INVESTIGATION OF ENERGY SAVING DUE TO LOAD CURTAILMENT ACTIVATION (LCA) IN TORONTO, CANADA

M. Ebrahim Poulad[1*], Alan S. Fung[1], L. He[1], and T. Fotinakopoulos[2]
[1]Ryerson University, Mechanical and Industrial Engineering Department, Toronto, Ontario, Canada
[2]Toronto Hydro, Toronto, Ontario, Canada
[*]corresponding author: mpoulad@ryerson.ca

ABSTRACT

A technique is proposed and developed to predict the household hourly electricity demand. The developed Artificial Neural Network (ANN) model of residential hourly demand is employed to estimate the potential impacts of Load Curtailment Activation (LCA) on electricity demand on the activation days. LCA occurs once per day for no more than four consecutive hours. Electricity demand increases dramatically after peaksaver/LCA is completed on July 6 and August 30 of 2010. Both days show saving if the data are not normalized. Unnormalized load reductions for individual event hours ranged between 0.35 and 0.64 kWh/h or 14% and 24%, respectively.

INTRODUCTION

Sustainable development requires wise energy management and strategic Demand Response (DR). In any management style, prediction/forecast is a golden key to success. Precise forecast of energy demand may reduce the investment on energy production plant without compromising the comfort for clients. Recently, investigation of the demand side of energy management is getting one of the most complex and important technical initiatives in the literature (Palensky & Dietrich, 2011).

To predict the energy demand pattern, it should be precisely modeled. Researchers are trying to find a model of energy demand in different demographic situations and weather conditions to assist energy managers to implement effective DR. Efforts to obtain energy models/patterns have been done for sustainable progress of (and not limited to) the following regions:

- The energy consumption pattern in Bandung, Indonesia (Permana et al., 2008)
- The household energy consumption pattern for a county in Tibet (Liu et al., 2008)
- Simulation of national energy consumption of the residential sector in Japan (Shimoda et al., 2010)

Amongst all models developed for energy demand forecasts, electricity has special consideration. Electricity demand models are developed to predict short term, medium term and long term loads, including nationwide forecasting. Energy demand modelings are categorized in twelve different headings, of which Artificial Neural Network (ANN) is one. ANN has been used as one of the best and most accurate techniques to predict energy demand (Suganthia & Anand, 2012). Neural network has been successfully used to model energy consumption of appliances, lighting, and space-cooling in Canadian residential sector (Aydinalp, et al., 2003).

Artificial Neural Networks (ANNs) are simplified mathematical models of biological neural networks. They 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. The ANN approach has been used successfully (and not limited) to model the following:

- The energy demand in South Korea (Ekonomou, 2010)
- Forecast of long-term energy consumption of Greece (Shayeghi, et al., 2009)

Load management and demand response are conservative approaches that have been interesting subjects in shifting peak energy demand recently. Newsham et al. (2011) analyzed the peak load reductions due to a Direct Load Control (DLC) program for Air Conditioners (AC) in southern Ontario in 2008. They increased the 195 participant thermostats by 2℃; and compared the hourly load demand of the participants with 268 non-participant households (control group). Four different methods were used for analysis: comparison of a peaksaver group to a control group, comparison of the peaksaver group on event days to non-event days, time-series regression, and simple, multiple regression. They reported average peak load reductions of 10-35% (Newsham, et al., 2011).

Peak electrical load reduction in the cooling season (summer) is implemented by Toronto Hydro for its participating customers. It is a fact that only 32 hours of electricity consumption in each year is responsible for the top 2000 MW of Ontario's 27,000 MW peak demand (Faruqui, et al., 2007). Load management is implemented to move electricity use from peak period (on-peak) to off-peak periods. Thus, load management should be tied closely to dynamic pricing infrastructure. Dynamic pricing infrastructure should address the marginal cost of producing electricity. The Government of Ontario presented a dynamic pricing system based on Time-of-Use (TOU), Figure 1. Schedules differ based on the season. They are divided into three periods: on-peak, mid-peak and off-peak (OEB, 2012).

The main objective of this project is to predict the reduction in energy demand due to the LCA. Research findings show that it is possible to save energy and reduce cost by slightly increasing the higher set point during the peak period. Higher set point is the temperature at which the air conditioning starts to keep the indoor temperature lower than that. In the Desert Southwest of the US, a 2.2℃ increase in thermostat temperature from 23.9℃ to 26.1℃ during the peak period (4pm to 7pm) decreased the average demand during the period by 69% for a typical home (Sadineni & Boehm, 2012).

