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An adaptive fuzzy logic system for residential energy management in smart grid environments

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HIGHLIGHTS

- An autonomous system via supervised fuzzy learning under dynamic electricity prices.
- New adaptive model for adapting to pattern changes while maintaining existing rules.
- A fuzzy logic technique for residential load reduction in smart grids.
- Implementing a house energy simulator for energy management in smart grids.

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ABSTRACT

Heating, Ventilation and Air Conditioning (HVAC) systems represent a significant portion of total residential energy consumption in North America. Programmable thermostats are being used broadly for automatic control of residential HVAC systems while users initialize their everyday schedules and preferences. The main aim of smart grid initiatives such as time-varying prices is to encourage consumers to reduce their consumption during high electricity demand. However, it is usually a hassle to residential customers to manually re-programme their thermostats in response to dynamic electricity prices or environmental conditions that vary over time. In addition, the lack of energy management systems such as thermostats capable of learning autonomously and adapting to users' schedule and preference changes are major obstacles of existing thermostats in order to save energy and optimally benefit from smart grid initiatives. To address these problems, in this paper an adaptable autonomous energy management solution for residential HVAC systems is presented. Firstly, an autonomous thermostat utilizing a synergy of Supervised Fuzzy Logic Learning (SFLL), wireless sensors capabilities, and dynamic electricity pricing is developed. In the cases that the user may override the decision made by autonomous system, an Adaptive Fuzzy Logic Model (AFLM) is developed in order to detect, learn, and adapt to new user's preferences. Moreover, to emulate a flexible residential building, a 'house energy simulator' equipped with HVAC system, thermostat and smart meter is developed in Matlab-GUI. The results show that the developed autonomous thermostat can adjust the set point temperatures of the day without any interaction from its user while saving energy and cost without jeopardizing user's thermal comfort. In addition, the results demonstrate that if any change(s) occurs to user's schedules and preferences, the developed AFLM learns and adapts to new modifications while not ignoring energy conservation aspects.

1. Introduction

HVAC systems approximately constitute 64% and 57% of total residential energy consumption in Canada and the U.S. respectively [1,2]. Thus, residential HVAC systems are one of the main electrical loads for peak load management during peak demand periods. For example, these devices nearly comprised of 50% of the additional critical peak electricity consumption during hot summer days in California [3].

On the other hand, one of the main goals of smart grid incentives is to improve sight in order to lower network voltages as well as to enable customers' engagement in the operation of the power system, particularly through smart meters [4], smart energy management systems, and smart homes [5]. Moreover, the significance of distributed generation at medium and low voltages and other small renewables such as photovoltaic in consumer-side to locally

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Nomenclature

AFLM	adaptive fuzzy logic model
AC	air conditioning
ASHRAE	American society of heating, refrigeration and air conditioning engineers
DR	demand response
FLC	fuzzy logic controller
HVAC	heating, ventilation and air conditioning
KB	knowledge base
MF	membership functions
PCT	programmable communicating thermostats
SFLL	supervised fuzzy logic learning
SP	set point
TOU	time-of-use
RTP	real-time pricing
WSN	wireless sensor networks
L_v	learning vector
l_n	elements of the learning vector, $n = 1, 2, \ldots, N$
w_n	associated weights of the elements of l_n
A_{z_m}	adapting vector for zone m
L_{Z_m}	learning vector for zone m
A_v	adapting vector
a_k	elements of adapting vector $k \leqslant n$
f_k	'overridflag' associated with each adapting vector
C_{ij}	weekday cluster, 'i' is day of week, '$j = m$' the number of occurrences within a particular day
$\hat{A}$	corresponding adapting vector
$A_{vc_{im}}$	a set of adapting vector under observation
$\hat{L}_v$	corresponding learning vector
$L_{v_{cim}}$	a set of learning vector under observation
Z_m	number of zones in the house, Z_1 (zone 1), Z_2 (zone 2)
$H_{k_{z_m}} cij$	heat set point value of the day i for set point number k
$C_{k_{z_m}} cij$	cool set point value of the day i for set point number k
$S_{k_{z_m}} cij$	start time of heat/cool set point
$E_{k_{z_m}} cij$	end time of heat/cool set point
$W_{H_{k_{z_m}}} cij.$	weights associated with set point $H_{k_{z_m}} cij$
$W_{C_{k_{z_m}}} cij$	weights associated with set point $C_{k_{z_m}} cij$
$W_{S_{k_{z_m}}} cij$	weights associated with start time $S_{k_{z_m}} cij$
$W_{E_{k_{z_m}}} cij$	weights associated with end time $E_{k_{z_m}} cij$
I_{Tz_m}	set point interval for time T in zone m
f_{kz_m}	'overrideflag' associated with set point number k in zone m

