Artificial Intelligent Models for Improved Prediction of Residential Space Heating

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Abstract: Using artificial intelligence (AI) models, cost effective electricity meter, and easily accessible weather data, this paper discusses a methodology for improved prediction of hourly residential space heating electricity use. Four AI models [back propagation neural network (BPNN), radial basis function neural network (RBFNN), general regression neural network (GRNN), and support vector regression (SVR)] were used for predicting hourly residential heating electricity use. For this study, a typical single-family house was used to obtain the data used for AI prediction models. Results showed SVR's ability to predict hourly residential heating electricity use was better when compared with other AI models. Furthermore, through comparison of prediction performance in different time periods, additional investigation was conducted to evaluate the effect of dynamic human behaviors on the prediction accuracy of the AI models. Results revealed that dynamic human behaviors have a negative effect on the prediction performance. **DOI: 10.1061/(ASCE)EY.1943-7897.0000342.** © *2016 American Society of Civil Engineers.*

Author keywords: Residential buildings; Space heating; Electricity use prediction; Artificial neural networks (ANNs); Support vector regression (SVR).

Introduction

In the United States, buildings consume 41% of the primary energy compared with industry (30%) and transportation-related (29%) energy use (Building energy data book 2011). Residential and commercial buildings use 54% and 46%, respectively. To achieve overall energy use reduction, research in the residential buildings' arena is significant as they take up a large percentage of building energy use. Within the residential building sector, the largest proportion of energy use is noticed in space heating, i.e., 40% of overall energy use (U.S. Energy Information Administration 2013). Needless to say, the prediction of household space heating energy use is a crucial component of building energy efficiency, particularly when energy is in demand. Energy estimation for the purposes of predicting household space heating are currently conducted using either engineering- or sensor-based approaches. The engineering-based approach uses thermo-physical properties to solve heat transfer physical equations to estimate energy, whereas the sensor-based approach uses existing data to develop models to represent complex relationships inherent in the system.

Several engineering-based simulation tools to predict building energy use exist; (e.g., EnergyPlus, BLAST, DOE-2, ESP-r). These tools use data such as weather, geometry, and envelope configuration (including material properties, operating schedules, system and plant data) to estimate energy use (Zhao and Magoules 2012). The complexity and difficulty in collecting data and modeling geometry makes them somewhat hard for widespread use. However, an alternative approach (that is more practical, easy to use, and particularly effective for implementation for retrofit projects) is the sensor-based prediction method, which has been widely applied in several research works recently. Sensor-based prediction methods use data (e.g., from energy meters, building management systems, and weather stations) and apply artificial intelligence (AI) models to estimate or predict energy use by inferring the complex relationship between building energy use and variables such as environmental factors, time of day, and, in some cases, occupant behaviors (Jain et al. 2014). Sensor-based approaches have been used to predict energy consumption for commercial buildings (Ekici and Aksoy 2009; Hou et al. 2006; Yalcintas and Akkurt 2005; Li et al. 2009a). However, there are only a few sensor-based studies that primarily focus on the energy prediction for residential buildings (Edwards et al. 2012; Jain et al. 2014).

This paper primarily focuses on hourly space heating electricity use prediction for residential buildings. Typical energy estimations are either on an hourly or daily basis. There are instances when even minute-by-minute predictions are necessary. Hourly predictions (short-term) use detailed input, on an hourly basis, to capture system behavior in a greater manner, whereas daily predictions (long-term) fail to capture system behavior because only a cumulative 24 h of data are used. Especially for space heating electricity use, hourly data are more suitable and appropriate, and accordingly, the authors have monitored hourly electricity use.

In this study, four AI models [back propagation neural network (BPNN), radial basis function neural network (RBFNN), general regression neural network (GRNN), and support vector regression (SVR)] are used for predicting the space heating electricity use. Specifically, this paper develops a robust, easy-to-use AI-based approach to predict hourly residential space heating electricity use with limited weather data. An electricity meter is used to collect space heating electricity use data, whereas weather data are retrieved from local weather station. Natural gas was not metered on an hourly basis, however, the electricity use of the furnace was

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monitored in an hourly manner. Although hourly natural gas data may provide improved representation of space heating, the blower fan which operates in synchronous with the burning of natural gas was monitored on an hourly basis and used in this study. Moreover, the blower fan was a single-speed fan, in that it exactly parallels the behavior of natural gas consumption at all times, and it adequately represents the electricity use portion and overall behavior of the residential house's space conditioning requirements. For this study, a typical single-family house was used to validate the prediction performance of the developed models. Human behavior, i.e., the model data used to train and test included occupant interference for realistic modeling of energy use scenario. By comparing the prediction performance in different time periods, further investigation was performed to evaluate the effect of dynamic human behaviors on the prediction accuracy of the proposed models.

This paper is organized as follows. First, a review of prior research and discussion of the importance of AI-based residential space heating energy prediction. Next, the research methodology, including the evaluation methods and data collection, is discussed. Then the data processing methods are described and the prediction results are analyzed, followed by an elaborate discussion of the effect of dynamic human behaviors on prediction performance. Finally, conclusions and future directions of this study are presented.