Toronto Hydro initiated, developed and implemented the peaksaver program in 1995 that cycles central air conditioners using proven technologies. The Ontario Power Authority (OPA) expanded the ***peaksaver*** program province wide.

Three province-wide events were initiated in 2010. Moreover, OPA called a one-hour general test event on May 20th at 2 PM. Finally, for the purpose of evaluation, OPA called two Evaluation, Measurement and Verification (EM&V) events on August 4th from 2 PM to 6 PM and September 1st, from 1 PM to 5 PM. The EM&V events only affected a residential sample selected for measurement, rather than the full peaksaver population. It was reported that the average impact during Ontario-wide events was 0.47 kW, that is 38% load reduction. Although 50% cycling strategy was used, the average load reduction was less than 50% (38%, 37% and 37%, chronologically). Energy savings were calculated by multiplying the average per CAC unit impact by the number of available control devices for each hour of each event, and also including the hours after the event to capture post-event snap-back. These values are then added up over each event day to get a total energy value. 104,971 residents (42,657 with PCTs and 62,314 with switches) were participating in the *peaksaver* program in Ontario in 2011 (George & Perry, 2011).

METHODOLOGY

This section includes two parts:

A. Preparation of inputs

A commercial ANN was employed to predict the hourly load demand. The ANN was trained using hourly energy consumption of single residents by combining the load profile data with the Toronto weather conditions (i.e., temperature, dew point, relative humidity, wind direction, wind speed, standard pressure, and Humidex) and date (year, day, hour, and day type (i.e., weekday or weekend)). Humidex is a scale indicating the levels of heat and humidity in current weather conditions (from humid + (in)dex). It is defined as:

$$\text{Humidex} = T + \frac{5}{9}\left[\frac{6.112RH}{100}10^{\left(\frac{7.5T}{237.7+T}\right)} - 10\right] \quad (1)$$

where T is the ambient temperature in degree centigrade and RH is the relative humidity in percentage.

Toronto weather information was obtained from National Climate Data and Information Archive (NCDIA). The average hourly electricity demand of different regions (with different postal codes) was used as representative of load of a typical hour of the day. Conveniently, residential homes have a 100A or 200A, 240V, 2-line single phase service in Canada; therefore, to have a typical residential representative input, the values less than or equal to zero and over 24 kW (200A times 120V Line-Neutral) are skipped. After skipping the higher and lower mentioned values, the quality of the data were checked (e.g., any repetition). Finally, the average, minimum and maximum load of each client in each hour and each day were calculated (Figure 2). It is noticeable that zero loads are also excluded because it means that the resident(s) is/are living somewhere else (hotel, cottage, visiting relatives, etc) or in a blackout condition. Essentially, zero is not energy consumption and it shows that there is no real energy demand for that/those resident(s). Electricity demand data were collected at fifteen-minute intervals but averaged to an hourly level for the analysis.

After quality control of the data, accepted data were transferred into an Excel spreadsheet in desired order (i.e., each row represents all inputs and related energy demand, target, for specific hour of the day) for further use. 352 days (8,448 hours/rows) of data in summer in 2008 (2 days), 2009 (114 days), 2010 (117 days), and 2011 (119 days) were prepared to input into ANN. These data extracted from energy consumption of 100,886 points (27,287 clients in 2008, 24,569 clients in 2009, 24,574 clients in 2010, and 24,456 clients in 2011). Some of the clients participated in more than one year, so the mentioned number of points is not necessarily the number of different clients. Considering 24 hours of information for each client, 2,421,264 rows of data had been processed. After calculating the average hourly energy/power demand, the weather information of that hour was added to the same row in the spreadsheet. Columns of each row were ordered (from left to right) as follows: year, day type, month of the year, day of the month, time of the day, ambient temperature and dew point both in degree centigrade, relative humidity in percent, wind direction in degree, wind speed in meter per second (m/s), visibility in meter, standard pressure in kilo Pascal (kPa), Humidex, weather condition, average power demand (Target). To reduce the texting, the weather conditions were indexed as Table 1 presents. As the extraction of the data from Environment

Canada was a manual process, indexing was very helpful in saving time.