utilize them during peak demand periods in existing electricity supply has also been explained in [6]. Additionally, with advancements in communication networks and proliferation of deploying smart meters, management of peak load problems are being shifted towards the customer-side [7–9]. In [7], a holistic review has been conducted to summarize the initiatives and facilities that have capability to assist residential users to potentially save energy. The authors concluded that energy display devices by providing feedback to customers about their energy consumption can significantly help reduce energy consumption through shifting their electricity demands to off-peak hours. Authors in [8] attempted to propound the ways and services such as employing smart devices and smart meters that can encourage end-users such as residential customers in future to have an active role in future smart power grids. A novel air conditioning system has been developed by considering two demand response strategies namely demand side bedding and frequency controlled reserve in [9]. They used these strategies to bring up the role of both demand response programs and smart meters in saving energy and improving grid efficiency. In all communication networks within smart grids, considering the security issues is very important. A study on security issues in Microgids project platform has been conducted in [10], and the authors concluded these issues can be one of serious challenges in future smart power systems. As a result, smart meters as shared technology between users and power grids can enable residential customers to become an integral part of the electric power system. Moreover, time-varying electricity prices such as time-of-use (TOU) rates, real-time pricing, and combinations of these mechanisms provide various opportunities for residential users to reduce consumption and electricity bill by shifting the operation of their home appliances from on-peak rates to off-peak rates [11]. Nevertheless, load management strategy for residential HVAC systems can usually be performed by load shedding in response to different parameters such as time-varying prices [12], variations of ambient temperature [13], and in-home user activity (occupancy) [14]. Authors in [12] have accomplished a survey, where 15 houses as pilots have been used to compare the role of applying time-varying prices such as time-of-use and critical peak pricing in improving grid efficiency as well as saving energy. Additionally, the role of employing occupancy sensors in smart grids for saving energy through reducing the set point temperature of HVAC systems when the home in unoccupied was explained [14]. However, the authors in all these works only considered one parameter such electricity price or occupancy for controlling the energy consumption in the houses.

Fortunately, technology options such as employing home are networks [15] and installing energy display devices for monitoring HVAC energy consumption [16] as well as programmable thermostats [17] are also currently available to assist residential customers in order to manage and reduce their electricity consumption by shedding the demand of home appliances and HVAC systems during high electricity rates. Programmable communicating thermostats (PCTs) and price-responsive thermostats [18], and occupancy-responsive thermostats [19] are being used widely to automatically control residential HVAC systems while users initialize their everyday schedules (i.e., time intervals) and preferences (i.e., set point temperatures). PCTs and price-responsive thermostats potentially have capabilities for two-way communication such as using ZigBee communication protocols (IEEE 802.15.4) with utilities through deployed smart meters in order to participate in demand response (DR) programs with user choice [20]. The PCTs and price-responsive thermostats can receive price signals from smart grid and automatically decreases or increases the initialized set points to a level pre-defined by the user. Occupancy-responsive thermostats also keep monitoring occupancy and automatically change set points when a space or room is unoccupied. However, there exist major disadvantages to these thermostats. It has been reported repeatedly that users lose their thermal comfort particularly in cold winter days or hot summer days when they participate in DR programs during high electricity prices [19,21]. Authors in [19] found out that even existing smart home energy management devices cannot always save energy due to their dependent on user engagement. In this case, the users constantly re-adjust the pre-defined offsets in order to maintain their thermal comfort. However, it is often an inconvenience to residential users to continuously re-set the offset values in response to time-varying prices or occupancy [19]. Additionally, occupants often forget, neglect or even in many cases give up to re-set their thermostats when their thermal comforts are threatened during participating in DR programs. The main reason that this happens is lack of leaning and adapting to user thermal preferences in existing PCTs or occupancy-based thermostats. Hence, developing autonomous fuzzy techniques for future smart thermostats can help users participate in DR programs without any interaction with their thermostats to save energy and cost but maintaining thermal comfort. In [22], a synergy of model predictive control and weather forecasting was developed to improve the energy efficiency in commercial buildings while providing occupant's thermal comfort. However, the approach would be computationally expensive for implementing in residential scales because the processing should be performed by small embedded microcontroller integrated into thermostats.

A dynamic demand response controller (thermostat) based on RTP for peak load reduction is discussed in [23]. The proposed thermostat operates like price-responsive thermostats while attempts to maintain thermal comfort in ASHRAE thermal comfort-zone. However, they have not considered how their controller can provide thermal comfort during high prices if the initialized set points become close to lower boundaries of thermal comfort-zone. To address problems related to existing PCTs as well as the proposed approach in [23], we have recently developed a fuzzy logic approach added to PCTs [24]. The PCT equipped with our approach is able to smartly respond to different parameters such as dynamic electricity pricing and outdoor temperature to maintain user's thermal comfort while not ignoring energy conservation aspects.

Furthermore, the capabilities of wireless sensor networks (WSNs) to measure, detect, and monitor different variables of interest have been investigated and evaluated to improve the limitations of existing energy management systems such as thermostats [25–27]. In [25], an occupancy-based thermostat using a combination of passive infrared (PIR) sensors and door sensors has been installed in a house to evaluate the role predicting occupancy in different parts of the house in energy conservation. To do so, they have applied Hidden Markove Theory for predicting user occupancy states, namely away, home, and sleep. However, they have not considered smart grid initiatives such as time-varying prices in their approach. A combination of a control strategies and wireless communication for comparing centralized control of HVAC systems versus decentralized control have been proposed in [26]. A new system which is able to reduce the run time of the HVAC system in a residential building through controlling the airflow for each specific zone of house by installing different wireless sensors such as humidity, occupancy, etc. was proposed in [27]. The system can decrease the amount of energy used and increasing the comfort of the home occupations due to using different wireless sensor nodes. A testbed for demand management of AC systems in buildings from a central server to save energy and provide user comfort was developed in [28]. The system utilizes power line communication to control the thermostats of an AC system. However, the authors did not consider peak demand curtailment under dynamic electricity pricing. Additionally, a decentralized architecture for autonomous ploygeneration microgrids using computational intelligence techniques in order to study the needs in remote area which can consist of electrical energy and space heating and cooling systems [6].