Background

Both statistical and AI models have been widely used in building energy use estimation. Statistical models have been used to predict building energy use for the past two decades. Bauer and Scartezzini (1998) proposed a simplified correlation method to estimate the heating and cooling loads. Dhar et al. (1998) developed a Fourier series approach to modeling hourly energy use in commercial buildings. Lei and Hu (2009) used single variable linear regression model on the basis of outdoor dry-bulb temperature to predict annual energy consumption for office buildings. Catalina et al. (2013) used a multiple regression prediction model to predict heating energy demand. These studies indicate that statistical models are capable of estimating building energy consumption because of their ease of use and acceptable performance of prediction accuracy. Conversely, the low accuracy and lack of flexibility of statistical models make them hard to apply to real-time prediction. Therefore, AI models, with better accuracy and more flexibility, have stepped into researchers' visions.

Artificial neural networks (ANNs) are widely used in building energy prediction owing to its effectiveness and better performance at solving complex nonlinear problems. In the past two decades, many studies have been carried out to analyze various types of building energy use, such as cooling and heating loads, and overall energy consumption by applying ANNs. Ben-Nakhi and Mahmoud (2004) applied GRNN to predict the cooling load for commercial buildings. Their findings indicated that a well-designed GRNN is able to predict the cooling load of a building only on the basis of external temperature. Ekici and Aksoy (2009) BPNN to predict the heating energy requirements of three different buildings. Their research proved the reliability and accuracy of BPNN in prediction of building heating loads. Yokoyama et al. (2009) used BPNN to predict cooling demand of a building in which they introduced a global optimization method, called modal trimming method, to identify the model parameters to improve the prediction performance. Li et al. (2011) used neural network and a hybrid genetic algorithm [adaptive network-based fuzzy inference system (GA-ANFIS)] to predict building energy use.

Meanwhile, some comparisons between ANNs and other prediction models were performed by researchers. Aydinalp et al. (2002) compared ANNs with traditional engineering models in predicting residential appliance, lighting, and space cooling energy uses. Their research showed that ANNs can achieve higher prediction accuracy than engineering models. Aydinalp-Koksal and Ugursal (2008) compared ANNs with conditional demand analysis (CDA) for predicting residential end-use energy consumption. Neto and Fiorelli (2008) compared ANNs with EnergyPlus for predicting building energy use. The results showed that both models are capable of building energy consumption prediction, although ANNs provide a slightly better prediction result than EnergyPlus.

SVR has been used in building system fault detection and diagnosis (Yan et al. 2014) and building system operation analysis (Li et al. 2014). In recent years, SVR has been widely used to predict energy consumption for commercial buildings. Dong et al. (2005) first applied SVR in the area of building energy consumption prediction. Similarly, Li et al. (2009a) used SVR to predict hourly cooling load of an office building. Weather condition information, such as outdoor dry bulb temperature, relative humidity, and solar radiation intensity, were used as input parameters to predict hourly cooling loads. Their results demonstrated SVR as a promising alternative approach to predicting building cooling loads. Several works have been completed to demonstrate the superiority of SVR in building energy prediction. Li et al. (2009b) compared SVR with other ANN techniques in predicting building hourly cooling load. Their study indicated that SVR and GRNN can achieve better accuracy and generalization than the BPNN and RBFNN. Chou and Bui (2014) used five AI models to estimate cooling and heating loads for 12 different buildings. The comparison results showed that SVR and the ensemble approach (SVR+ANN) were better for predicting cooling and heating loads.

Besides investigating commercial buildings, some researchers have turned their attention to residential buildings as well. Li et al. (2010a) used four AI models to predict annual energy use of residential buildings. Edwards et al. (2012) applied seven machine learning algorithms to predict next hour electricity consumption of a residential building. The result of their study also showed that SVR is the best technique for predicting energy consumption for residential buildings. The finding of their research is significant, although the implementation of their method is not practical as the prediction is on the basis of 140 sensor-monitored parameters. Jain et al. (2014) applied SVR to predict the energy consumption of multi-family residential buildings. A further study has been carried out to investigate the effect of temporal and spatial monitoring granularity on performance accuracy. Their research indicated that SVR based energy prediction can be applied to multi-family residential buildings and the most effective prediction model was built on the basis of hourly interval at the floor level. A summary of studies related to SVR is shown in Table 1. These studies are different in building type (commercial and residential), energy type (heating, cooling, and overall), prediction timescale (year, month, day, and hour), and type of input data (building, weather, and schedule). For example, Dong et al. (2005) focused on using SVR and weather data to predict monthly overall energy consumption of a commercial building, whereas Edwards et al. (2012) aimed to use SVR to predict hourly overall energy consumption of residential buildings by learning their building and schedule data.

Besides the research on different prediction models, some researchers have focused on finding important input parameters and investigating their effect on the prediction accuracy. Tsanas and Xifara (2012) developed a statistical machine learning framework to study the effect of eight input variables (e.g., relative compactness, surface area, wall area, and orientation) on residential