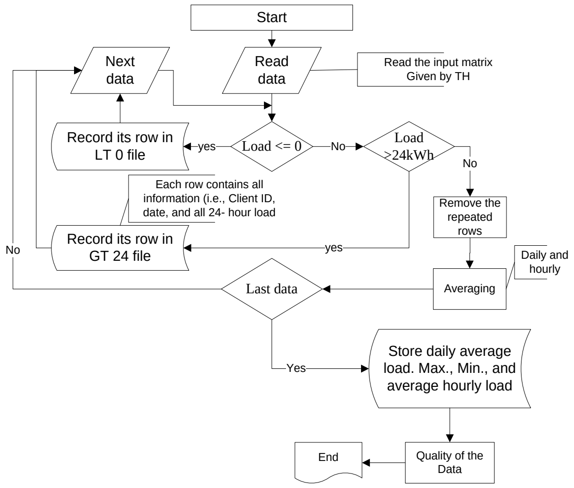

Figure 2: Quality control flow chart of the received data

B. ANN Forecasting Process

Figure 3 shows the flow chart of the ANN forecast process. AE or ARE was selected to stop training iteration (AE and ARE are absolute error and absolute relative error. It is the difference between the actual value of the target column and the corresponding network output. The difference will be displayed in absolute values and in percentage terms) and hyperbolic tangent was used for the activation function, tanh, activation function that has a sigmoid curve and is calculated using the following formula: F(x) = $(e^x - e^{-x})/(e^x + e^{-x})$. Its output range is [-1..1]. Empirically, it is often found that this function performs better than the logistic function. Out of the 8,448 hours of qualified and selected data, the rows with information in the temperature range of the target day were fitted into ANN to train it. The last column of Table 2 shows the number of equivalent rows fitted into ANN to predict each target day's electricity demand. Equivalent rows contain information, which is within the target-day temperature range. July 6 and August 30 are the event days with four hours peaksaver activation.

August 31 is the reference or equivalent day to check the uncertainty of the ANN forecast process. This day was selected because its temperature range is between the two event days.

Two hot days in 2010 were analyzed to investigate the effects of LCA on cost and electricity demand on those days. Table 3 shows the temperature and humidex data of the event days and the equivalent day (August 31). Load curtailment activation started from 3 PM to 7 PM on July 6th; and on August 30th from 2 PM to 6 PM.

For winter energy consumption model, 77 inputs (e.g., weather conditions and date) are transformed into one output (i.e., electricity demand) through 154 neurons (hidden layer). This structure (77-154-1) found to be the best structure, with R-square value of 0.96, for prediction. To input the weather condition in winter, a 3-digit index is used (see Table 1). For example, if the weather is "Clear", then the value is "1"; if the weather condition is "Rain Showers Fog", then the value is "674" and so on.

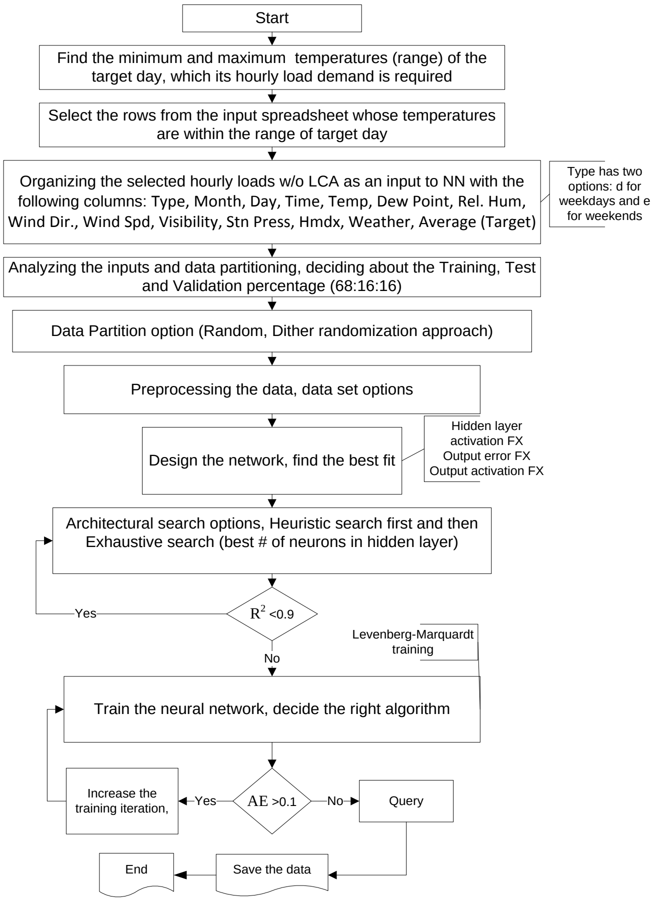

Figure 3: Artificial Neural Network forecasting flow chart

RESULTS AND DISCUSSION

The preliminary results, for load forecast of August 31, 2010 show that the ANN is capable of predicting the load/power demand properly. Figure 4 shows the ANN forecast and average real load demand. The average and maximum deviations are 2.4% and 9.1%, respectively. The maximum deviation occurs at 3:00am, which might be due to fluctuation in ambient temperature. Conveniently, residents are not responding to the fluctuations, but ANN responded to the increase in the temperature by increasing the demand at the moment.