Furthermore, the integration of wireless sensor capabilities and neural networks for control of HAVC systems in public buildings into save energy and provide thermal comfort has been considered in [29]. They applied a model predictive control strategy using several neural network models through measuring several parameters such as air temperature received from wireless sensor networks. Although energy savings resulting from the proposed method is notable, lack of considering electricity rates as one of important parameters for energy saving is the major drawback of this approach. A fuzzy logic system capable of maintaining and adapting to occupant's thermal comfort based on on-line fuzzy learning was considered in [30]. Authors used several thermal factors such as air speed and air temperature into one single thermal index, where the index value was described in a set of fuzzy rules as thermal sensation. As a result, the proposed algorithm on-line learns from occupant's thermal comfort preferences and adapts to new thermal comforts by applying specific set of labels defined in a static set of fuzzy rules. However, they have not taken into consideration the role of time-varying prices and smart grid incentives for peak load management in their research. Recently, several model-based strategies have been developed for identifying DR measures in office buildings. A meta-model based method for integrated building energy simulation was developed in [31] to evaluate to what degree simplified buildings models are accurate before using such models in design, control and decision making processes for demand reduction. However, the approach focuses on the way buildings are designed and operated based on internal and external actions such as weather and occupancy to incite developing new technologies and solutions in building energy efficiency. A holistic study on calibration model outputs with measured data to obtain more accurate representation of real building operation was also described in [32]. They have conducted a study on current strategies to model development and calibration, concentrating on the significance of uncertainty analysis in the calibration process to help identify saving opportunities in office buildings.

On the other hand, user behaviors such as occupancy and user negligence are important parameters that may impact the operations of thermostats resulting in more energy and bill savings. Researchers attempted to model occupants' activities and evaluate the most influential parameters in occupant behavior for energy saving using model predictive control strategies [33,34]. In terms of the influence of user behaviors on thermostats in smart grid environments, in many cases the residential customers with smart thermostats forget or neglect to participate in DR during high electricity prices [12]. In other cases, households forget to train their smart thermostats particularly during sudden rise or drop in outdoor temperature [18,19]. In fact, responding to time-varying prices and environmental conditions strongly depends on customer's acceptance and participation. These cause that even advanced thermostats such as NEST [35] cannot often compromise between saving energy and user's thermal comfort [19]. Besides, in day-ahead electricity pricing, households rarely check prices to reschedule their devices properly, because it is a hassle to users to constantly respond to hourly prices manually [36]. Given these problems, users cannot optimally benefit from time-varying prices applied by utilities particularly the ones whose electricity bills are significantly influenced by HVAC systems. As a result, lack of autonomously learning and adapting to user's schedule and preference changes is a major disadvantage to existing smart thermostats. Recently, some researches have been conducted for better energy management in buildings by developing regression models using data mining techniques [37,38]. In [37], a daily clustering using energy interval data taken from smart meters was proposed to perform condition monitoring and short-term load prediction for demand response measures in office buildings.

In residential scales and thermostat technologies a part of aforementioned problems has been addressed in NEST thermostat. However, NEST is entirely an interactive-based thermostat in which the thermostat must be trained by its user. Based on the summarized information shown in Table 1 which surveyed from recent studies about home energy management systems (HEMS) in smart grids, we believe there still exist neglected potentials for energy management and conservation which reside in the use, control, and interaction of HEMS such as thermostats. For example, in many cases, the adjusted set points at different inter-

Table 1
Abridged listing of home energy management systems (HEMS) in smart grids via considering important parameters as well as learning capabilities of the approaches used by the source.

Source	Considered parameters and techniques						
	Method	Occupancy as control parameter considered?	Electricity prices as control parameter considered?	Thermal comfort as control parameter considered?	Smartness of HEMS considered?	Adaptability to user pattern changes considered?	User interaction with HEMS for providing thermal comfort?
[3,9,11,12,18,23]	Conventional rule-based learning strategies	No	Yes	No	No	No	Required
[6,14,16,26,27,34]	Multi-sensor agent control approaches	Yes	No	Yes	Yes	No	Required
[7,8,10,11,13,16,17,21]	Public awareness programs	No	Yes	Yes	No	No	Required
[30,35,41]	Adaptive learning techniques using fuzzy logic, or neural networks	No	No	Yes	Yes	Yes	Required
[22,29,33]	Model predictive control	Yes	No	Yes	No	No	Required
[24,39]	Supervised fuzzy logic learning	Yes	Yes	Yes	Yes	No	Not required
[25]	Hidden Markov model	Yes	No	Yes	Yes	No	Required

vals of weekdays are not certain values for that specific time interval(s) [19,21]. During weekdays there exist apparent variations in load demand because of sudden rises or drops in outdoor temperature or consumers preferences. This results in wasting energy due to lack of autonomous decision making systems. Because from user-side, occupants often neglect or forget to modify (setback) set point temperatures or their schedules accordingly. From device-side (existing smart thermostats), there is lack of responding to environmental conditions (ambient temperature) without user interaction [19].

In this paper, our endeavors are dedicated to present an autonomous and adaptable energy management solution for residential HVAC systems in smart grid environments. The proposed system is a synergy of fuzzy logic techniques, wireless sensors capabilities, and dynamic electricity pricing. The main advantage of fuzzy logic controllers (FLCs) compared to other types of controllers resides in the fact that no mathematical modeling is required for the design of the controller. In fact, the inputs and outputs of FLC are real variables mapped with linear/nonlinear functions. They are connected through a set of IF-THEN rules to obtain the corresponding output (s). In this paper, the proposed system takes into account different parameters and information that directly relate to energy management and thermal comfort in residential buildings. Since one of the main objectives of our study is to save energy and cost without sacrificing thermal comfort, fuzzy logic is feasible and implementable to compromise between these interests.