Table 1. Summary of SVR-Based Building Energy Prediction Studies

Year	Authors	Building type		Energy			Scale				Data type			Method	
		Commercial	Residential	Cooling	Heating	Overall	Annual	Monthly	Daily	Hourly	Building	Weather	Schedule	SVR	Other
2005	Dong et al. (2005)	X	—	—	—	X	—	X	—	—	—	X	—	X	—
2009	Li et al. (2009a)	X	—	X	—	—	—	—	—	X	—	X	—	X	—
2009	Li et al. (2009b)	X	—	X	—	—	—	—	—	X	—	X	—	X	BPNN, RBFNN,GRNN
2009	Hou and Lian (2009)	X	—	X	—	—	—	—	—	X	—	—	—	X	ARIMA
2014	Chou and Bui (2014)	X	—	X	X	—	—	—	—	—	X	—	—	X	ANN, CART, CHAID, GLR
2010	Li et al. (2010a)	—	X	—	—	X	X	—	—	—	X	—	—	X	BPNN, RBFNN,GRNN
2012	Edwards et al. (2012)	—	X	—	—	X	—	—	—	X	X	—	X	X	LR, FFNN, LS-SVM, HME, FCM-FFNN
2014	Jain et al. (2014)	—	X	—	—	X	—	—	X	X	—	X	X	X	—
2009	Zhang and Qi (2009)	X	—	—	X	—	—	—	—	X	—	—	—	X	Markov chains
2010	Lv et al. (2010)	X	—	X	—	—	—	—	—	X	X	X	—	X	PCA
2010	Li et al. (2010b)	X	—	X	—	—	—	—	—	X	—	—	—	X	FCC
2012	Zhao and Magoulès (2012)	X	—	—	—	X	—	—	X	—	X	X	X	X	—

building heating and cooling load prediction. Zhao and Magoules (2012) selected optimal energy influence parameters for building energy prediction by two feature selection methods, namely, the correlation coefficient method and regression, gradient-guided feature selection method. Kwok and Lee (2011) used a probabilistic entropy-based neural model to predict the cooling load of an office building. To investigate the effect of occupancy on the prediction accuracy, two input parameters (dynamic occupancy area and rate) were introduced in their prediction model. The finding indicated that the use of occupancy data has significantly improved the predictive accuracy of the proposed model. All these studies agree SVR is an effective and accurate model for building energy prediction.

Nevertheless, most of the previously discussed research is rather hard, (i.e., needs a high degree of effort to setup and run the experiments), if not impossible, to apply to single-family energy prediction as they require abundant data and intensive efforts. Moreover, human behavior or occupancy data may also influence energy use, potentially improving the prediction accuracy of AI models, which almost all of the studies discussed previously ignored. Dynamic human behavior involves the interaction and/or interference of building occupants and their effect on energy use. Although most of the existing prediction models have inherently avoided occupants' behavior in their models, their prediction accuracy may vary depending on human interference with the system under investigation. What is more, methods used in these studies are difficult to widely apply to typical U.S. single-family homes as they require several more sensors to collect the energy influential parameters.

Using AI models, a cost effective energy meter, and easily accessible weather data, this paper discusses improved prediction of hourly residential space heating electricity use. On the basis of the literature review, the research on energy prediction of single-family houses has not been studied sufficiently. This research fills this gap by investigating the feasibility of using SVR and other prediction algorithms to predict energy consumption of a single-family house. The input data used in this research were a few weather parameters, which can be acquired easily from a local weather station. This important feature makes the proposed method possible to be widely applied to energy prediction of other single-family houses. Moreover, this paper predicts building energy in a more detailed level (i.e, heating energy), which would enable users to elaborately manage their houses.

Methodology, Data Collection, and Processing

Fig. 1 shows the flowchart of the household space heating electricity use prediction procedure. It has four major steps. The first step is to collect sufficient electricity use and weather data to meet the experiment's needs. The second step is to preprocess the acquired data by certain data transformation strategies (such as data aggregation, interpolation, integration, and normalization) to consolidate the original data into forms appropriate for prediction. The third step is selecting parameters for the proposed prediction models and training the models. For this study, four AI-based building energy prediction models were used to predict hourly heating electricity use. These models include: BPNN, GRNN, RBFNN, and SVR. The last step is comparing the prediction results of each model and identifying the model with the best prediction accuracy for single-family homes.

A typical two-story single-family residential house, located in Omaha, Nebraska, was used for this study. The house was built in 2005 and has a total floor area of 421.41 m^2. The type of materials for the foundation, exterior walls, and roof of the studied

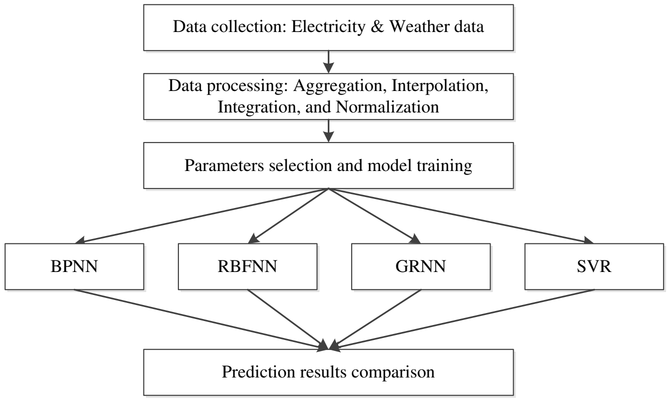

Fig. 1. Flow chart of household space heating electricity use prediction procedure

Table 2. Specification of Furnace 1 and Furnace 2

Specification type	Furnace 1	Furnace 2
Model number	Lennox G40UN-48B-090	Lennox G40UN-36A-070
Input (kW)	25.8	19.3
Output (kW)	21.1	15.6

house were concrete, vinyl siding, and composition shingle. The *R* values of the house's envelope were: basemen, R-9; walls, R-17; and attic, R-50. Space heating was supplied by two gas furnaces: Furnace 1 provided space heating to the basement and the first floor; and Furnace 2 supplied heat to the second floor. The operation of the furnaces was automatically controlled by a central thermostat, which was constantly set at 20.8°C for space heating during the data collection period. The manufacturer specifications of these two furnaces are shown in Table 2 (G40UH(X) - Lennox HVAC Manuals 2006).