Table 2:

Number of data set used to train ANN for different target days

Target Date	Temperature Range (℃)	Number of Rows/Hours
July 6, 2010	23.6 to 33.1	1718
August 30, 2010	21.4 to 34.2	2959
August 31, 2010	22.7 to 32.9	1530

To match the peaksaver pre-event profile with the ANN forecast, the load estimator (ANN forecast) are normalized. The normalization factor (NF) intends to address the systematic difference between electricity use and ANN forecast when there is no activation. It is a multiplier applied to all hourly energy use values of estimation on the event day. To find the best NF, several epochs were tested. Finally, it was found that from start of the day until 11am on the event day gives the best epoch to use. The normalization factor is the ratio of energy forecast by the ANN to that of the peaksaver clients during this period. This approach is consistent with other research (Newsham, et al., 2011), (Piette, et al., 2005). Later, this factor would be multiplied to ANN forecast to produce normalized values.

Figures 5 and 6 show the mean daily electrical energy use profiles for the event days, normalized ANN, peaksaver homes, ANN ex ante forecast, and one day after for each event day. The day after is added to the graph for comparison. The electrical energy use profiles of the normalized ANN forecast and the peaksaver clients generally matched each other pre-event. Due to the peaksaver participants using less energy between 9:01 a.m. and noon (normalization factor < 1) the normalized plot is under the ANN ex ante forecast plot in the pre-dawn hours. On August 30, 2010 (Figure 6), due to the relatively small normalization factor (0.91) the relative savings were potentially overestimated by ANN. Additionally, the ambient temperature plot is added to each day graph as secondary vertical axis because it is the main parameter/factor in CAC demand. The ANN forecast is practically hourly basis. That means, the ANN predicts the load based on the inputs related to that hour, not based on the previous or after hour load information. It does not mean that ANN cannot predict based on the previous or after hour information, but for this forecast only current hour inputs are used. That makes daily load forecast non-smooth and rough. A degree four polynomial regression is used to smooth the ANN ex ante forecast plot. In this regression, x is the hour ending and y is the average load in kW. The regressions with their R^2s are shown on the graphs, as well.

Tables 4 and 5 list hourly load and price reductions for each of the four event hours and whole day on each event day, and the mean for the event hour as a whole; calculations for the normalized and unnormalized ANN profile are shown. As mentioned earlier, load/price reductions (difference between ANN forecast and average load) generally decreased over the course of the event hours. Load reductions for individual event hours (normalized) ranged between 0.14 and 0.60 kWh/h or 6% and 23%, respectively. The percentages are calculated by dividing the reduction to ANN forecast multiplied by 100:

$$\% \text{ reduction} = \frac{ANN\ Forecast - average\ load}{ANN\ Forecast} * 100 \qquad (2)$$

where ANN Forecast (in numerator) may be normalized or unnormalized values (it depends on type of reduction is being calculated as reported in Table 4), but in the denominator unnormalized values is always used. Load reductions for individual event hours (unnormalized) ranged between 0.37 and 0.64 kWh/h or 15% and 24%, respectively. Table 5 reports the price reduction in Canadian cents (¢). Price reduction is calculated based on off-peak, mid-peak and on-peak rates of 6.5, 10 and 11.7 ¢/kWh, respectively, plus 4.066 ¢/kWh (1.216 ¢/kWh for transmission, 1.52 ¢/kWh for distribution, 0.63 ¢/kWh for wholesale operations, and 0.7 ¢/kWh for debt retirement).

The day before July 6th is Monday, which is attached to long weekend due to Canada day. That is a possible reason that load profile on July 5th (see Figure 5) is lower than event day. The day before August 30th is weekend; therefore, that is why load profile on a day before is lower than the event day (see Figure 6). In addition, the day after is almost as warm as August 30th (see Table 3); therefore, people tend to increase using AC due to two successive hot day.

