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Demand response control of residential HVAC loads based on dynamic electricity prices and economic analysis

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During peak hours, electrical loads of residential HVAC systems can cause imbalance between electricity supply and demand. Demand response control has the potential to facilitate supply–demand balance. The demand side load control can help reduce electricity consumption through demand response programs. Since HVAC loads are the major contributors to peak loads, reducing HVAC load at peak hours is an objective of many demand response technologies. This article analyzes performance of the dynamic thermostat controller of HVAC systems in homes that have dynamic price of electricity. Based on a price signal, the dynamic thermostat controller sets back the thermostat temperature to save electricity consumption and costs. The consumers choose participation in the demand response program based on the real-time price of electricity and set a threshold price that the thermostat uses to set the temperature during peak power price period. The performance of dynamic thermostat controller was analyzed for two cities, Austin TX and Chicago IL, and historical market price data were used to generate hourly based real-time price. In addition to different climate zones, two different types of residential buildings were modeled. Based on detailed energy simulation, the changes in HVAC system operation were analyzed when considering electric energy saving, peak power reduction, cost saving, as well as the potential thermal discomfort. The specific results show that dynamic pricing combined with dynamic thermostat controller results in 12% annual energy cost savings for HVAC operation with the energy saving of up to 6%, but without significantly changing the thermal comfort.

Introduction

Wholesale electricity markets experience rapid electricity price changes depending on supply and demand (FERC 2015). During the peak time, the price of electricity is high, and the efficiency of power grid decreases. Demand response (DR) has the potential to reduce energy costs as well as to increase the stability and efficiency of electric power grid by decreasing electric power consumption. For example in January of 2014, the Pennsylvania-New Jersey-Maryland (PJM) Interconnection had an emergency case where the demand was very high due to severe cold weather and DR was activated to maintain the stability of the power grid (FERC 2014). Furthermore, DR showed its value to save energy and costs in PJM, New York ISO (NYISO), Midwest ISO (MISO), and other independent system operators (ISOs) and regional transmission operators (RTOs; Cappers et al. 2010; Faruqui et al. 2010). For instance, the DR programs in PJM and NYISO presented the potential to reduce energy consumption by 4∼15% in residential buildings (Walawalkar et al. 2010). In addition, the costs to maintain system balancing for the generation, transmission, and distribution of electricity can be decreased by DR (Vlachos et al. 2013). Not limited to the United States, European countries have also adopted DR programs in their power grid (Torriti et al. 2010).

In respect of the demand side, DR for residential and commercial buildings has the great potential to save energy and costs (Wang et al. 2014b). Several utilities in the Electric Reliability Council of Texas (ERCOT) provide DR programs to their customers (ERCOT 2014). However, the market barriers such as: (1) misplaced incentives, (2) cost, and (3) insufficient information about DR slow down the penetration of DR programs (Breukers et al. 2011; Golove and Eto 1996). Furthermore, the current DR devices designed to respond to a request to decrease electric peak power and installed on the consumer side of the electric grid are still not as convenient for residential consumers and further improvement is needed (Kim and Shcherbakova 2011). To increase user participation in DR programs, simple, low-cost, and user-friendly controllers need to be developed. Current successful DR controllers for the electric hot water heater already show results related to electricity savings during peak period (Atikol 2013; Kepplinger et al. 2015). However, managing just the electric hot water heater is not sufficient for places with a hot climate, like Arizona and Texas, where peak demand is driven by res-

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idential AC. Thermal storage in (Mathieu et al. 2015; Xue et al. 2014) can reduce AC loads during peak time but the size of equipment is not small enough to install in a home. In addition, the cost for thermal storage is expensive. Precooling/preheating method was considered in (Oldewurtel et al. 2010) for DR. While precooling and preheating could be used in addition, the current research focuses only on thermostat control strategy during the peak period. Another approach to deal with residential AC is to use an electric energy storage system (ESS; Li et al. 2014a; Hong et al. 2015). However, the cost to retrofit current residential HVAC systems with the ESS is high, because of additional equipment such as inverters, and batteries, management systems. A less expensive alternative to ESS is a temperature setback thermostat for the HVAC control that reacts to electric price signal, energy saving, and thermal comfort preference of occupant. These systems have great potential to reduce both energy use and costs (Gils 2014). Studies show that temperature setback thermostats that use electric price signals save energy and money while providing acceptable thermal comfort (Yoon et al. 2014a, 2014b). As the HVAC use for cooling and heating is expected to further increase (Gouveia et al. 2012), a setback controller for on HVAC system for DR programs provides significant potential to decrease electricity loads while providing electric grid stability and cost saving for consumers.

This article analyzes the dynamic thermostat controller (DTC) for HVAC systems that setback the temperature setpoint. DTC utilizes a price for electricity that is assumed to be based on wholesale market prices. In addition to previous studies in this field (Jewell 2014; Li and Zhang 2014b; Li et al. 2014c; Wang and Paranjape 2014a; Zhang et al. 2012), this article provides detailed residential models with different internal loads setting. When compared to the Equivalent Thermal Parameter (ETP) used in previous studies (Jewell 2014; Zhang et al. 2012), where the model house is based on a simple electrical circuit, the model used in this article adds a component that considers preferences of building occupants related to setback temperature. In addition, detailed models of systems used in this paper study include the impacts of building characteristics such as of shades, environmental conditions such as solar radiation, and specifics of the HVAC systems. Another previous study on DTC considered indoor activities and operation schedules of buildings (Wang and Paranjape 2014a); however, the information of building envelopes and equipment is not considered when estimating the power consumption in buildings. A study that used detailed modeling of building systems (Li and Zhang 2014b, Li et al. 2014c) used eQuest (Hirsch et al. 2010) to design homes. Even though this approach provides advancement in DTC analyses there is still much space for improvement. For example, the use of more detailed energy simulation software such as EnergyPlus provides more functions such as building equipment setting, external interface to link with other programs, and variable simulation step when compared to eQUEST (Zhu et al. 2013). The use of EnergyPlus for DR performance by DTC has been demonstrated in (DOE 2012), where the algorithm of DTC is generated by additional control algorithm implemented in MATLAB/SIMULINK control module, and the same approach is used in this article.

Beside detailed modeling techniques the presented study uses a dynamic electricity price. The electricity price is an important factor for DR programs, as DTC takes the price signal for DR and changes the set-point temperature based on the threshold price. Control methods in previous studies (Arteconi et al. 2014; Jewell 2014) manage HVAC system but the price data is not used in the control algorithm. In addition, the values of electricity price are different depending on wholesale market of electricity. For example, ERCOT has an energy-only market but the PJM Interconnection and New England Independent System Operator (NEISO) have a capacity market. Therefore, the maximum price of electricity and change rate of price per day are different. A previous research in Yoon et al. (2014a, 2014b) used the historical price data from ERCOT wholesale market. As further advancement of this work, this article considers the characteristics and changes of electricity price in different markets to check the performance of the proposed DTC.

The energy consumption by HVAC system is significantly influenced by locations and the size of internal loads. Energy efficiency codes varies with climate zones (PNNL 2009). So, the building behaviors and electric energy consumption are different even if the buildings have the same architectural features such as floor plan, shape, window area, etc. A previous study (Yoon et al. 2014a, 2014b) used residential model for single location with hot weather condition and dominant cooling load. There are studies that considered internal loads in (McLoughlin et al. 2013) and considered indoor activities (Shosh et al. 2012). However, neither of these two studies considers locations and characteristics of the building envelope. Furthermore, unlike in other studies (Li et al. 2014c; Fernandes et al. 2014; Safdarian et al. 2014), the DTC used in previous research considers thermal comfort during peak load curtailment to maintain customer comfort while the set-point temperature changes due to the price signal. This prevents large temperature swings and minimizes the thermal discomfort, encouraging customers' continued participation in DR programs.

In summary, this article assesses the potential benefits from DTC as realistically as possible taking into account building characteristics, climate, occupants, and different price dynamics. It uses two locations: Austin, TX for hot weather, and Chicago, IL for cold weather, considers different house sizes, and models the internal loads for each case. The overall goal is to assess the performance of DTC in widely different environments and operating conditions.