In general, there are three major components that affect overall building energy use: the building, the external environment, and the occupants. Although the building component includes the building envelope and other energy systems of the building, the external environment refers to a building's surrounding weather conditions (e.g., outdoor temperature, humidity, wind speed, and solar radiation). Finally, the occupants component consists of the number of occupants and the types of activities. Comparing with the environment and occupants components, which vary frequently, the status of the building component is relatively stable. The initial values of the building-related parameters typically acquired from building drawings and manufacturers do not alter and remain constant during the day-night cycle. The electricity use owing to space heating results from the building envelope characteristics and occupant behavior. Whereas the former (building envelope characteristics) is static, the latter (occupant behavior) is periodic, i.e., the activities change and need to be studied in detail. Prediction models for space heating, in this case, can rightfully omit building envelope data for the reason that their behavior is already captured in the resultant metered electricity use, as applied in this study as well.

Data Collection

The weather data, including outdoor temperature, humidity, and wind speed, were obtained from a local weather station, which is 3.5 km east of the house (Millard KNEOMAHA83 2016). The solar radiation data was obtained from another local weather station, which is 8 km northeast of this house.

Table 3. Sample of Electricity Use Data by Furnace 1 and Furnace 2

Date and time (h)	Furnace 1 (W/min)	Furnace 2 (W/min)
01/26/2011 0000	7	44
01/26/2011 0001	6	146
01/26/2011 0002	3	549
01/26/2011 0003	93	533
01/26/2011 0004	201	532
01/26/2011 0005	487	529
01/26/2011 0006	484	529
01/26/2011 0007	482	528
01/26/2011 0008	479	527
01/26/2011 0009	477	499
01/26/2011 0010	420	424
01/26/2011 0011	349	75
01/26/2011 0012	7	6
01/26/2011 0013	7	6
01/26/2011 0014	7	6
01/26/2011 0015	7	6
01/26/2011 0016	7	6
01/26/2011 0017	7	6
01/26/2011 0018	7	6
01/26/2011 0019	7	6
01/26/2011 0020	7	6

Table 4. Sample of Collected Outdoor Temperature, Humidity, and Wind Speed Data

Date and time (hrs)	Temperature (°C)	Humidity (%)	Wind speed (km/h)
01/26/2011 0010	−4.78	88	7.40
01/26/2011 0030	−4.61	84	9.33
01/26/2011 0050	−4.22	81	11.10
01/26/2011 0110	−2.89	76	11.10
01/26/2011 0130	−2.78	73	13.04

A nonintrusive real-time electricity monitor system, called E-Monitor (Powerhouse Dynamics 2012), was used in the data collection process to obtain the house's minute-by-minute electricity use data. A total number of 1,440 data points (i.e., 60 min $\times$ 24 h) were recorded for each day. To obtain representative and sufficient electricity use data, a data collection process of 50 calendar days was held from January 26, 2011, to March 16, 2011. A sample of furnace electricity use data is shown in Table 3.

The outdoor temperature, humidity, and wind speed were recorded for every 20 min. Table 4 shows a sample of the weather condition data. Solar radiation data is recorded with inconsistent intervals. A sample of collected solar radiation data is shown in Table 5.

Data Processing

Because the collected data has different intervals, some data transformation strategies were used to consolidate the original data into forms appropriate for prediction. Strategies used in this research include data aggregation, data interpolation, data integration, and data normalization.

Data Aggregation

Data aggregation is a type of data mining process in which data are searched, gathered, and expressed in a summarized format to

Table 5. Sample of Collected Solar Radiation Data

Date and time (h)	Solar radiation (W/m^2)
1/26/2011 0801	14
1/26/2011 0804	16
1/26/2011 0806	21
1/26/2011 0809	21
1/26/2011 0811	23
1/26/2011 0814	23
1/26/2011 0816	19
1/26/2011 0819	18

achieve a specific research purpose. For this study, the minute-by-minute furnaces' electricity use data were aggregated for each hour to obtain hourly electricity use data.

Data Interpolation

To calculate the hourly solar radiation ratio, data interpolation was used to reduce the inconsistencies of the original data. Because the original solar radiation data has inconsistent intervals, linear interpolation was used to calculate the solar radiation ratio for each minute, which is the shortest interval in the original data. The equation for linear interpolation is defined as

$$y = y_0 + (y_1 - y_0) \times \frac{x - x_0}{x_1 - x_0}$$

where (x_0, x_1) = original interval; x = time point happens in interval (x_0, x_1); y_0 and y_1 = solar radiation value on time x_0 and x_1; and y = insert value on time x.

Data Integration

Because the furnace electricity use data and the weather data were collected from different sources and with different intervals, data integration was required to reduce and avoid redundancies and inconsistencies of the data. Data integration can help improve the accuracy and speed of the subsequent data mining process (Han et al. 2012). The electricity use prediction was hourly based; thus, the interval for both furnace electricity use data and weather data should be extended to one hour. Hourly electricity use data of the two furnaces was calculated by data aggregation. Hourly spacing heating electricity use was considered as the combination of the hourly electricity use data of Furnace 1 and Furnace 2. For weather data, the original data was first partitioned into minute-by-minute intervals by data interpolation, and the arithmetic mean value of each hour was then calculated and considered as the hourly weather data. Table 6 shows a sample of integrated data.