Due to various factors such as dynamic electricity pricing and users' negligence, we have recently developed an 'autonomous thermostat' to make intelligent decisions without any interaction from the user to adjust set point temperatures in response to time-varying prices and environmental conditions (e.g., occupancy) [39]. Indeed, the thermostat autonomously accommodates the set point values based on the developed supervised fuzzy logic learning (SFLL) approach while saving energy and cost without sacrificing thermal comfort.

However, it is anticipated that in some cases the occupant may not feel comfortable with the decision made by autonomous system. Inevitably, the adjusted set point temperature is overridden by user manually. In this study, an Adaptive Fuzzy Logic Model (AFLM) utilizing WSN capabilities is developed to learn and adapt to new user's preference and schedule changes.

The rest of paper is organized as following. In Section 2, the big picture of the problem and '*autonomous thermostat*' is discussed. The AFLM utilizing WSN capabilities is presented in Section 3. The decision-making process and routines are described in Section 4. We will go through the simulation results and the performance of the developed AFLM in Section 5. The paper is concluded in Section 6.

2. Problem description

Generally speaking, an autonomous system is a self-ruling and independent system based on the learned data. Indeed, user is not required to concentrate on controlling the system. Nowadays, due to various factors such as users' preferences and users' negligence; self-adjusting and self-scheduling of the operation of in-home energy management devices such as thermostats should be gaining increasing attention because of difficulties in their manual adjusting. It is being more difficult particularly when the relevant energy management factors such as electricity prices, ambient temperature, and energy demand continually vary with time. Hence, the need for developing thermostat to work autonomously while saving energy and cost but maintaining user thermal comfort is necessary.

In Fig. 1, a conceptual design of "adaptable autonomous thermostat" in a house platform is shown. In this figure, different information is received from various distributed wireless sensor nodes in order to provide information with the main controller unit called "smart thermostat". These sensor nodes are used to measure indoor and outdoor temperatures or to detect occupant activities such as presence in different zones (rooms) of the house. The thermostat can also communicate with the deployed smart meter through ZigBee or Wi-Fi communication to read price signals applied by utilities.

As illustrated in Fig. 1 the "smart thermostat" utilizes fuzzy rule-based algorithms to make decision(s) to autonomously adjust new set point temperatures based on the new information received from wireless sensors and smart grid (i.e., dynamic electricity prices). In this situation the thermostat plays the role of an "autonomous thermostat". It finally sends the control signals to actuate a relay which results in turning on/off a residential HVAC system.

Fig. 2 shows a one day scenario that the "autonomous thermostat" sets the set point temperatures based on ten multiple changes applied to input parameters. The objective of fuzzy rules is to save energy and cost by autonomously responding to changing in input parameters as well as maintaining user thermal comfort in ASHRAE thermal comfort-zone. The developed "autonomous thermostat" integrates residential HVAC systems into smart grids. More details regarding the developed "autonomous thermostat" and its input-output parameters have been discussed in [39]. Additionally, the details related to "house energy simulator" and the house thermodynamic model used in the simulator were elaborated in [24].

However, it can be anticipated that in some cases the occupant may not feel comfortable with the set point value(s) adjusted by autonomous thermostat. Hence, the occupant may take a correc-

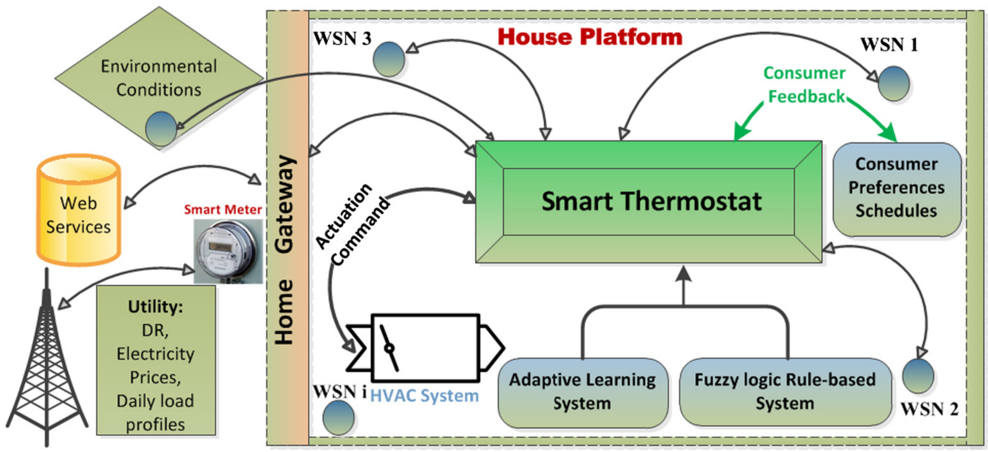

Fig. 1. Synergy of wireless sensors, electricity prices, and smart thermostat in a house platform for control of a HVAC system.