Section 2 provides details about the modeling of the dynamic electricity price and residences. The control algorithm of the proposed DTC and the simulation cases are also introduced in Section 2. Section 3 shows the results of electricity and cost savings and discusses results. That section also presents the thermal comfort at residential models. The conclusion and discussion are presented in the final section.

Methodology

Hypothetical dynamic electricity prices in Austin, TX and Chicago, IL based on wholesale electricity price are designed

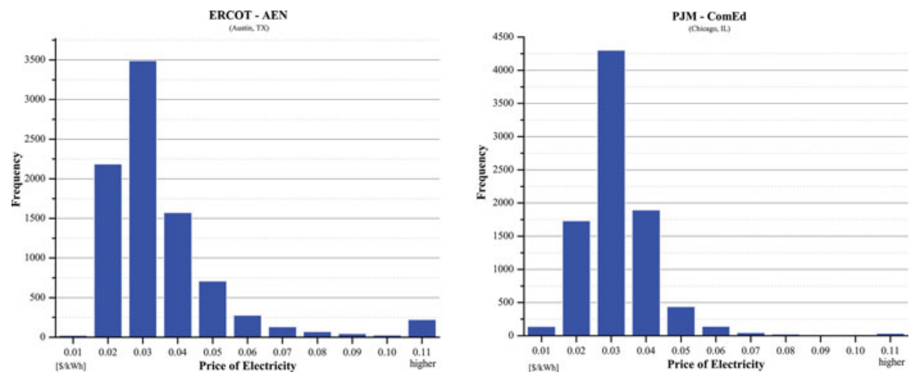

Fig. 1. The histogram of electricity price in Austin, TX and Chicago, IL.

in this section. Two different residential models with various internal loads are built using EnergyPlus. In addition, the control policy for the proposed DTC is introduced.

Real-time electricity price

A dynamic price of electricity that changes every hour, or more often, is a key factor for price-based DR. In this article, the authors assume that the target residential models are located in Austin, TX and Chicago, IL. Thus, two different wholesale markets are chosen; ERCOT and PJM. ERCOT manages the power grid in most of Texas, including the Austin area. PJM Interconnection services a wholesale market in the United States including the Chicago area. The ERCOT and PJM markets are similar in most other respects, with a main exception that the PJM market includes a "capacity market," while the ERCOT market does not (FERC 2015).

Some other studies, such as (Surles et al. 2012), used a time of use (TOU) rate for residential DR. TOU rate maintains a fixed high price during peak time that is higher than the off-peak price. However, actual changes of electricity price at the wholesale market are not reflected. Several DR programs in ISO/RTOs, including PJM, CAISO, NYISO, and MISO, are based on dynamic pricing that reflects wholesale prices (Yoon et al. 2014b). For example, the PJM market provides DR programs based on both day-ahead and real-time price (RTP) of electricity. On the other hand, NYISO and NEISO utilize a DR program based on day-ahead price (DAP) only. Furthermore, several other DR programs use day-ahead electricity price (Chakrabarti et al. 2012; Sezgen et al. 2007). Therefore, this article uses the hourly DAP rather than the RTP for the proposed HVAC controller.

The weather condition of year 2011 was the hottest year in Austin, TX. So, AC loads were not only very high, but the price of electricity was also high. In contrast, Chicago suffered the coldest weather during winter from 2013 to 2014. To maximize the effect of DR, the year 2011 of historical price data for Austin, TX is selected at Austin Energy Network (AEN; ERCOT 2011). For Chicago, IL, the year of 2013 at Commonwealth Edison (ComEd) is used for the price data (PJM Interconnection 2013). In practice, DR to reduce electricity demand at peak is typically requested when weather conditions are extremely hot or cold. Thus, the authors choose years with severe weather (2011 and 2013) to evaluate significant energy and cost savings by the proposed controller for DR. DR savings in years with moderate weather would be smaller.

Figure 1 presents the histograms of the annual historical price data at AEN (in 2011) and ComEd (in 2013) for a year. The price data at AEN has higher frequency of prices higher than \$0.11/kWh compared to the price at ComEd. The monthly minimum (MIN), average (AVG), and maximum (MAX) prices of electricity over 2011 (for Austin, TX) and 2013 (for Chicago, IL) are shown in Figure 2. The maximum price of electricity at AEN is much higher than at ComEd

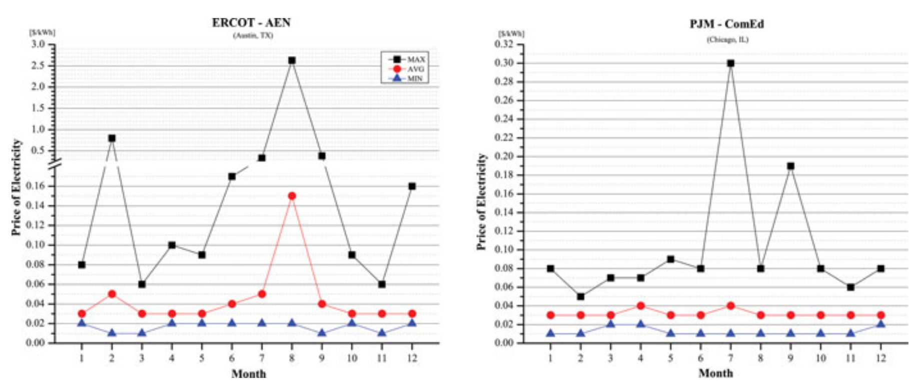

Fig. 2. The monthly maximum, average, and minimum of electricity price in two cities.

even though both locations experienced severe weather conditions. As a result, the average electricity price at ComEd maintains almost constant price under \$0.05/kWh but AEN price is higher than ComEd and also fluctuates depending on demand. There are several reasons why the electricity price at AEN is higher than at ComEd. An important one is that ERCOT does not have a capacity market and prices in its energy-only market are expected to provide remuneration for both operating and capital costs, and therefore typically have higher values during times of tight supply (Lee et al. 2012). Due to the different type of wholesale market, ComEd energy price is lower than the energy price at AEN.

Large-scale DR may impact the electricity price in wholesale market (Cole et al. 2014; Faria and Vale 2011; Ju and Chassin 2004; Koliou et al. 2014; Mathieu et al. 2011). Previous work by Pacific Northwest National Laboratory (PNNL) in (Ju and Chassin 2004) shows that loads due to HVAC which are managed using the electricity price signal can influence wholesale electricity markets. In PNNL's article, however, HVAC loads are synchronized and simply modeled with the same operation cycle. HVAC units in residential buildings have different cycles depending on types. Furthermore, electricity consumption of HVAC system varies by capacity, type, efficiency, and internal loads. Therefore, individual residential loads have heterogeneous characteristics. Thus, we assume that the theoretical price data would not be significantly changed after DR, although this assumption would not necessarily hold with high penetration of DR.

House models based on EnergyPlus

The residential models are created using EnergyPlus and OpenStudio. EnergyPlus provides various functions to calculate energy consumption and to analyze building behavior (DOE 2012). In other studies such as (Jewell 2014; Zhang et al. 2012), the simplified house model, ETP, models the electricity consumption by converting the thermal model to an electrical circuit. However, ETP cannot consider internal loads changes and sunlight/shade effects on the calculation of energy consumption. Similar to ETP, simple home models that only considered outdoor temperature to calculate cooling/heating load were used in (Cole et al. 2014). Reference (Wang et al. 2014a) used the Richardson model to model electricity loads at residential buildings. This model considers building schedules such as people occupancy and indoor activity but the characteristics of building envelope such as insulation, size of building, location, and types of equipment are not used to calculate energy consumption. Another work (Li et al. 2014c) used eQuest to generate the residential model. eQuest is a building simulation tool similar to EnergyPlus but there are limitations in the ability to customize building model. For example, the simulation report from eQuest is fixed to hourly report with summary. Different from eQuest, EnergyPlus can generate the results with a detailed report in various time steps. In addition, EnergyPlus is able to configure the HVAC system depending on house types but eQuest provides pre-set models only. Finally, MATLAB/SIMULINK can work with EnergyPlus via building control virtual test bed (BCVTB). This function is not provided by eQuest (Zhu et al. 2013). EnergyPlus not only simulates building models with various functions such window and shade models but also works with external programs (LBNL 2013), which is crucial for this research in order to model the adjustment of the thermostat based on prices.