Data Normalization

To avoid dependence on the choice of measurement units, a linear transformation method (min-max normalization) was applied in this research (Han et al. 2012). The formula for min-max normalization is

$$X_{i,A\,\text{to}\,B} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \times (B - A) + A$$

where X_i = original data; $X_{\min}$ = minimum value in the original data set; $X_{\max}$ = maximum value in the original data set; A and B = lower and upper limit of the normalization interval; and $X_{i,A\,\text{to}\,B}$ = normalized value. In this study, A and B were set to 1 and 2, respectively. Fig. 2 shows the comparison between the initial furnace electricity use data and the normalized data. From the comparison, it can be

Table 6. Sample of Integrated Data

Date and time (h)	Furnace (kWh)	Outdoor temperature (℃)	Outdoor humidity (%)	Wind speed (km/h)	Solar radiation (W/m^2)
01/26/2011 0001–0100	0.32	−6.75	85.67	9.90	0.00
01/26/2011 0101–0200	0.30	−6.93	75.17	12.99	0.00
01/26/2011 0201–0300	0.30	−7.11	72.33	10.22	0.00
01/26/2011 0301–0400	0.31	−7.30	72.17	12.36	0.00
01/26/2011 0401–0500	0.28	−7.62	74.33	9.58	0.00
01/26/2011 0501–0600	0.31	−7.98	80.50	15.18	0.00
01/26/2011 0601–0700	0.37	−8.50	84.17	10.57	0.00
01/26/2011 0701–0800	0.26	−8.93	85.50	12.36	2.22
01/26/2011 0801–0900	0.13	−6.37	85.50	13.00	30.38
01/26/2011 0901–1000	0.00	−6.12	83.67	11.46	86.59
01/26/2011 1001–1100	0.00	−5.73	84.67	12.36	202.88
01/26/2011 1101–1200	0.00	−5.96	82.00	13.57	264.53
01/26/2011 1201–1300	0.00	−6.15	81.50	10.49	315.61
01/26/2011 1301–1400	0.07	−5.22	80.83	10.83	409.22
01/26/2011 1401–1500	0.69	−5.18	80.67	7.45	248.50
01/26/2011 1501–1600	0.56	−4.92	77.83	8.56	163.00

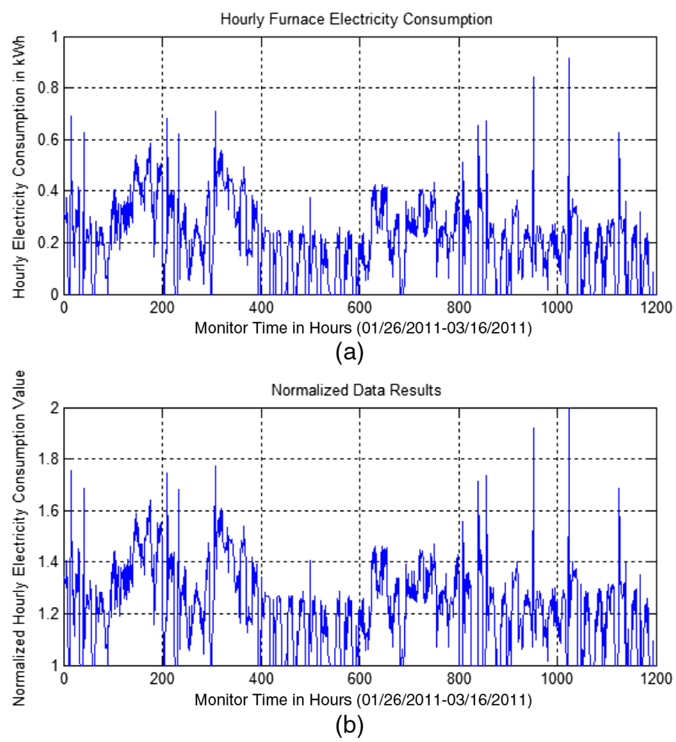

Fig. 2. Data normalization for furnace electricity use: (a) initial hourly furnace electricity use data; (b) normalized data results with interval set to be [1, 2]

observed that the scale of the data changes whereas the shape of the data maintains after data normalization.

Evaluation Parameters

To evaluate the prediction performance of the models, the following evaluating parameters were computed: coefficient of variance (CV), mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), and linear correlation coefficient (R). For further discussion of these evaluation parameters, see Appendix.

Table 7. Information for Module 1 and Module 2

Module type	Time period (hrs)	Data points
Module 1	0001–0800	$8 \times 50 = 400$
Module 2	0001–2400	$24 \times 50 = 1200$

Results

In this study, all experiments were performed on a Windows 7 machine with a 2.67 GHz Intel Core i7 chipset and 4GB of RAM. *MATLAB* was used as the programming language. The SVR model was built using LibSVM (Chang and Lin 2014), a customized optimization package.

Because the furnace electricity use data was collected from an occupied single-family house, the effect of human behavior or occupants' factors (e.g., the number of occupants, different activities of occupants, and actual operations of the furnaces) varied from daytime to nighttime. To investigate the effect of occupants' behavior on the performance of the prediction models, two modules with different time periods (Module 1 and Module 2) were conducted in this analysis.