Percent reduction can be taken as greenhouse gas (GHG) emission reduction as explained later. As normalization factors are less than one (0.98 and 0.91 on July 6 and August 30, respectively), unnormalized values show more reduction. Daily reduction is from -2.15 kWh (or 2.15 kWh extra energy demand per household in given event day!) to 0.30 kWh on normalized electricity demand. On unnormalized condition, there is a saving ranged between 1.19 and 1.82 kWh per household in given event days. For the sake of brevity, there is no conclusion on a daily basis, because there is only two days taken into consideration.

Finally, GHG emission reduction is calculated (see Table 6) based on values reported for emission to generate electricity in Ontario in 2006. GHG emission factor was calculated hourly from (Gordon & Fung, 2009):

$$HCO2 = (HECOAL)A + (HEOTHER)B \qquad (3)$$

where,

$HCO2$= hourly CO_2 production (kg)

$HECOAL$ = hourly electricity generated by Coal plants

$HEOTHER$ = hourly electricity generated by other sources (natural gas, etc.)

A = CO_2 emission factor

B = Environment Canada natural gas emission factor

Table 6 represents the results. The GHG emission found to be between 83.6 and 117.7 gram per hour per house.

In winter, two typical days (November 16, 2010 and January 10, 2009) are selected. January 10 is a weekend and November 16 is a weekday. Figure 7 shows the ANN forecast and actual demand plots along the ambient temperature profiles. It is clear a break on weekday energy demand plot at 8am. This is because most residents leave home for work at that time. There is no break on weekend demand plot because, generally, people stay home and need indoor comfortable temperature. This figure shows that ANN can predict, precisely, the energy demand trend in winter as good as in summer.

CONCLUSION

Electricity demand information from 100,886 Toronto Hydro points in summer (starting June ending September) is used to train an Artificial Neural Network (ANN). Trained ANN is employed to predict the effect of LCA on electricity demand on the activated days. LCA occurs once for four hours on the event days. Reductions of load/price decreases over the course of the event hours; therefore, it seems that activation of once per hour may give more reduction than one activation for four hours. For the current technology (i.e., available sensors and relays to control functions of AC devices), it is possible to apply LCA in any other hour. Electricity demand increases after the activation hours on both days (i.e., July 6 and August 30 of 2010). Both days show saving if the data are not normalized. Finally, it is concluded that ANN is able to predict electricity demand in summer as well as winter very accurately.

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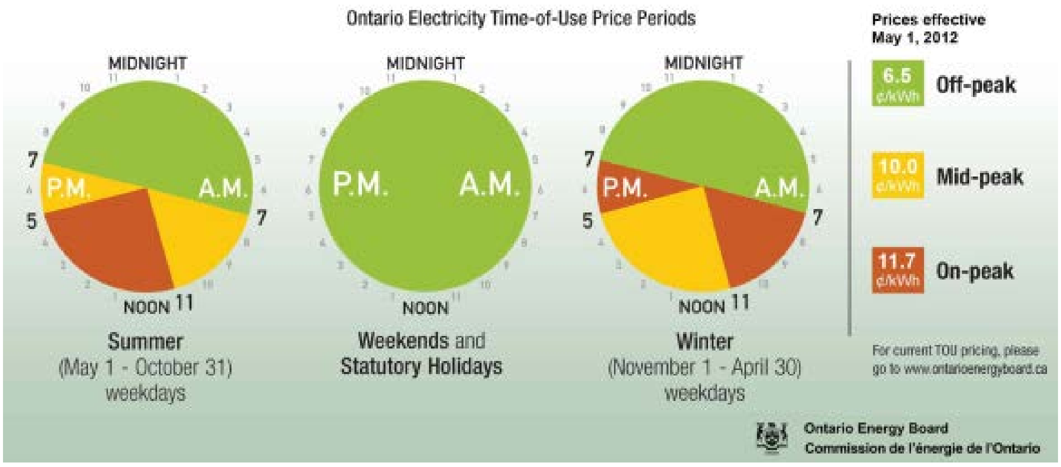

Figure 1: TOU rates in summer and winter in Ontario, Canada

Table 1:
Numerical index used for weather condition to train ANN in summer (top row) and winter (middle and bottom rows)