Table 1 shows the characteristics of building envelopes for two residential models in different locations. The large house is twice as big as the small house. Both houses orient to the South. To set the insulations of wall and window efficiency, 2009 International Energy Conservation Code (IECC) is used for building models (PNNL 2009). Two different locations are chosen: Austin, TX and Chicago, IL. Austin is located in climate zone 2—hot and moist. Opposite to Austin, the weather condition in Chicago is cold and moist: climate zone 4 and 5. Due to cold weather, homes in Chicago have high R-values in walls and ceiling. Also, U-value of windows in Chicago is significantly lower than Austin to minimize thermal loss during winter season.

The internal loads are differently set for heavy and normal loads. A heavy internal load is generated with 140% of lighting loads and 150% of internal equipment such as electronics, and appliances compared to a normal load. This paper aims to demonstrate that the proposed HVAC controller is effective for the DR in any house size and with different internal loads. So, each house model, a large and small houses, has two different internal load settings to analyze the different levels of internal load impact on energy consumption at these homes.

A packaged terminal heat pump system is used for both large and small houses. The capacity of HVAC is the same for both levels of internal loads. For the large house, it is assumed that multi-zone heat pump system is used. The cooling and heating capacities are the same but the second floor has about half the capacity of the first floor due to half size of floor area. So, the total cooling and heating capacities of the large house are 17 kW (58,000 BTU/hr) each. The small house has 156 m^2 of floor area which is half of the floor area of the large house. So, the capacity of heat pump is half of the large house heat pump capacity: 8.5 kW (29,000 BTU/hr). Table 2 presents the capacity of heat pump in kW (BTU/hr) and coefficient of performance (COP) for cooling and heating.

The control algorithm of a dynamic thermostat

The proposed DTC takes the price signal of electricity to participate in the utility's DR program. Then, the set-point temperature in a thermostat is automatically increased or decreased depending on cooling and heating mode while considering the thermal comfort. In addition, DTC is designed to function as a universal controller that works with various type of HVAC systems and in many places. In contrast, the HVAC controller described in (Zois et al. 2014) directly controls a compressor motor in HVAC system using variable frequency drive (VFD) technology. This technology is complicated so that the cost to deploy or retrofit a controller into homes will be increased. Furthermore, VFD technology does not guarantee the compatibility with other HVAC systems by different

Table 1. Building geometry features of large and small houses.

Components		Small house	Large house
Floor area		156 m^2 (1679 ft^2)	305 m^2 (3282 ft^2)
Floors		Single story	Two stories
Floor plan		3 bedrooms, 1 garage	5 bedrooms, 1 garage
Orientation		South	South
Windows to wall ratio		8%	18.1 %
Internal loads	Occupants	4 residents	4 residents
	Lighting	Normal: 2.6 W/m^2 Heavy: 3.5 W/m^2	Normal: 2.6 W/m^2 Heavy: 3.5 W/m^2
	Equipment	Electronics, PC, electric water heater, kitchen appliances, washer, dryer	
Thermal zones		3 zones	4 zones
Infiltration		0.25 ACH	0.25 ACH
Austin, TX			
Windows		$U = 3.69$ $W/m^2{\cdot}K$, SHGC = 0.3	$U = 3.69$ $W/m^2{\cdot}K$, SHGC = 0.3
Wall		$R = 2.29$ $m^2/K{\cdot}W$	$R = 2.29$ $m^2/K{\cdot}W$
Ceiling		$R = 5.28$ $m^2/K{\cdot}W$	$R = 5.28$ $m^2/K{\cdot}W$
Chicago, IL			
Windows		$U = 1.99$ $W/m^2{\cdot}K$, SHGC = 0.3	$U = 1.99$ $W/m^2{\cdot}K$, SHGC = 0.3
Wall		$R = 3.52$ $m^2/K{\cdot}W$	$R = 3.52$ $m^2/K{\cdot}W$
Ceiling		$R = 6.69$ $m^2/K{\cdot}W$	$R = 6.69$ $m^2/K{\cdot}W$

manufacturers. Thus, the proposed controller in (Zois et al. 2014) may not be feasible to install in many buildings. In addition, HVAC system management in (Mathieu et al. 2011) used information about the building occupation schedule to reduce the electricity consumption of the HVAC system when DR was requested. The work described in (Surles et al. 2012) made a simple offset of 3°F or 6°F from the set-point temperature during the peak time. The adjusted set-point temperature was maintained during the peak time even if the price of electricity was not significantly higher than off-peak. Therefore, DR will be activated on a daily basis, likely significantly impacting the comfort level, even though most of the peak times did not correspond to extreme system conditions. Another controller, described in (Vrettos et al. 2013), managed HVAC loads by setting a limit on power consumption to 2 kW. When the HVAC system consumed over 2 kW of power, a controller turned it off for energy savings. Different from these various other controllers, the DTC maintains the current thermostat system by adding functions with sophisticated a DR algorithm that is intended to respond to actual electricity system conditions as reflected in the price.

Table 2. The capacity of heat pumps COPs.

	Capacity, kW (BTU/hr)			
	large house		Small house	
Type	1st floor	2nd floor	main floor	COP
Cooling	11.7 (40,000)	5.3 (18,000)	8.5 (29,000)	$COP_c = 3.0$
Heating	11.7 (40,000)	5.3 (18,000)	8.5 (29,000)	$COP_h = 4.0$

Estimation of HVAC electricity consumption for use in DR control law

For the results presented in Section III, detailed EnergyPlus calculations were performed based on modeling the conditions individually each day. However, the DR algorithm to control the HVAC as implemented in the DTC requires a model that estimates power consumption. In this section, this estimation is described. It is to be emphasized that the estimation in this section is a preliminary calculation used to set parameters in the DR control law, whereas the results in Section 3 represent the results of actually simulating the houses using the control law and modeled ambient conditions.

The equations to estimate steady-state HVAC power consumption when the current indoor temperature reaches the target set-point temperature are obtained using a statistical method. The Richardson model in (Wang et al. 2014a) also estimates electricity loads in residential houses. Another research in (Mathieu et al. 2011) illustrated cooling/heating load forecasting using outdoor temperature and occupation schedule. However, these models do not consider house size, equipment type, and load changes. Different capacity or COP for HVAC consume different amount of electricity In addition, the different set-point temperature settings also cause changes of electricity power consumption.

The current controller uses a simplified representation of the electric power consumption of the HVAC system for the HVAC control equation based on linear regression. Two house models in various conditions such as different set-point temperature, internal load changes, and weather conditions were simulated. The first order simple linear model uses two parameters; Zone Mean Air Temperature, and HVAC electricity. EnergyPlus was used to evaluate the "Zone Mean Air Temperature" considering dynamic thermal phenomena of a building. When HVAC was applied to thermal zones, Zone Mean Air Temperature was maintained equal to the set-point temperature for a time step. The average electricity consumptions of HVAC as a function of the set-point temperature changes were calculated by evaluating for each fixed set-point temperature settings. The set-point difference (ΔT_{sp}) ranges were from –6°C to 6°C. Negative ΔT_{sp}correspond to cooling mode. On other hand, positive ΔT_{sp}correspond to heating mode. Figure 3 il-

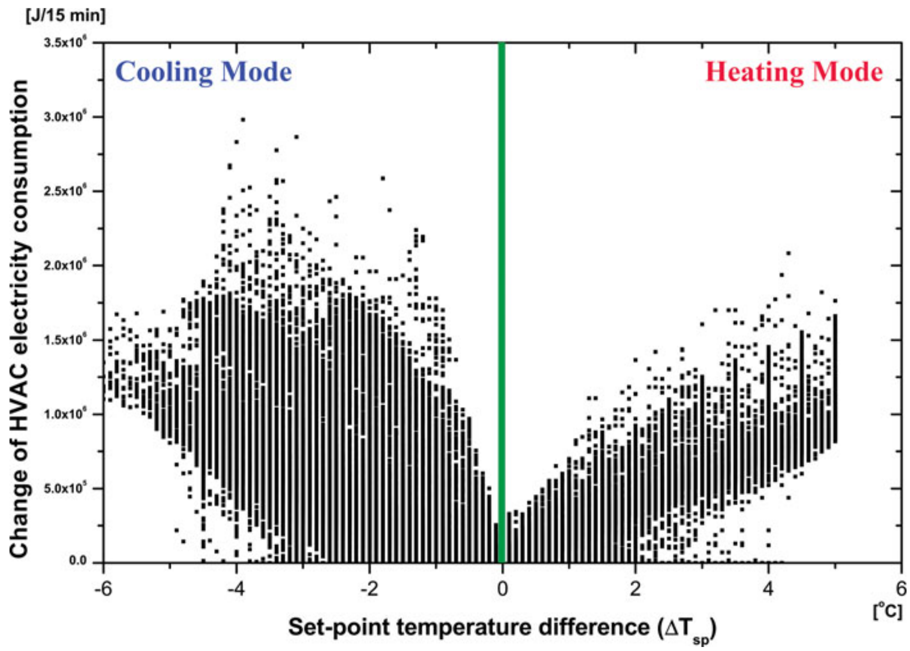

Fig. 3. The scatter of electricity consumption over set-point temperature differences.

lustrated the scatter of electricity consumption of HVAC over set-point temperature (zone mean air temperature) difference.