Module 1 covered the time period between 0001 to 0800, when there were few occupants' behaviors involved and their effect on the space heating electricity use was little and constant. Module 2 covered the whole time period of each day, from 0001 to 2400, when many occupants' behaviors could happen and affect the operation of the space heating facilities. For each module, the data were divided into two subsets: the first 75% as a training data set, to train the models; and the remaining 25% as the testing data set, to validate the performance of each prediction model. Thus, Module 1 had 300 data points as its training data set and 100 data points as its testing data set, whereas, for Module 2, the number of training and testing data points were 900 and 300, respectively. The information of the two modules is summarized in Table 7.

Parameter Selection

1. BPNN: For BPNN, the learning rate is used to determine the step size of weight update in the model training process. It is crucial to the speed and quality of the learning process. When the learning rate of the BPNN is either too large or too small, the convergence of the network is adversely affected. At a high learning rate, the neurons will be trained faster. However, it would also result in oscillation of synaptic weight and the failure of network convergence. On the contrary, a low learning rate would cost too much time to train the model. On the basis of the observation that convergence might be improved if the oscillation in the trajectory is smoothed out, the momentum parameter, which is a weight adjustment schema by introducing a fraction of the previous weight changes, was introduced in this model. Therefore, the momentum parameter can help smoothing out the decent path by preventing extreme changes in the gradient attributable to local anomalies. In this research, after numerous computation tests were made, it was found that the best convergence was possible at a learning rate of 0.1 and a momentum of 0.9, respectively. The number of epochs used to train the model was set to 100 and the goal for mean square error (MSE) was set to 0.0000004. A stepwise validation was used to determine the optimal number of hidden layer neurons. Table 8 shows the results for different numbers of hidden layer neurons in Module 1. For each number of neurons, the model was run for ten times and minimum, maximum, and average performance of CV, MAPE, and R were obtained. By comparing the performance of CV, MAPE, and R, the optimal number of hidden layer neurons was determined. The optimal number of hidden layer neurons for Modules 1 and 2 were 6 and 9, respectively.
2. RBFNN: In this research, a Gaussian function is used as a nonlinear transfer function for each hidden neuron. The Gaussian function has a spread parameter, σ, which controls the performance of the model. Therefore, the choice of the spread parameter is crucial for training the RBFNN. An inappropriate spread could cause potential overfitting or underfitting. The spread value should be large enough to receive promising output results, although too large a value will cause the calculation difficulty in the training process. In this study, the spread was selected by trials. Fig. 3 shows the trial results of Module 1. Because of the significant magnitude difference, the logarithmic scale values of CV, MAPE, and R were used for optimal spread value selection. The results indicated that CV, MAPE, and R converge on the point at which spread is 170. Thus, the optimal spread for Module 1 was 170. The spread selection of Module 2 was conducted in the same manner as in Module 1, with 16 being chosen as the optimal spread value for Module 2.
3. GRNN: Similar to RBFNN, the spread of GRNN was essential to the prediction performance of the model. A stepwise validation

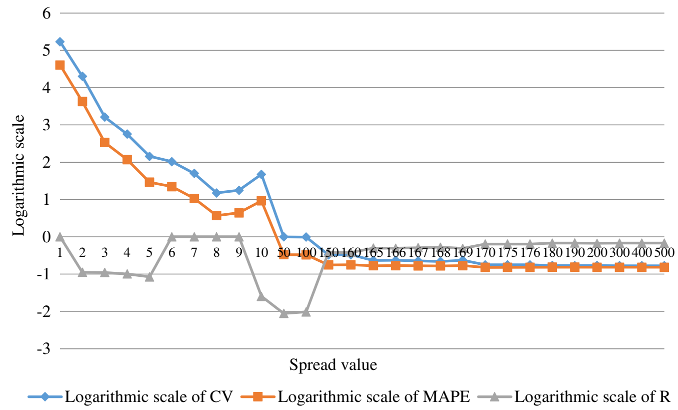

Fig. 3. Spread value trail results for Module 1

Table 8. Trial Results for Module 1

Number of neurons	CV			MAPE			R		
	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum	Average
4	16.01	19.90	17.47	14.11	16.70	15.30	0.58	0.70	0.65
5	16.32	22.86	18.79	14.77	17.76	16.07	0.54	0.69	0.63
6	16.12	17.92	16.69	14.27	16.47	15.00	0.67	0.70	0.68
7	15.87	21.79	17.86	14.11	17.22	15.58	0.54	0.69	0.64
8	16.55	23.01	18.43	14.95	19.94	16.21	0.45	0.69	0.62
9	16.54	20.84	18.13	14.93	16.82	15.77	0.57	0.69	0.63

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Table 9. Parameters Selection Results for SVR

Module type	C	e	K-CV MSE
Module 1	0.70711	0.70711	0.001724
Module 2	0.25	1.4142	0.001914

range from 0.1 to 200, with a step width of 0.1 was applied to select the optimal spread value. The optimal spread value for Modules 1 and 2 was set as 0.2.

4. SVR: The performance of the SVR highly depends on the selection of two parameters (i.e., the insensitivity zone, e, and the penalty parameter, C). These two parameters determine the trade-off between the training error and Vapnik-Chervonenkis (VC) dimension of the model (KECMAN 2001). It is not known beforehand which e and C are best for a given problem; thus, a parameter selection process should be carried out to identify optimal e and C so that the SVR can accurately predict unknown data (Hsu et al. 2010). There are several parameter selection methods [e.g., hold-out method, k-fold cross validation (K-CV), and leave-one-out cross validation (LOO-CV)]; however, K-CV was applied in this research because it can prevent the overfitting problem (Hsu et al. 2010).