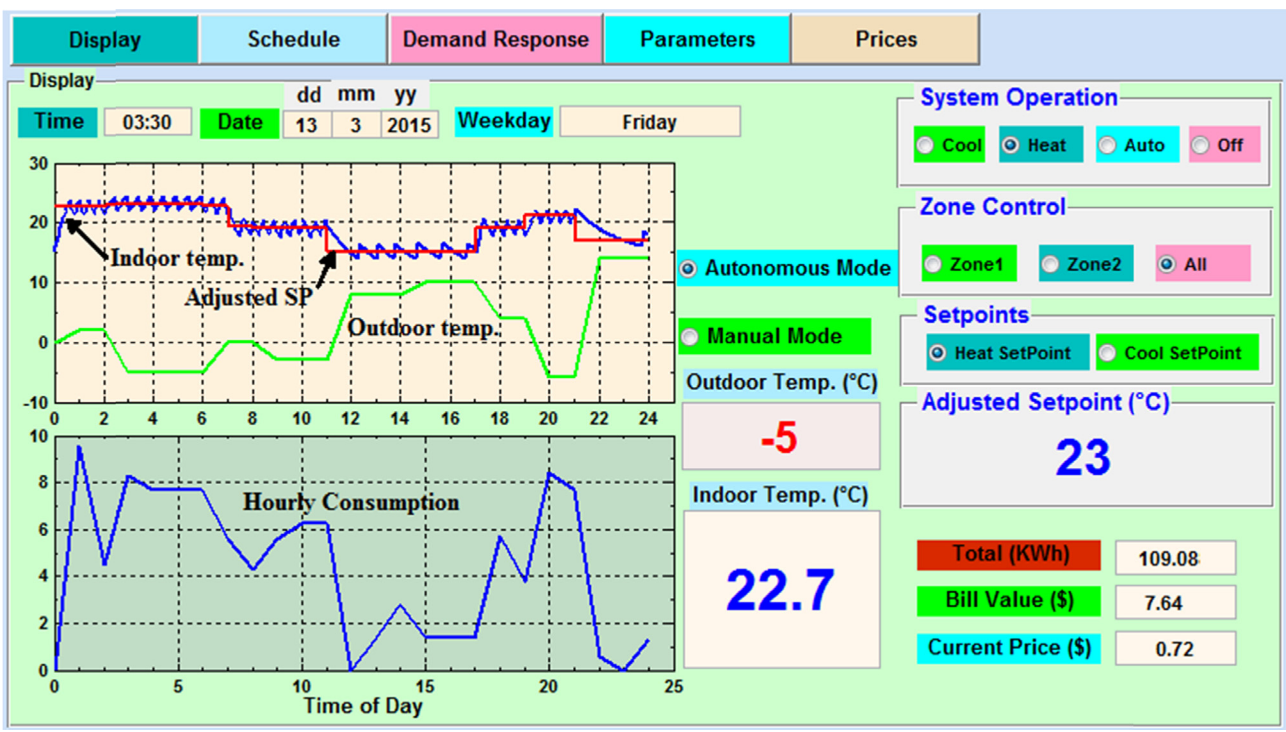

Fig. 2. Adjusted set points by autonomous thermostat for one day based on information from wireless sensors and electricity prices.

tive action which can be performed by manually overriding the set point values (refer to consumer feedback block in Fig. 1). This action leads to changing in that specific set point which has already been adjusted by autonomous system. Based on the changes occurred to user preference(s), two questions arise and will pose challenges:

(i) How to build and update a rule-based model without eliminating existing knowledge (existing SFLL rules)?
(ii) How the thermostat can differentiate between a corrective interaction (overridden values) and a normal behavior that is autonomously performed by "autonomous thermostat"?

To answer these questions, there must be an adaptive learning principle in background in order to enable the thermostat to learn and adapt to new user preferences as well as to act differently in these situations.

3. Adaptive fuzzy logic model

3.1. Model formulation

Automating the operations of an in-home device is not a long-term solution because inhabitants are likely to change their activity and usage patterns with time depending on the factors such as weather conditions and electricity prices. As a result, in addition to making autonomous systems, we need to find a solution to adapt to the user behavior changes that may occur over time. This leads us to go through the problem from 'systems perspective', where the interaction of different subsystems, each with its own attribute exists. In this way, we can maintain the generality of the system so that the developed '*adaptable autonomous system*' such as our developed thermostat can be employed in any house.

Fig. 3 shows the conceptual block diagram of AFLM and depicts the main blocks of the system. As shown in Fig. 3, AFLM consists of

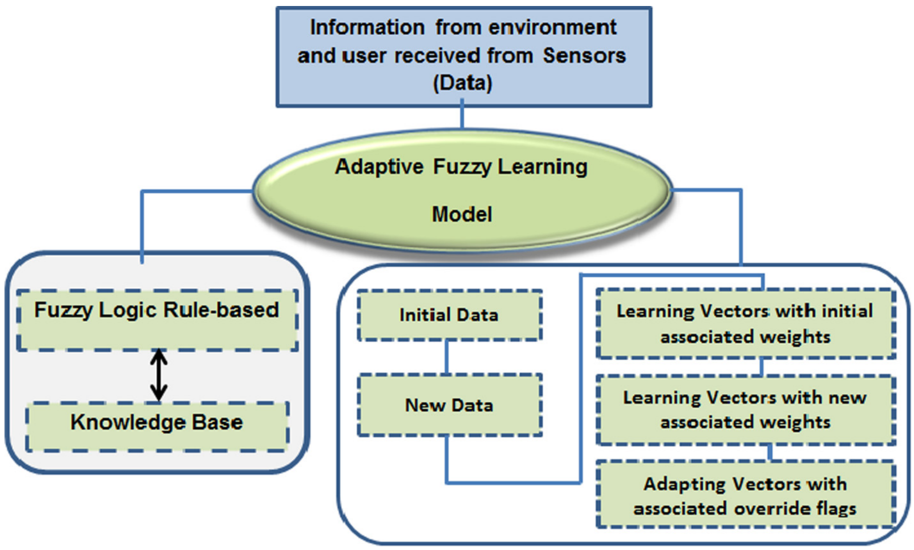

Fig. 3. Conceptual block diagram of AFLM.