The electricity consumption for AC use in Figure 3 seemed to be non-linear as a function of set-point temperature changes. However, a high order regression function (2nd, and 3rd orders) gave small differences for the performance of the current proposed controller when results on energy and cost savings were compared with a linear regression fit curve. Consequently, the power consumption coefficients for HVAC (k) in two locations are derived. The value of the constant term from the linear regression results is so small that it can be ignored. So, only the gradient of the linear equation is used to estimate HVAC power consumptions. This power consumption in kW is the average power consumption for 1 hour because the simulation step in this article is 1 hour. Table 3 shows that cooling (k_c) and heating (k_h) coefficient of power consumption are calculated for both large and small houses in two locations.

The temperature difference (ΔT) is defined in Equation 1. The estimated power consumptions of HVAC for each mode are modeled as follows in Equations 2 and 3.

$$\Delta T = \left| T_{in} - T_{sp} \right| \tag{1}$$

Table 3. Temperature-electricity constant for cooling (k_c) and heating (k_h).

	Austin, TX		Chicago, IL	
[kW/C°]	large house	Small house	large house	Small house
	0.09	0.044	0.092	0.057
	0.049	0.036	0.068	0.041

$$E_c = k_c \times \Delta T \tag{2}$$

$$E_h = k_h \times \Delta T \tag{3}$$

A previous work (Yoon et al. 2014a, 2014b) did not consider the characteristics of HVAC equipment in DR algorithm. Other work (Jewell 2014) shows that the size of heat pump capacity significantly impacts on energy consumption in residential buildings. So, the characteristics of HVAC equipment are considered in the HVAC control algorithm. Equations 4 and 5 convert the thermal capacity of HVAC equipment to electrical energy by considering the efficiency of the HVAC.

$$kW_{rating}^{cool} = \frac{BTU/hr}{3412.142 \times COP_c} \tag{4}$$

$$kW_{rating}^{heat} = \frac{BTU/hr}{3412.142 \times COP_h} \tag{5}$$

In a previous work, the correlation between historical electricity price data and local weather data is required to convert an HVAC electricity estimate to temperature unit (Yoon et al. 2014a, 2014b). To find this correlation coefficient, local historical price data must be utilized. For example, when local historical price data are updated every year, the coefficient should be calculated again. The change of electricity market rules also causes changes to the coefficient. This is a big limitation to deploy the controller in other locations. The current work aims at a universal controller that can work with various types of heat pump in different locations. So, the estimated electricity consumptions of heat pump for cooling and heating with ΔT are normalized by the rating power of HVAC

(kW_{rating}) as follows below.

$$HVAC_c = \frac{E_c}{kW_{rating}^{cool}} \tag{6}$$

$$HVAC_h = \frac{E_h}{kW_{rating}^{heat}} \tag{7}$$

Normalized electricity price signal

The DTC takes the signal of dynamic electricity price to change the set-point temperature for DR program. Thermostat control in (Fuller et al. 2011) adapted the price signal to control the set-point temperature. However, the controller only responded to the signal of price for DR without consideration of customer's preferences. Depending on economic situations, incomes in each household are different. Therefore, the electricity bills that household can afford to pay are dissimilar. The proposed DTC considers the economic ability in a household and adapts the threshold price (P_{th}) when customers participate in the DR program. Depending on overall loads, the electricity price changes. For instance, 2011 was the hottest year in Austin, TX. AC loads were significant loads in the power grid. As a result, DAP of electricity in ERCOT wholesale market occasionally approached the maximum price, \$3,000/MWh. The fluctuation of electricity price was also very high within a particular day between on-peak and off-peak time. The previous control algorithm in (Yoon et al. 2014a, 2014b) does not reflect the price fluctuation that causes sudden change of the set-point temperature. To consider it, the standard deviation of electricity price for a day (σ_{day}) is calculated based on the DAP which is announced 1 day before. The standard deviation σ_{day} normalizes the price difference ($P_c - P_{th}$) between the current price of electricity (P_c) and threshold price (P_{th}). The normalized price (P_N) is presented in Equations 8 and 9. DTC changes the set-point temperature when P_c is higher than P_{th}. Otherwise, the set-point temperature maintains the preset temperature (T_{sp}) that customers set. From Figure 1, the threshold price (P_{th}) is set to \$0.04/kWh because the dynamic prices of electricity in both Austin and Chicago maintain under \$0.03/kWh for most hours. Thus, DTC starts to operate when P_c is higher than \$0.04/kWh.

$$P_N = \begin{cases} \dfrac{P_c - P_{th}}{\sigma_{day}} & \text{for } P_c > P_{th} \qquad (8) \\ 0 & \text{for } P_c \leq P_{th} \qquad (9) \end{cases}$$

The change rate of the set-point temperature

The proposed DTC changes the set-point temperature in a thermostat depending on the price difference while considering thermal comfort. The thermostat control in (Li et al. 2014c) sharply changes the set-point temperature when the price is low or high. In addition, DR controller in (Surles et al. 2012) adjusted the set-point temperature with fixed offsets during peak time. These step changes cause thermal discomfort due to sudden temperature change. In contrast, when DTC begins to adjust the set-point, it increases by a 1°C (2°F) step from the preset set-point temperature (T_{sp}) during cooling mode. Opposite to AC mode, DTC decrease heating set-point temperature by 1°C (2°F). To maintain indoor thermal comfort, the maximum temperature change by DTC is limited to ±3°C. Equations 10 and 11 express the change rate of the set-point temperature (ΔT_{sp}^{mode}) for cooling and heating modes.

$$\Delta T_{sp}^{cool} = HVAC_c \times P_N \times \Delta T \tag{10}$$

$$\Delta T_{sp}^{heat} = HVAC_h \times P_N \times \Delta T \tag{11}$$

Finally, new adjusted set-point temperature (T_{sp}^{new}) is determined in Equations 12 and 13. When P_{th} is higher than P_c, ΔT_{sp} goes to zero. So, DTC maintains the preset environment for thermal comfort. Otherwise, DTC controls the set-point temperature depending on the difference price between P_c and P_{th}. In this article, T_{sp} for cooling is 25°C (77°F) and heating T_{sp} is 21°C (70°F).

$$T_{sp}^{new} = \begin{cases} T_{sp} + \Delta T_{sp}^{cool} & \text{for cooling mode} \qquad (12) \\ T_{sp} - \Delta T_{sp}^{heat} & \text{for heating mode} \qquad (13) \end{cases}$$

Simulation cases

DTC is designed as a universal thermostat controller to deploy in any size of house in various locations. However, in previous works (Yoon et al. 2014a, 2014b), are limited to one location. To demonstrate the performance of DR enabled thermostats, two different internal loads conditions in two different locations are chosen for the analysis of energy and cost savings in this article. Both large and small houses each have two different loads settings; heavy and normal loads. They are assumed to be located in Austin, TX and Chicago, IL. The energy consumption and cost savings with DTC are compared to the fixed set-point temperature without DTC. A total of 16 cases are simulated to analyze the performance of DTC. For fixed set-point temperatures cases, thermostat temperatures for cooling and heating are fixed. The temperature setting for both cooling and heating are 25°C (77°F) and 21°C (70°F)—the preset set-point temperature. DTC sets new set-point temperature based on these set-point temperatures. The cooling of days in Austin, TX are from March to October. All other months are heating season. In Chicago, IL, the heating of days are January to April, November, and December. The months from May to October are the cooling period.

