures, activation functions and scaling intervals will be tested to identify those that produce the best predictions. Once the overall NN model is complete, it will be used to predict the end-use energy consumption of all houses in the 1993 SHEU database. So far, only the ALC network is completed.

The ALC network used a total of 55 input units. These were:

- ownership of 33 appliances,
- size of main and second refrigerator, and main and second freezer,
- number of weekly loads of clothes washer, clothes dryer and dish washer,
- number of hours of central air conditioner usage and number of hours of window air conditioner usage,
- heating degree days,
- cooling degree days,

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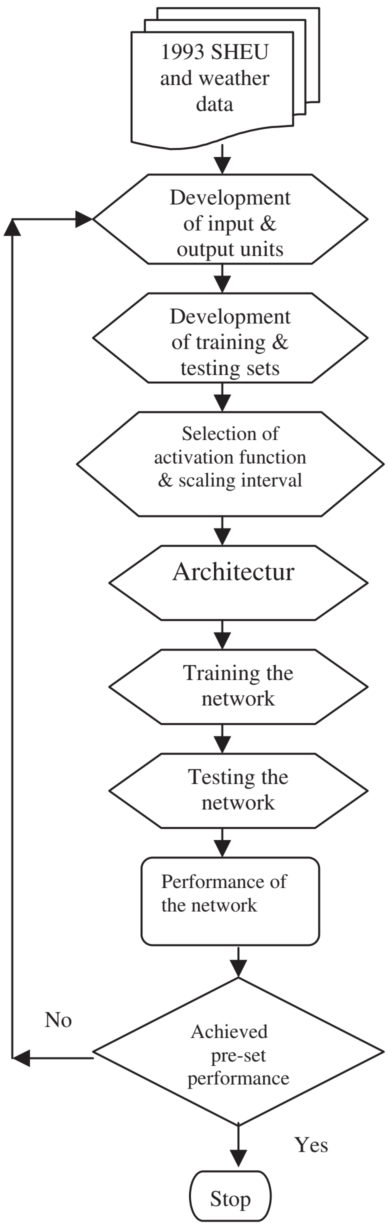

Figure 3. Development steps of the NN model.

- number of incandescent, fluorescent, and halogen lamps,
- total heated area,
- household income,
- dwelling type,

- dwelling ownership,
- size of area of residence,
- employed adult ratio,
- number of children,
- number of adults.

To determine the best network architecture, the following variations were tested:

- five different scaling intervals: [0.1–0.9], [−0.5–0.5], [0.0–1.0], [−1.0–1.0], [−0.9–0.9],
- logistic, hyperbolic tangent, and identity hidden and output layer activation functions,
- scaling of all, or only continuous data,
- standard backpropagation, enhanced backpropagation, quickprop, resilient propagation and backpropagation with weight decay learning algorithms,
- the number of hidden layers was varied from one to three,
- the number of units in the hidden layers was varied from 1 to 30.

As a result of these tests, it was found that a NN model with the following characteristics provides the best predictions:

- 55 input, 27 hidden, one output units,
- three hidden layers,
- nine neurons in each hidden layer,
- trained with quickprop learning algorithm,
- using logistic function as the hidden layer activation function and identity function as the output layer activation function,
- all data scaled to [−0.5–0.5] interval.

COMPARISON OF THE THREE METHODS

Although all three methods can be used to model residential energy consumption, each has different capabilities, advantages and disadvantages, and hence, they are useful for different purposes and uses.

Among the three types of models, the EM-based models provide the highest level of detail and flexibility. Consequently, EM-based models require detailed data on the housing stock, and substantial engineering expertise is necessary to develop and use EM models. Because of the high level of detail and flexibility provided by EM models, they can be used to evaluate the impact of a wide range of scenarios for energy conservation on residential energy consumption and green house gas emissions (Guler *et al*., 1999, 2000). However, incorporating socioeconomic factors in an EM-based model is difficult.

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 socioeconomic parameters in the model if such data is available in the database.

Based on the research and development work done on NN-based models so far, it can be inferred that in terms of their data requirements, flexibility of assessing the impacts of a variety

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of energy conservation scenarios, and the ease of development and use, NN-based models are somewhere in between the EM and CDA-based models. However, to be able to make definitive conclusions on the feasibility of using NN method for residential energy modelling, further development and testing work is needed.

To provide a limited view on the performance of the three models in predicting residential energy consumption, a comparison of the accuracy of their predictions are presented here based on the ALC energy consumption estimates.

The NN method estimated an average ALC consumption of 9243 kWh yr^{-1} for the houses in the testing data set, which actually had an average consumption of 9111 kWh yr^{-1} obtained from the billing data. The average ALC consumption estimated by the EM for the houses in the same data set was 9512 kWh yr^{-1}. Thus, it can be concluded that the EM over-estimated the ALC consumption compared to the NN method. The over-estimation of electrical consumption by the EM was also pointed out by Farahbakhsh (1997). The multiple correlation coefficient (R^2) obtained by the EM and NN models were 0.78, and 0.91, respectively.

CONCLUSION

Three methods for modelling of residential energy consumption were presented and compared. These are the EM, CDA method and the NN method. Each method was found to be suitable for different applications, and has certain strengths and shortcomings. The estimates obtained by the NN-based model for the appliance, lights and space cooling energy consumption were more accurate than those obtained by the EM-based model. However, more development and testing work is required to make definitive conclusions regarding the comparative performance of the three methods.

NOMENCLATURE

AED_i	= annual energy consumption of dwelling i
AERS	= annual energy consumption by the residential sector
AF_{ij}	= features of household i's appliance j
ALC	= appliance, lighting and space cooling
ANN	= artificial neural network
b_j	= bias value of the hidden layer neuron j
CDA	= conditional demand analysis
CREEDAC	= Canadian residential energy end-use data and analysis centre
CREEM	= Canadian residential energy end-use model
DHW	= domestic hot water
EDC_i	= economic and demographic characteristics of household I
e_{ijt}	= random error term for the end-use
EM	= engineering method
HEC_{it}	= end-use energy consumption by household i in period t
m	= no. of types of appliances in household i
MC_{it}	= market conditions of household i during period t
M_i	= multiplier for dwelling i in the database

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MLP	= multi layer perceptron
n	= number of dwellings in the database
N	= number of neurons in the input layer
NDRS	= number of dwellings in the residential sector
net_j	= total input of the hidden layer neuron j
NN	= neural network
R^2	= multiple correlation coefficient
SH	= space heating
SHEU	= survey of household energy use
S_{ij}	= binary indicator of household i's ownership of appliance j
STRUC_i	= relevant structural features of household i
UEC_{ijt}	= end-use energy consumption by appliance j in period t
UP_{ijt}	= utilization patterns relating to appliance j
v_{ij}	= weight between the input layer neuron i and hidden layer neuron j
WC_{it}	= weather conditions of household i during period t
x_i	= input to the hidden layer neuron j from input layer neuron i

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