different subsystems that sharing their knowledge and data to gain a better outcome. In this Figure the fuzzy logic rule-based provides the decision rules, and continually compares the existing knowledge with the new knowledge received from sensor nodes as the system inputs. The current state of output (set point values) must constantly be compared with existing set point in order to realize whether or not it was manually overridden by user. The Knowledge Base (KB) contains information about membership functions (MFs), parameters of HVAC system, house parameters such as house dimensions, wall and windows thicknesses, as well as thermal characteristics of the house such as thermal coefficients of the wall and windows materials [22]. In terms of MFs, KB consists of MFs of input parameters such as outdoor/indoor temperatures, electricity prices, and occupancy to provide information for autonomous decision-making which adjusts the output parameter which is set point temperature of HVAC system [37]. KB also contains MFs of changes in user preferences and schedules which are reflected from overriding the decisions made by autonomous systems (overriding set point values by users) and/or changing in occupancy which will be explained in details in Section 4.

The role of learning vectors shown in Fig. 3 is to learn preferences based on the user feedback and sensors. These preferences are returned in the weight factor of each element. The adapting vectors extract information from the learning vectors and adapt to new preferences based on the defined fuzzy rules if new changes are detected.

3.2. Model of the system

In order to model the system we consider the problem as follows:

Let $l_1, l_2, \ldots, l_{n-1}, l_n$ represent the elements of the "learning vector" and $w_1, w_2, \ldots, w_{n-1}, w_n$ represent their associated weights respectively. Therefore, we define the vector L_v as learning vector as follows:

$$L_v = \langle l_1, l_2, \ldots, l_{n-1}, l_n, w_1, w_2, \ldots, w_{n-1}, w_n \rangle \quad (1)$$

In statement (1), $l_1, l_2, \ldots, l_{n-1}, l_n$ represent the actual values of interest such as time intervals of a day or set point (SP) values adjusted by autonomous system. The weights are the error between the values adjusted by autonomous thermostat and corrective values (overridden by user). Therefore, w_1 to w_n are the weights associated with learning elements l_1 to l_n respectively.

Furthermore, let $a_1, a_2, \ldots, a_k$ represent the elements that must be adapted if any change happens to occupant schedules and preferences. They are called "adapting vector" elements. In order to adapt to new changes, the system has to realize whether the output has been set based on normal behavior of the system (autonomously) or it has been overridden by user. For this purpose, a separate "override flag" is assigned to each element of adapting vector. Hence, we define the adapting vector as follows:

$$A_v = \langle a_1, a_2, \ldots, a_k, f_1, f_2, \ldots, f_k \rangle \quad k \leqslant n \quad (2)$$

In statement (2), $f_1, f_2, \ldots, f_k$ is the "override flags" associated with elements $a_1, a_2, \ldots, a_k$. Therefore, the vector A_v only includes the elements of interest and their associated flags. Hence, for each element l_1 to l_n in the learning vector, there is a corresponding element of the adapting vector a_1 to a_k.

Since the users' schedules and preferences may change during a day or week, we cluster the days of week into seven slots as "weekday clusters". We assign 1 for Monday cluster, 2 for Tuesday cluster, etc. There are seven different clusters under consideration corresponding to a week. Therefore, we assume C_{ij} as weekday clusters that are under monitor. In this cluster i shows the day of week and $j = 1, 2, 3, \ldots, m$ shows the number of occurrences within a particular day. For example, $C_{1j}, C_{2j}, \ldots, C_{7j}$ shows different weekdays from Monday to Sunday and j represents the number of occurrences for every element under monitor for each day of week.

Besides, let $\hat{A}$ indicate corresponding adapting vectors as follows:

$$\hat{A} = \langle A_{vc_{i1}}, A_{vc_{i2}}, \ldots, A_{vc_{im}} \rangle \quad (3)$$

The vectors $A_{vc_{i1}}, A_{vc_{i2}}, \ldots, A_{vc_{im}}$ show a set of adapting vectors under observation for each weekday occurrences.

Moreover, $\hat{L}_v$ represents a set of learning vectors under observation defined follows:

$$\hat{L}_v = \langle L_{v_{ci1}}, L_{v_{ci2}}, \ldots, L_{v_{cim}} \rangle \quad (4)$$

It is assumed that the initial weight conditions for every learning vector $\widehat{L}_v$ are $w_n = 1$ and -1. '-1' indicates that the value of element corresponding to its associated weight has not changed; while, '1' shows a change has been detected.

3.3. Adaptation model for autonomous thermostat

As pointed out in previous subsection, the "override flag" with conditional checks is used in order to detect the state of system when it swaps from autonomous control mode to event-based control mode. Hence, in event-based control mode it is important to know "when" (Start Time) a decision has been overridden, "until when" (End Time) it has been lasted, and finally "how much" the new value(s) has been shifted from the value(s) initialized by user or autonomous system.