Results

This section demonstrates that the proposed DTC reduces the electricity usage to operate HVAC system in various homes even though weather conditions and prices of electricity are different. The energy savings decrease the electricity bill for HVAC operations. In addition, the indoor thermal discom-

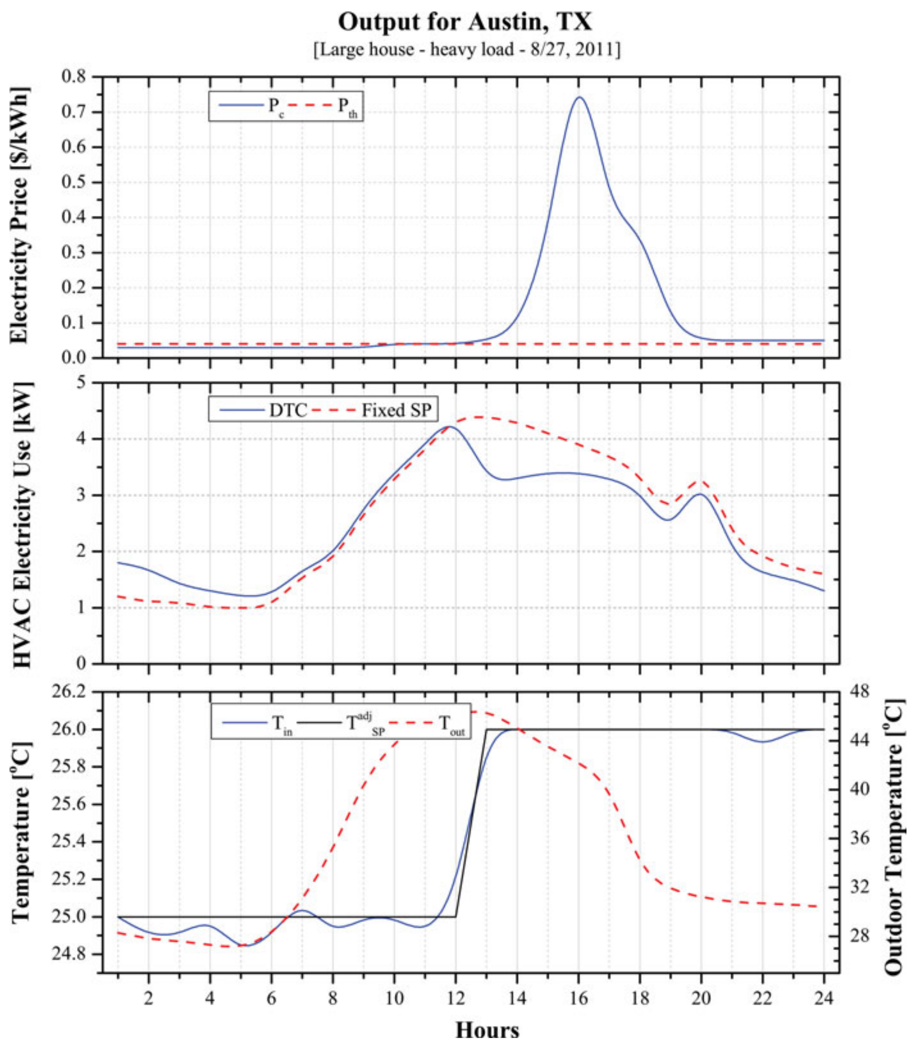

Fig. 4. Outputs for Austin, TX with DTC at extreme hot weather.

fort is minimized even though the DTC is changing the set-point temperature in the thermostat to participate in DR programs.

Savings at extreme day

Severe weather conditions such as extremely hot or cold cause high demand of electricity for climate control. The prices of electricity at wholesale markets are also increased to meet high demand of electricity. The current controller is designed to reduce energy use of HVAC system at these times by adjusting the set-point temperature while considering thermal comfort. Austin, TX suffered extreme hot weather condition on August 27, 2011. The outdoor temperature reached 46.6°C (116°F) around noon. As a result, AC use was significantly high to maintain comfort of the indoor environment. Figure 4 presents the performance of the DTC in the extreme hot weather condition. The price of electricity (P_c) was higher than the threshold price (P_{th}) after noon. DTC adjusted the set-point temperature to 26°C (79°F) to save energy and cost. Savings of energy was 15% while DTC adjusts the set-point temperature. There is 13% of cost savings by DTC.

Opposite to Austin, TX, extreme cold weather hit Chicago, IL on December 24, 2013. The outdoor temperature was decreased to –19°C (–2°F) in the early morning. Heating load was very high to maintain comfort level. DTC changes the set-point temperature to 20°C (68°F) in the morning and evening. Energy use for heating was saved by 10% when the set-point temperature was adjusted. In addition, DTC gives 10% of cost savings when P_c was higher than P_{th}. Figure 5 illustrates how DTC works to save electricity and cost during extreme cold.

Savings of electricity consumption

The summer hot weather condition in Austin, TX drives AC loads in residential buildings. The large house with heavy internal loads, and no DTC consumes annually 6,570 kWh of electricity for cooling and 2,796 kWh for heating (Figure 6). Dominant summer season and heavy internal heat gains results in cooling loads that are about 2.3 times larger than heating loads. When DTC is installed in the same house, the

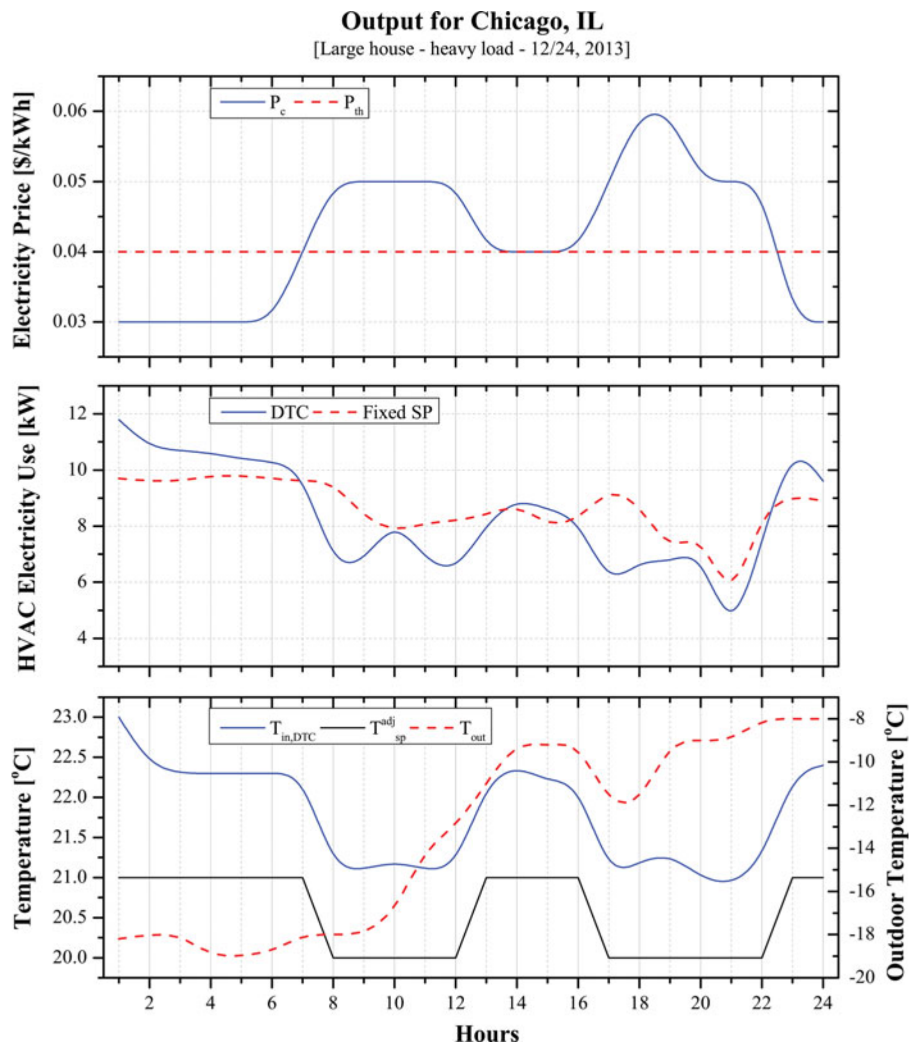

Fig. 5. Outputs for Chicago, IL with DTC at extreme cold weather.

electricity consumptions for cooling and heating are decreased to 6,147 and 2,657 kWh each. This shows that DTC saves 6% of electricity used by the home HVAC system.