In K-CV, training data are divided into k equal size subsets. For each $k = 1, 2, \ldots, K$, a single subset is chosen as the validation data for the testing model, and the remaining subsets, $k - 1$, are used as training data. The cross-validation process is then repeated k times, with each of the k subsets used exactly once as the validation data. The best e and C is chosen from the subset that has the least MSE. In this study, a three-fold cross validation was applied to select optimal parameters for the SVR model. Table 9 shows the optimal parameter selection results.

Results Summary

Once the optimal parameters for each model were selected in the training process, the testing data sets were used to validate the prediction performance of each model. For BPNN, RBFNN, and GRNN, the test was repeated 10 times and the average performances of the trials were used for comparison. Tables 10 and 11 summarize the results of evaluation parameters of all prediction models for Modules 1 and 2, respectively. The results illustrate which model performed the best on hourly space heating electricity use prediction for the studied house.

The MAPE measures the percentage of difference between the actual electricity use data and the predicted data. For Module 1, as shown in table 10, the MAPE for BPNN, RBFNN, and GRNN were approximately 10%, for testing, and 15%, for training, which is acceptable in hourly prediction. The predicted values for SVR were closer to the actual values than the other three models, with a MAPE value of 1.20%, for testing, and 1.74%, for training. For Module 2, because some of the actual electricity use data equaled 0, the MAPE of Module 2 was infinite. To circumvent this problem, another parameter named SMAPE, which compares the residuals with the sum of both actual data and predicted data, was introduced in this study. As shown in Table 11, the SMAPE for BPNN, RBFNN, and GRNN were close to one another, which indicates that the performances of these three models were similar. The SMAPE of SVR was much smaller than that of the other three models, which indicates that SVR has the best fitting capability to solve the prediction problem.

In summary, according to the results of evaluation parameters, SVR had the smallest CV, MAE, MAPE, RMSE, and SMAPE values, and the largest R value among all prediction models. This indicates that SVR had a better prediction performance over BPNN, RBFNN, and GRNN. The superiority of SVR attributes to its principle, which aims to minimize the upper bound of the generalization error rather than the training error.

Furthermore, comparing the Module 1 prediction results with the Module 2 prediction results shows that all prediction models performed better in Module 1 than in Module 2. The difference was attributable to the effect of dynamic human behaviors in Module 2. A further discussion of the effect of dynamic human behaviors on the prediction performance is conducted in the next section.

Computing speed is another essential factor that should be evaluated. A desirable prediction model should have a high computing efficiency. Table 12 depicts computing time for each model. It is to be recalled that all models were executed on the same PC for consistency purposes. As shown in Table 12, computing time for all models in Module 1 was shorter than that for Module 2. This is because of the increment of data points and the change of parameters in Module 2. In other words, the computing time for different models depends on the number of training samples and the parameter settings. GRNN and RBFNN are faster than BPNN because they do not need to train the data iteratively. SVR consumes more time than most of the other models because of the K-CV. Despite of the difference in computing time, all prediction models can predict hourly heating electricity use within seconds. Therefore, all these

Table 10. Results for All Models in Module 1

Model type	CV (%)	MAE	MAPE (%)	RMSE	SMAPE (%)	R
			Training			
BPNN	13.12	1,836.34	11.52	2,424.57	4.93	0.9183
GRNN	11.66	1,567.41	9.58	2,153.21	4.24	0.9377
RBFNN	12.53	1,759.10	11.05	2,316.30	4.75	0.9250
SVR	1.19	181.99	1.20	219.58	0.49	0.9994
			Testing			
BPNN	16.69	1,915.43	15.00	2,438.31	6.45	0.6844
GRNN	17.65	1,983.21	16.13	2,578.24	6.59	0.6309
RBFNN	17.71	1,947.70	15.11	2,587.00	6.59	0.6417
SVR	2.19	228.31	1.74	319.44	0.78	0.9958

Table 11. Results for All Models in Module 2

Model type	CV (%)	MAE	RMSE	SMAPE (%)	R
			Training		
BPNN	36.74	3,319.41	4,873.85	12.51	0.8404
GRNN	31.09	2,811.24	4,124.21	10.51	0.8918
RBFNN	34.98	3,186.50	4,640.40	12.00	0.8563
SVR	3.06	274.65	405.49	1.04	0.9990
			Testing		
BPNN	63.68	3,756.33	6,148.48	19.47	0.6252
GRNN	64.27	3,727.60	6,206.45	18.75	0.6199
RBFNN	65.66	3,934.10	6,340.60	20.23	0.5968
SVR	8.87	498.95	856.18	2.57	0.9949

Table 12. Computing Time (in Seconds) for All Models

Module type	BPNN	GRNN	RBFNN	SVR
Module 1	2.10	0.83	1.14	1.83
Module 2	2.51	0.93	1.92	5.58

Table 13. Prediction Results Comparison of SVR in Modules 1 and 2

Data sets	Module	CV	MAE	MAPE	RMSE	SMAPE	R
Training	1	1.19	181.99	1.20	219.58	0.49	0.9994
	2	3.06	274.65	Inf	405.49	1.04	0.9990
Testing	1	2.19	228.31	1.74	319.44	0.78	0.9958
	2	8.87	498.95	Inf	856.18	2.57	0.9949

models can be used to build a real-time building energy management system.