To simplify the expressions from now on, 'S' indicates 'Start Time', 'E' stands for 'End Time', and 'C' and 'H' represent the current cool/heat set point value for different times of day. The set of learning vectors under monitor based on set point values of a day ($H_{k_{z_m}}cij, C_{k_{z_m}}cij, k = 1, 2, \ldots, 24$) associated with Zone1 and Zone2 ($m = 1, 2$) for each active day i ($i = 1, 2, \ldots, 7$), can be described as follows:

$$L_{Z_m} = \langle H_{k_{z_m}}cij, C_{k_{z_m}}cij, S_{k_{z_m}}cij, E_{k_{z_m}}cij, W_{H_{k_{z_m}}}cij, W_{C_{k_{z_m}}}cij, W_{S_{k_{z_m}}}cij, W_{E_{k_{z_m}}}cij\rangle \quad (5)$$

In the expression (5), the elements from 1 to 4 are Heat Set Point, Cool Set Point, Start and End time of Set Points, and from 5 to 8 are their respective weights. In addition, j represents the number of occurrences for learning vectors under observation.

The set of adapting vectors for smart thermostat for zones 1 and 2 ($m = 1, 2$) are defined as follows:

$$A_{z_m} = \langle I_{1z_m}, I_{2z_m}, \ldots, I_{Tz_m}\rangle \quad (6)$$

Each element in A_{z_m} represents a time interval for each day of week that has a 'Start Time' and 'End Time'. In turn, they start from 00:00 A.M. until 24:00 for each day of week. In statement 6, each interval contains set point values for 24 h of a day which are autonomously computed by SFLL based on information received from wireless sensors and electricity prices.

We assume the information from wireless sensors and electricity prices are received every one hour, therefore, we have 24 set points as shown in (7). These set points values are $SP_{1z_m}, SP_{2z_m}, \ldots, SP_{24z_m}$.

In Eq. (7), $f_{1z_m}, f_{2z_m}, \ldots, f_{24z_m}$ represent the 'override flags' associated with $S_{1z_m}, S_{2z_m}, \ldots, S_{24z_m}$ respectively if any corrective action is taken by user. Therefore, A_{z_m} has a structure as follows:

$$A_{z_m} = \langle SP_{1z_m}, SP_{2z_m}, \ldots, SP_{23z_m}, SP_{24z_m}, f_{1z_m}, f_{2z_m}, \ldots, f_{23z_m}, f_{24z_m}\rangle \quad (7)$$

The system automatically assigns each of set points SP_{1z_m} to SP_{24z_m} to intervals for each day of week.

However, as long as the 'override flags' are 'off' the smart thermostat keeps operating as an autonomous system based on the SFLL proposed in Section 2. When the state of "override flag" associated with each element in (7) changes to 'on' at any time, it means there must be a change related to elements in learning vector. Therefore, the system records as well as assigns this change to each element of interest in (5). The elements of adapting vector shown in (7) are populated only after they compared with the learning vector data. These elements are adapted by a proposed fuzzy rule-based algorithm explained in Section 4 if 'j' consecutive changes occur to each of them. The number of occurrences (j) in order to adapt to new patterns can vary depending on the application of the developed AFLM.

4. Fuzzy logic decision-making for adaptation

4.1. Inputs of system and their membership functions

A fuzzy membership function is assigned to each weight in learning vector if any change is detected in learning vectors. Figs. 4 and 5 show membership functions of weights associated with each element in learning vector. The reasons for defining triangular MFs are based on a few assumptions. We predict the user habit after three consecutive changes and the range of changes are not too large. Moreover, assigning other types of MFs such as trapezoidal do not have that effect on the accuracy of predicted values while choosing other MFs exponentially increase the number of rules which make the system computationally expensive. These weights are assigned to each particular element in the learning and adapting vectors for any daily cluster under observation based on their shifts from initial values. In these Figures, the weight 'High' indicates the major shift from initial values, while the 'Low' signifies a small shift from typical existing value. Additionally, the user can decide to override the set point value(s) at any time if he/she does not feel comfortable with the current indoor temperature. In this case, the system must detect as well as take into consideration the overridden value(s) as an event to the operation of main system (autonomous system), in order to swap to event-based control which might be new user's preference or habit. Hence, the HVAC controller (thermostat) keeps checking the state of the current set point and gives out the user override value as a fuzzy variable if any change occurs. To do so, we consider the state of "override flag" pointed out in the statement (7) as an input to the system. This value is fuzzified into two different linguistic variables 'off' and 'on' as shown in Fig. 6. It can be observed from Fig. 6; only one membership function can be received at one time. In the cases that the 'override flag' is 'on' meaning that the decision made by SFLL has been overridden by user. Therefore, the new decision (s) has to be recorded for adapting in future depending on the time of day. If the state of 'override flag' is 'off' meaning the system is still on normal mode.

4.2. Outputs of system and their membership functions

As pointed out in Section 3.3, the adaptation is performed if an occurrence is repeated for three consecutive times ($j = 3$). For example, if the user changes a set point temperature (e.g. set point number 8, S_8) in three consecutive days (Monday, Tuesday, Wednesday), this occurrence is considered for adaptation as user new habit. It is based on several assumptions. For example, when a person increases or decreases the current set point temperature sat by autonomous system at a specific time of day, this action (overriding the existing set point) might be due to very sedentary or activity at home. Another scenario can be when the inhabitant overrides temporarily the heat set point due to an extremely cold winter day or a sudden drop/rise in outdoor temperature. All these scenarios