WEATHER CONDITION	CLEAR	MAINLY CLEAR	MOSTLY CLOUDY	CLOUDY	HAZE/ FOG	RAIN	RAIN SHOWERS	THUNDER STORMS		SUM.
Index Number	1	2	3	4	5	6	7	8		
WEATHER CONDITION	CLEAR	CLOUDY	HAZE	FOG	DRIZZLE	RAIN	SHOWERS	ICE	SNOW	WIN.
Index Number	1	2	3	4	5	6	7	8	9	
WEATHER CONDITION	MAINLY	MOSTLY	MODERATE	HEAVY	GRAINS	PELLET	BLOWING	FREEZING	THUND. STORMS	
Index Number	1	2	3	4	5	6	1	2	3	

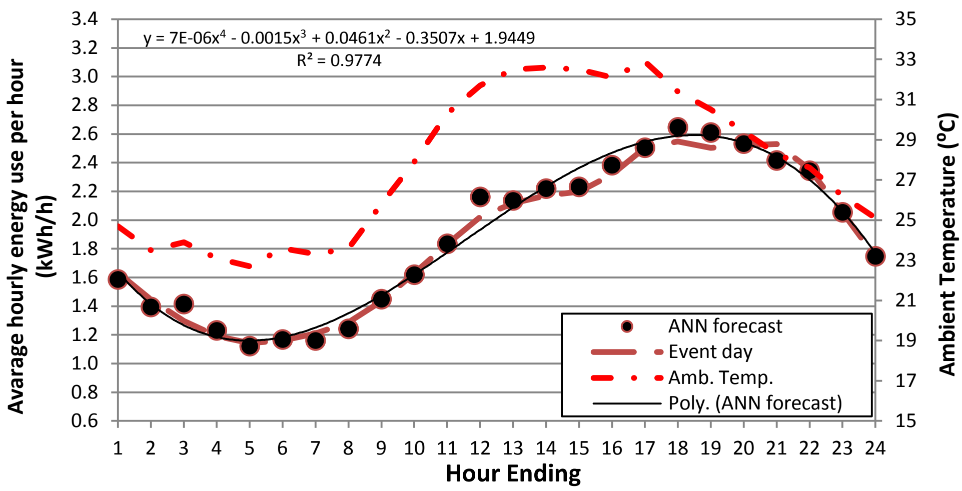

Figure 4: Neural network forecast for a selected day (Aug. 31, 2010) without peaksaver activation. Polynomial trend line is also inset on the graph

Table 3:
Temperature and humidex data of the event days in 2010 and their equivalent day

TARGET DATE	TEMP.; HUMIDEX (℃) MEAN	MIN.	MAX.	HRS ABOVE 24℃
July 6	28.7; 36.6	23.6; 31	33.1; 41	23
August 30	27.5; 34.1	21.4; 27	34.2; 41	16
August 31	27.6; 34.9	22.7; 29	32.9; 40	17

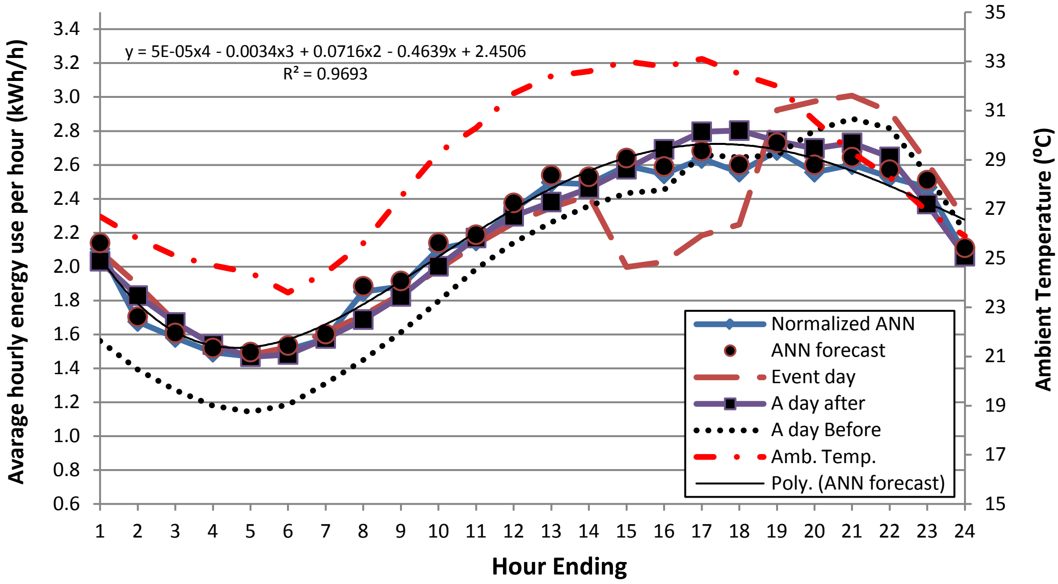

Figure 5: Normalized and unnormalized ANN forecast, event day, a day before, and a day after electrical energy demand on July 6th, 2010. Ambient temperature is plotted as secondary vertical axis, as well