When considering the impact of internal loads on energy consumed for cooling and heating, they create additional loads during summer season and decrease heating load in winter period. In the same large house with the normal (typical) internal loads the air conditioner consumes 6162 kWh for cooling and 3131 kWh for heating when DTC is not used and the thermostat has the fixed set-point temperature. However, both electric power consumptions for cooling and heating modes drop 6% (to 5738 kWh and 2999 kWh, respectively) when DTC is enabled.

The small house has significantly smaller floor area than the large house (Table 1) that reduces heat conduction through walls and a significantly smaller percentage of glazing area (Table 1) that even further reduces heat transfer through windows. This combined effects of the house and window sizes causes the small house to have less than 50% of the cooling demand compared to the large house (Figure 3). The comparison of heating energy consumption shows even larger discrepancy. The reason for this is the fact that internal heat gains in the small house cover a significant portion of heat loses while in the large house this is not the case. However, even with this small house the proposed DTC also brings significant electricity savings in Austin TX. For a house with heavy internal loads, DTC reduces 5.2% of electricity use compared to the case with the fixed set-point temperature. The HVAC system with DTC uses 2775 kWh for cooling and 266 kWh for heating. On the other hand, 2940 and 278 kWh are consumed in winter and summer, respectively, when the thermostat is not retrofitted with DTC. Similarly, in the same small house in Austin DTC contributes to a 6.2% reduction in the electricity consumption.

In Chicago, IL, the heating loads are the major contributor to peak electricity consumption due to severe cold weather during winter. But high internal loads that increase the indoor temperature offset the electricity consumption when customers use the heater. Figure 6 shows the comparison of annual electricity consumption by houses in Chicago, IL. A large house with heavy load consumes 15,255 kWh for heating but the cooling load, 4609 kWh, is about one-third of the heating

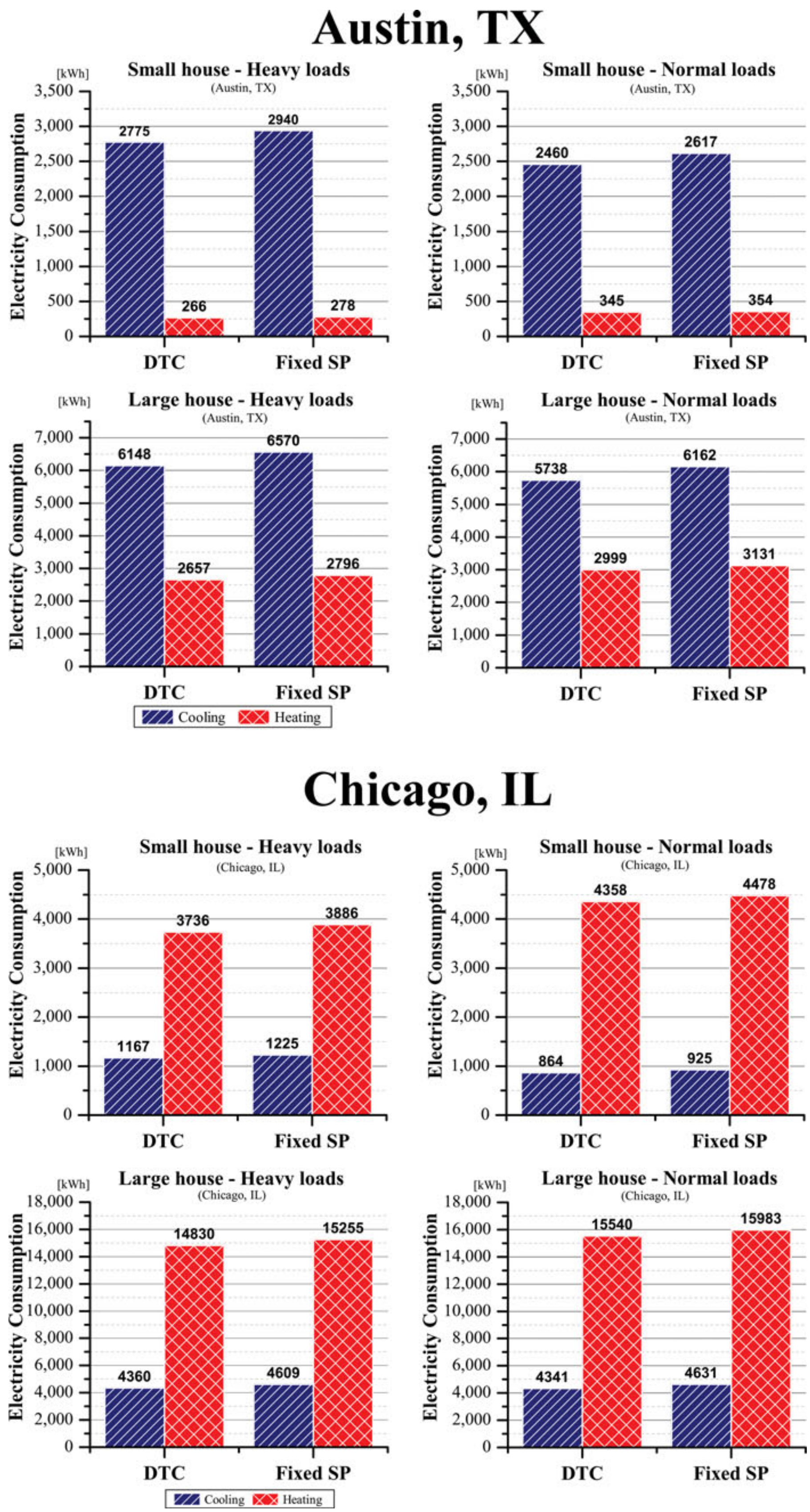

Fig. 6. The comparison of annual electricity consumption with the proposed controller in two cities.

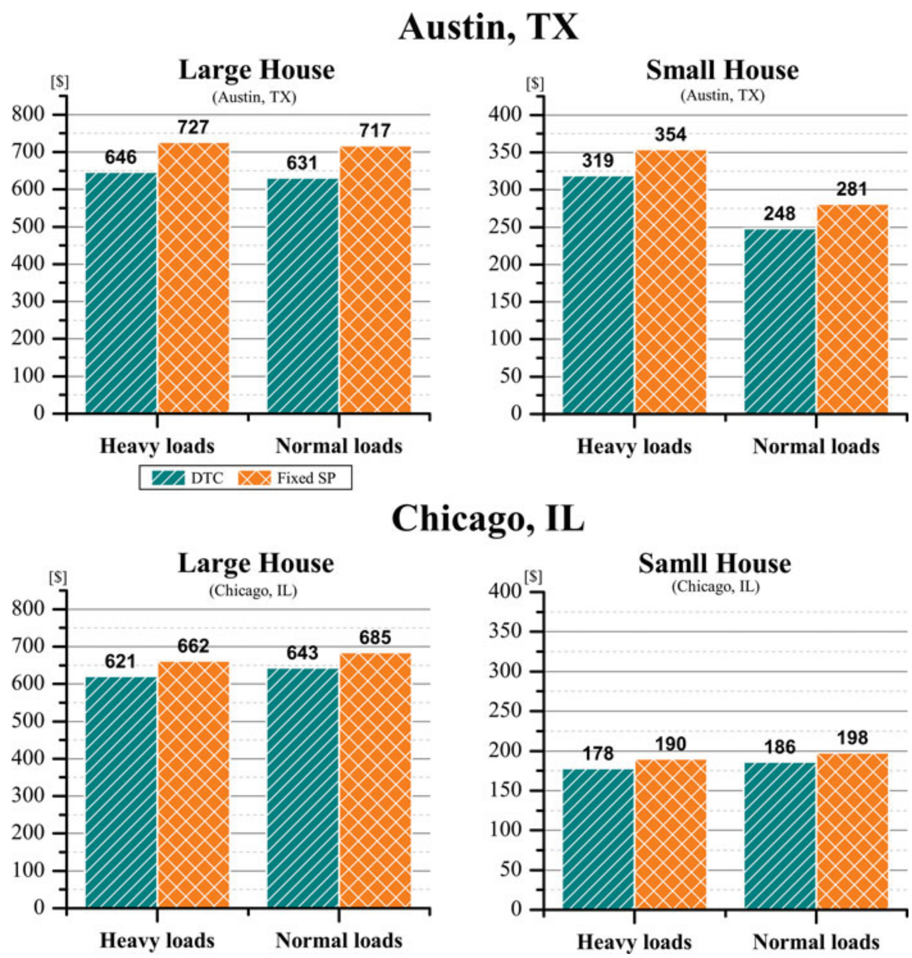

Fig. 7. Comparison of energy cost savings in two locations when DTC applied.