Discussions

Previous studies have proved that prediction can be improved by removing dynamic human behaviors from the model (Edwards et al. 2012). Whereas in this research, among others, the effect of dynamic human behaviors on the prediction performance was investigated by comparing the prediction results in different time periods. As discussed in the section "Results," two modules (Modules 1 and 2) were analyzed for effect attributable to dynamic human behaviors. Module 1 covered only the nighttime period when few human behaviors happen; Taking this a step further, Module 2 also included the daytime period when human behavior is active.

As the SVR has shown its superiority in hourly space heating electricity use prediction among all models, this study used SVR prediction results to investigate the effect of dynamic human behaviors on prediction performance. From the prediction results comparison between the two modules (Table 13), it is shown that all evaluation parameters in the training and testing data sets of Module 2 were worse than those of Module 1. This result indicates that the involvement of dynamic human behaviors has a negative effect on the weather information based household space heating electricity use prediction.

The effect of dynamic human behaviors on space heating electricity use may be explained as follows:

- The change of body heat radiation because of the presence of occupants;
- The change of facility heat radiation, owing of the use of household appliances (e.g., refrigerator, dryer, furnace, and lights);
- The change of outdoor-indoor heat exchange because of the opening and closing of doors and windows; and
- The change of space heat demand because of thermostat controls (e.g., change in operation of the furnace from auto to on mode and the increase or decrease of the set-point of the thermostatic valves).

Although the prediction results of SVR in the two modules were outstanding, the effect of dynamic human behaviors should not be ignored. Taking the CV as an example, in the SVR prediction results, dynamic human behaviors lead the CV to increase from 1.19 to 3.06 in the training data set, and from 2.19 to 8.87 in the testing data set. The increment of the CV was small, yet the amplitude of the increase was significant. This issue is more obvious in other prediction models in which the CV in the test data set increased from approximately 17.5 to 65.0, which is significant in both increment and amplification.

Conclusions

This study predicted hourly household space heating electricity use by using four outdoor weather conditions: outdoor temperature, humidity, wind speed, and solar radiation. Four AI models (including BPNN, RBFNN, GRNN, and SVR) were used to predict hourly electricity use. The results showed that the SVR model is promising with higher prediction accuracy and is the most suitable model for predicting hourly household space heating electricity use. The computing time analysis indicates the high computing efficiencies of all four models.

Additionally, the authors broadened their exploration to examine the effect of dynamic human behaviors on the performance of weather information-based space heating electricity use prediction by modeling for two different occupancy levels (daytime and nighttime). Comparative analysis revealed that dynamic human behaviors have a negative effect on the prediction performance. The study findings can be used for establishing building space heating electricity use baselines and calculating retrofit savings. Future work will focus on implementing machine learning models to predict other household energy uses, and introducing occupant behavior information to improve the prediction accuracy.

Appendix. Explanation of Evaluation Parameters Applied in This Study

1. Coefficient of variance (CV) measures the variability of the data. A high CV score reflects the inconsistency between the predicted and observed value. The CV is defined as follows:

$$\mathrm{CV} = \frac{\sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(x_t - y_t)^2}}{\bar{y}} \times 100\%$$

where n = sample size; x_t = predicted value; y_t = observed value; and $\bar{y}$ = mean of y_t.

2. Mean absolute error (MAE) is a quantity value which measures how close the predicted values are to the observed values. The MAE is given by

$$\mathrm{MAE} = \frac{1}{n} \times \sum_{t=1}^{n}(|x_t - y_t|)$$

3. Root mean square error (RMSE) stands for the sample standard deviation of the residuals between predicted and observed values. This measures is used to identify large errors. Compared with MAE, RMSE amplifies and severely punishes large errors. The mathematical formula for RMSE is

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \times \sum_{t=1}^{n}(x_t - y_t)^2}$$

4. Mean absolute percentage error (MAPE). The MAPE is a statistical measure to describe the accuracy of the prediction by comparing the residual with the observed values. It usually expresses accuracy in percentage and is effective for evaluating the performance of the prediction model by introducing the concept of relative values. The MAPE is defined by the formula

$$\mathrm{MAPE} = \frac{1}{n} \times \sum_{t=1}^{n}\left|\frac{x_t - y_t}{y_t}\right| \times 100\%$$

5. Symmetric mean absolute percentage error (SMAPE). In some cases, MAPE can be infinite when the denominator is small or zero. This is a particular problem when researchers are attempting to predict products with intermittent demand, for example. To solve this problem, a modified measure, called SMAPE, is introduced in this research. The formula for SMAPE is

$$\mathrm{SMAPE} = \frac{\sum_{t=1}^{n} |x_t - y_t|}{\sum_{t=1}^{n} (x_t + y_t)} \times 100\%$$

6. Linear correlation coefficient (R) measures the strength and the direction of a linear relationship between two variables. If two variables have a strong positive linear relationship, R is close to 1. An R value equal to 1 indicates a perfect positive fit. An R greater than 0.8 is generally described as strong, whereas a correlation less than 0.5 is generally described as weak. The mathematical formula for computing R is

$$R = \frac{n \sum_{t=1}^{n} x_t \times y_t - \sum_{t=1}^{n} y_t \times \sum_{t=1}^{n} x_t}{\sqrt{n \times \sum_{t=1}^{n} y_t^2 - (\sum_{t=1}^{n} y_t)^2} \times \sqrt{n \times \sum_{t=1}^{n} x_t^2 - (\sum_{t=1}^{n} x_t)^2}}$$

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