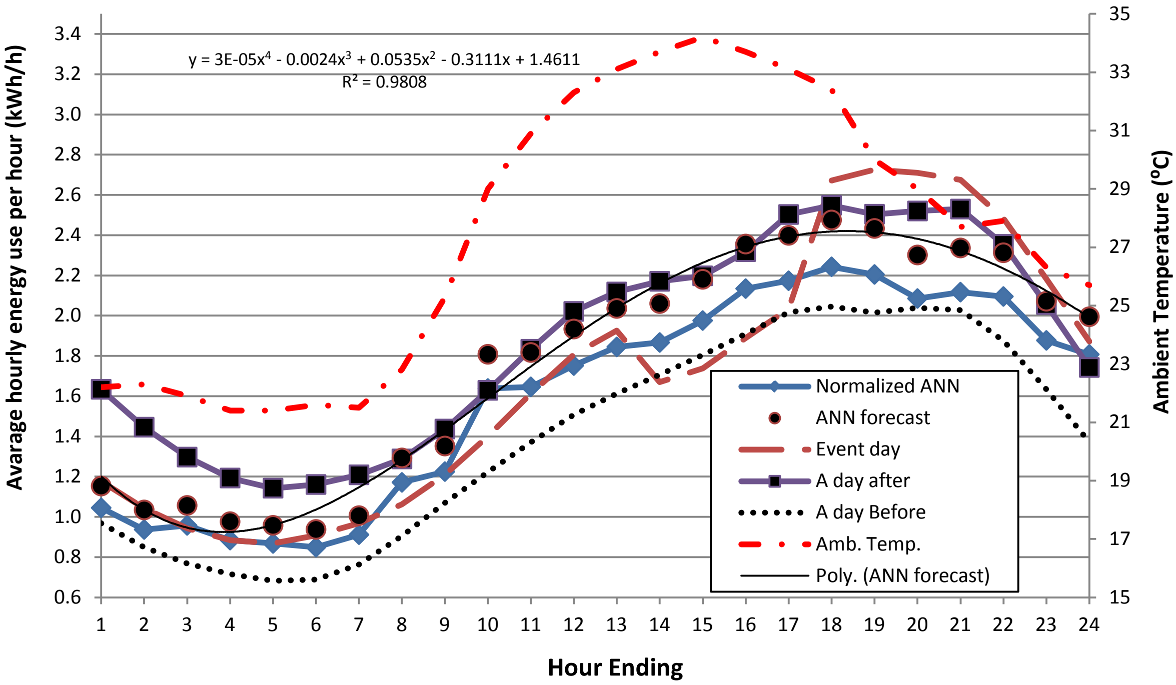

Figure 6: Normalized and unnormalized ANN forecast, a day before, and a day after electrical energy demand on Aug. 30th, 2010. A day before is a weekend day. Ambient temperature is plotted as secondary vertical axis, as well