load when the conventional thermostat with fixed temperature setting is installed. Using the DTC, the electricity usage for heating is dropped to 14,830 kWh and the power consumption of AC is decreased to 4360 kWh. This results in 3.4% of total energy savings for HVAC operation. Similarly, the DTC saves 3.6% of electricity for the house with normal internal load.

The impact of internal loads on energy consumed for heating is greater in cold climates such as Chicago, IL. The small house has half the size and windows to wall ratio as compared to the large house. So, the heating energy consumption is considerably lower at 4478 kWh with normal, fixed set-point temperature setting. The proposed DTC reduces the heating energy consumption by 2.7%. The small house with heavy internal loads spends less electricity for heating due to internal heat gains. When DTC is installed, the heat pump consumes 3736 kWh and 3.9% less electricity than when the conventional thermostat is deployed. Cooling loads of a small house in Chicago, IL is significantly lower due to long winter season.

The comparison of heating energy consumption for large and small house in Chicago, IL shows a very large discrepancy caused by the impact of internal heat gains and the characteristics of building envelope. In a small house, they cover significant portion of heat unlike in the large house. Moreover, a large house has a large floor plan with more windows.

Table 4. Summary of electricity and cost savings by DTC in two locations

Austin, TX								
	Heavy internal loads				Normal internal loads			
	Electricity		*Cost*		*Electricity*		*Cost*	
House type	[kWh]	[%]	[$]	[%]	[kWh]	[%]	[$]	[%]
Large house	561	6.0	81	11.1	556	6.0	86	12
Small house	177	5.5	35	9.9	166	5.6	33	11.7
Chicago, IL								
	Heavy internal loads				Normal internal loads			
	Electricity		*Cost*		*Electricity*		*Cost*	
House type	[kWh]	[%]	[$]	[%]	[kWh]	[%]	[$]	[%]
Large house	674	3.4	41	6.2	733	3.6	42	6.1
Small house	208	4.1	12	7.3	181	3.4	12	6.9

When considering the impact of DTC in both large and small house in a cold climate (Chicago, IL), the results show significant HVAC energy saving of 4.8 and 4.1% saving for the case with large and normal internal heat loads (Figure 6). Comparison of energy saving with DTC in homes in Austin and Chicago shows larger percentage for Austin. This is due to different types of wholesale market (Figure 1). The absence of a capacity market in the ERCOT means that the RTP of electricity in Austin, TX rises to higher levels than in Chicago, IL. As explained in Section 2.1, Austin has a higher frequency when the electricity price is higher than \$0.04/kWh compared with Chicago. As a result, DTC which is installed at homes in Austin, TX more often changes the set-point temperature than in Chicago so that the energy saving in Austin is higher than in Chicago.

Energy cost savings

The energy costs to run HVAC system changes depending on the price of electricity. The modeled electricity price in Austin is higher than in Chicago. So, households in Austin would be charged higher per kWh than in Chicago (ignoring the effect of any other charges in the respective retail bills). The energy cost saving with DTC is presented in Figure 7. A large house with heavy internal loads pays \$727 to use cooling and heating annually. However, DTC gives 11.1% of cost savings to customers. The annual energy cost is \$631 with DTC and heavy load. When heat loads are normal, customers pay \$717 with the fixed set-point temperature setting, and 12% of energy cost is saved by DTC. Total annual bill to run HVAC system with DTC is \$630. Residents who live in a small house pay less money for cooling and heating due to the significantly smaller house size. Customers spend \$353 with heavy internal heat loads. For DTC case, the cost is decreased to \$318 and 9% of electricity bill is saved. With the normal load, the annual energy cost for HVAC system with DTC is \$247 but the use of conventional thermostat results in annual cost of \$281. The DTC saves 11.9% in HVAC operation cost by changing the set-point temperature.

For Chicago, a large house with heavy loads spends \$662 for HVAC system while the indoor temperature is set to maintain the set-point temperature. However, DTC reduces the en-

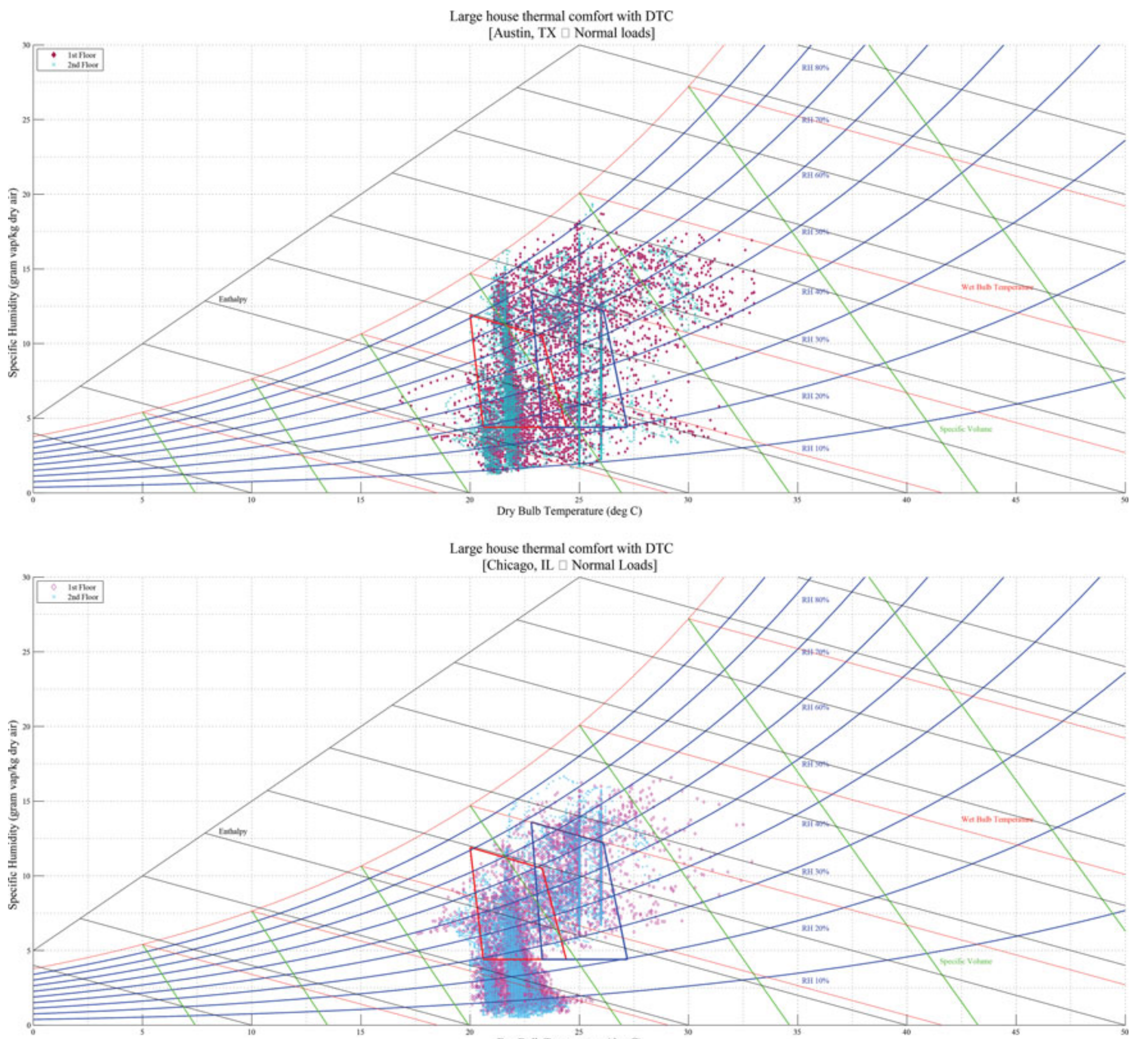

Fig. 8. Indoor thermal comfort of a large house with normal loads with DTC—Austin, TX and Chicago, IL.

ergy cost to \$621 (Figure 4), a reduction of 6.2%. For normal internal heat loads, the cost saving is the same 6.2%. Residents in a small house spend less money to use air conditioner and heater than a large house. The operation of HVAC system with no DTC requires \$167. The DTC reduce this to \$160, resulting in 7.4% saving. DTC produces a similar cost saving of 7% is for a house with normal load (Figure 7).