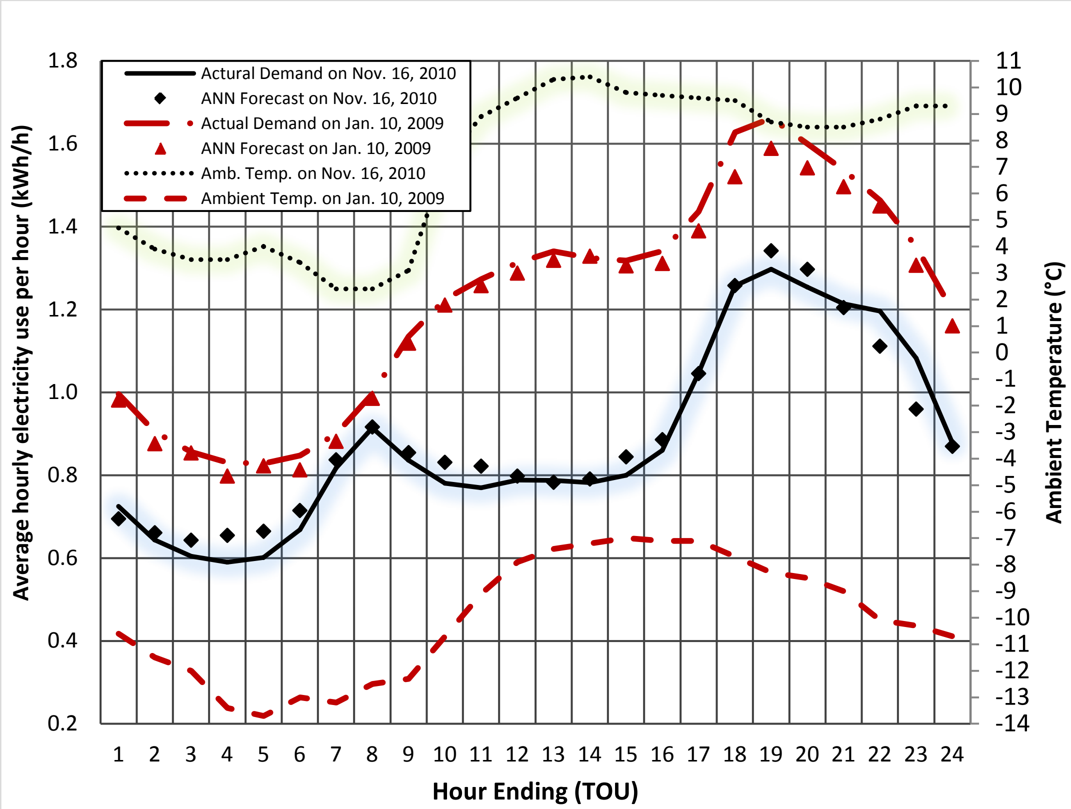

Figure 7: ANN forecast for two winter days. Secondary vertical axis shows the ambient (outdoor) temperature

Table 4:
Mean hourly and daily energy saving per house

DATES	COMPARISON	HOUR 1		HOUR 2		HOUR 3		HOUR 4		MEAN		DAY
		KW	%	KW	%	KW	%	KW	%	KW	%	KWH
July 6, 2010	Normalized	0.60	23	0.52	20	0.45	17	0.31	12	0.47	18	0.30
	Unnormalized	0.64	24	0.56	22	0.51	19	0.35	14	0.51	20	1.19
Aug. 30, 2010	Normalized	0.20	11	0.24	12	0.25	12	0.14	6	0.21	10	-2.15
	Unnormalized	0.39	19	0.44	20	0.42	20	0.37	15	0.42	19	1.82
Hour mean	Normalized	0.40	17	0.38	16	0.35	15	0.23	9	0.34	14	
	Unnormalized	0.52	22	0.50	21	0.47	20	0.36	15	0.47	20	

Table 5:
Mean hourly and daily electricity cost reduction per house

DATES	COMPARISON	HOUR 1		HOUR 2		HOUR 3		HOUR 4		MEAN		DAY
		¢	%	¢	%	¢	%	¢	%	¢	%	¢
July 6, 2010	Normalized	9.43	23	8.17	20	7.12	17	4.32	12	7.26	18	14.1
	Unnormalized	10.14	24	8.86	22	7.84	19	4.94	14	7.95	20	25.8
Aug. 30, 2010	Normalized	3.10	11	3.74	12	3.78	12	2.21	6	3.21	10	-21.1
	Unnormalized	6.15	19	6.97	20	7.36	20	5.77	15	6.56	19	30.9
Hour mean	Normalized	6.27	17	5.96	16	5.45	15	3.27	9	5.24	14	
	Unnormalized	8.15	22	7.92	21	7.60	20	5.36	15	7.26	20	

Table 6:
Mean hourly and daily GHG emission reduction in gram per house

DATES	COMPARISON	HOUR 1 (GRAM)	HOUR 2 (GRAM)	HOUR 3 (GRAM)	HOUR 4 (GRAM)	MEAN (GRAM)	DAY (GRAM)
July 6, 2010	Normalized	147.4	123.2	105.7	69.3	111.4	118
	Unnormalized	158.5	133.7	116.3	79.3	122.0	302
Aug. 30, 2010	Normalized	53.8	64.1	65.9	39.0	55.7	-506
	Unnormalized	106.8	119.5	125.4	101.7	113.3	475
Hour mean	Normalized	76.4	93.7	85.8	54.2	83.6	
	Unnormalized	132.7	126.6	120.9	90.5	117.7	