Table 4 summarizes energy [kWh] and cost [\$] and percentage savings when DTC is used in two significantly different homes located in two significantly different climates. The range of annual saving is from \$12 to \$81. Even though the annual saving of \$12 may not look large yet it can still cover the cost of the thermostat upgrade, which is estimated to be in the range of \$150 (Walker et al. 2008). These results show that even in the worst case scenario, the cost saving can justify DTC installation over certain period of time, and the saving can be much larger of up to 733 kWh per household.

Comparison of results in Table 4, while considering different types of wholesale market for electricity, show that the proposed DTC provides economic benefits to customers in Chicago even if the energy price in PJM is lower than in ERCOT market. If utilities provide the incentive program to their customers who want to take DR programs, the energy cost savings in Chicago will be close to Austin. For Austin, high cost savings with DTC are given to residents who live in a large or small house with both heavy and normal loads.

Thermal comfort

The thermal comfort is important for the indoor environment and acceptance of DTC, and Figure 8 shows the impact that DTC has on indoor thermal comfort at the two studied locations. If the indoor temperature maintains over or under the desired temperature for a long period of time, occupants will feel discomfort and may reject DTC. Unlike in other similar studies (Li et al. 2014c; Fernandes et al. 2014; Safdarian et al. 2014), the DTC is designed with a view to the indoor environment with the goal of minimizing thermal discomfort. The DTC considers thermal comfort as defined by ASHRAE Standard 55 (ASHRAE 2013). To prevent the high change of the set-point temperature by high price of electricity, which can cause severe thermal discomfort, the intensity and pace of temperature change is limited.

In this study, the preset set-point temperature for cooling is 25°C (T_{sp}^{cool}) and the heating temperature is set to 21°C (T_{sp}^{heat}). So, we assume that residents feel comfort when the indoor temperature maintains a preset temperature (25°C) or below during AC mode. Opposite to AC mode, the indoor temperature in heating mode remains the preset temperature (21°C) or higher. DTC increases or decreases the set-point temperature when DR signal is enabled by 1°C step. Figure 8 shows the indoor thermal comfort of a large house with normal loads when DTC is applied for Austin, TX and Chicago, IL. Equations 14 and 15 below are used to calculate how much the indoor temperature is over or below the preset temperature by DTC for cooling and heating modes from fixed set-point temperature cases. First, the thermal discomfort is calculated as the product of hours and temperature difference between the indoor temperature and the preset temperature. Next, the summation of thermal discomfort is divided by total hours of cooling or heating for normalization by period. Total hours of cooling and heating in Austin, TX are 5880 (245 days) and 2800 (120 days). For Chicago, IL, they are 4416 (184 days) for cooling and 4,344 (181 days) for heating. Normalized thermal discomforts ($T_{\text{discomfort}}$) are calculated for all cases. Then, cases with DTC is compared with the fixed set-point temperature cases.

$$T_{\text{discomfort}} = \begin{cases} \dfrac{\Sigma\left[(T_{in} - T_{sp}^{cool}) \times hr_{discomfort}\right]}{\Sigma\, hr_{cooling}} \quad \text{for cooling mode, where } T_{in} > T_{sp}^{cool} & (14) \\[2ex] \dfrac{\Sigma\left[(T_{sp}^{heat} - T_{in}) \times hr_{discomfort}\right]}{\Sigma\, hr_{heating}} \quad \text{for heating mode, where } T_{in} < T_{sp}^{heat} & (15) \end{cases}$$

The DR controller described in (Surles et al. 2012) changed the set-point temperature using a simple offset method during the peak period. Its result for Houston, TX showed indoor temperature maintained over 3°C (6°F) above the set-point temperature for 8 hours—during peak time. This long-term offset would cause thermal discomfort and very likely lead to departure of the customer from this DR program. Table 5 shows how much the DTC causes thermal discomfort com-

Table 5. Normalized thermal discomfort by days of cooling and heating with DTC by comparing with fixed set-point temperature modes [C°].

Austin, TX				
	Heavy internal loads		Normal internal loads	
Thermal zones	Cooling	Heating	Cooling	Heating
Large house				
1st floor	0.3	0.0	0.3	0.0
2nd floor	0.3	0.1	0.3	0.1
Small house				
Main floor	0.3	0.1	0.3	0.1
Chicago, IL				
	Heavy internal loads		Normal internal loads	
Thermal zones	Cooling	Heating	Cooling	Heating
Large house				
1st floor	0.4	0.0	0.2	0.0
2nd floor	0.2	0.0	0.2	0.0
Small house				
Main floor	0.4	0.2	0.4	0.2

pared with fixed set-point temperature modes when it changes the set-point temperature. The indoor environment with DTC does not average more than a 1°C deviation from the preset temperature where customers feel comfort. Thus, the indoor environments in large and small houses maintain in the thermal comfort zone for most hours so that 1°C or 2°C of the set-point change for few hours is not significantly disturbing thermal comfort. In results, DTC minimizes thermal discomfort even if the set-point temperature is responding to high electricity price. Furthermore, different environments such as cold/hot weather and different internal load sizes do not significantly impact on thermal comfort when DTC controls the HVAC systems.

Conclusions

In this article, the current DTC demonstrates that the electricity consumption and energy cost to use HVAC system are decreased while maintaining thermal comfort. First, the electricity consumptions are reduced by changing the set-point temperature in a thermostat by 3∼6% even if the internal loads and house sizes are different in two locations. In Austin, TX where the electricity price is high, DTC reduces annual energy consumption by about 5∼6%. In addition, it provides 6∼12% of energy cost savings to customers when DTC is installed at homes. If the electricity price is high, DTC brings more cost savings to customers who participate in DR programs. In the PJM wholesale market, the energy cost savings could be increased if utilities provide additional DR incentives to their residential customers. Finally, DTC minimize thermal discomfort. Residents experience an average deviation of about 1°C (2°F) of the indoor temperature from the preset set-point temperature for a whole year.

In summary, the energy consumptions of HVAC systems are changed depending on various environments such as sizes of residential buildings, internal loads, and location. The locations considerably influence total electricity consumptions because the energy efficiency codes for buildings and weather conditions are different. Furthermore, the wholesale electricity markets where the price of electricity is decided are different by location. Even though building environments are different, DTC provides advantages in the reduction of electricity consumption during peak period. Also, customers can receive energy cost savings while maintaining thermal comfort. Therefore, DTC contributes to induce many customers to participate in DR programs for increasing the efficiency of power grid.

The current research focuses on the potential of DR with DTC in a single residential building in this article. Evaluating the performance of DTC in the real buildings is important to assess the effect of DR by changing the set-point temperature. In future work, the hardware controller of DTC will be designed and deployed in a fully controllable residential house to demonstrate the performance of DTC. In addition, the aggregation of DR results is also important to maximize the effect of DR. For the future goal, the authors will consider adding a machine learning algorithm to the controller to find the optimized point for precooling/preheating before peak time while considering the characteristics of building envelope and thermal comfort. Also, the performance of the DTC at distribution level by aggregating DR will be studied.

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