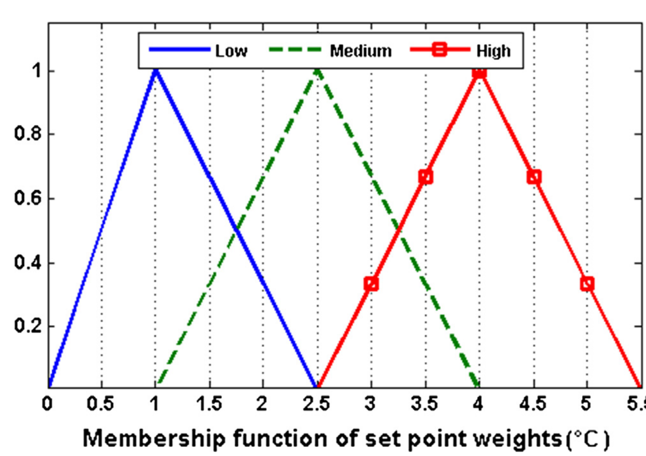

Fig. 4. Membership function associated with shifting in set point values as system input (weights).

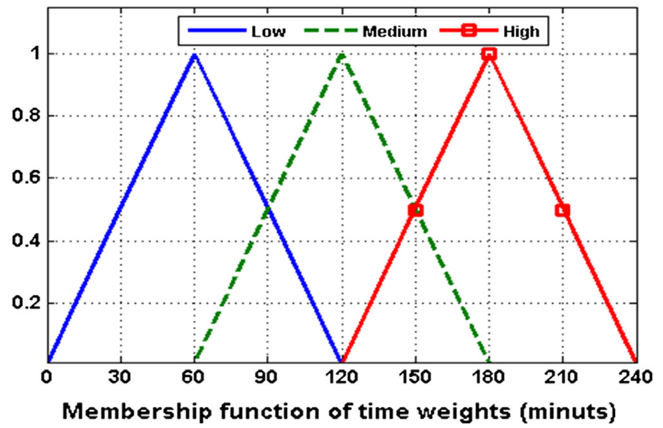

Fig. 5. Membership function associated with shifting in start time and end time as system input (weights).

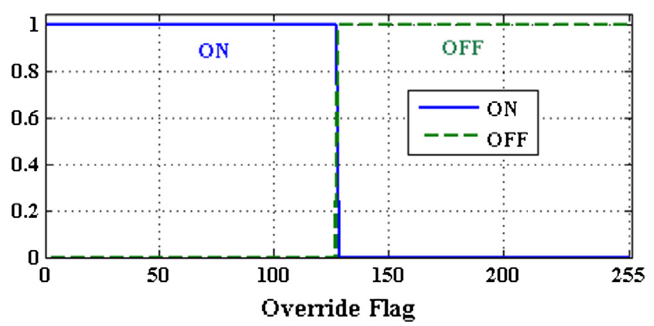

Fig. 6. Membership function of override flag.

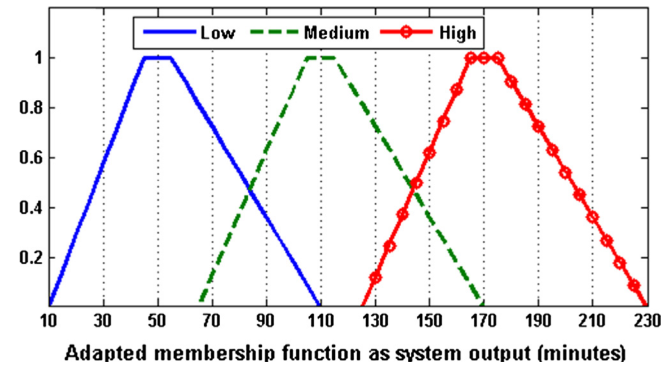

Fig. 7. Membership function associated with shifting in start time and end time as system output (weights).

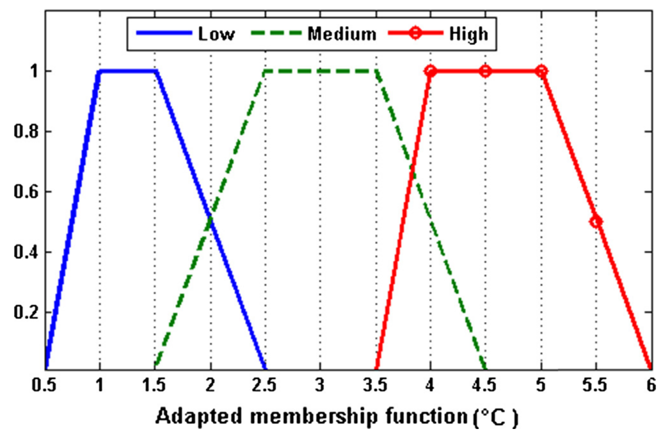

Fig. 8. Membership function associated with shifting in set point values as system output (weights).

might happen one time, and not be a preferred set point or a permanent habit of the user. Therefore, the system considers the changes that occur consecutively for three times. Figs. 7 and 8 show membership functions of system outputs based on changes in elements of learning vectors if a pattern is persistent for three successive times. These membership functions are defined based on some assumptions. As shown in Figs. 7 and 8, membership functions are in trapezoidal form in order to take into consideration user's thermal comfort based on the Predicted Mean Vote (PMV) and Predicted Percent Dissatisfied (PPD) [40]. In this way, the system can adapt to set point values which are closer to lower band of thermal comfort-zone [29,41]. By doing so, the thermostat can potentially save more energy and cost.

4.3. Fuzzy rules for adaptation

Three different weights were assigned to any daily vector based on their shifts from the initial values, for three successive occurrences of each day. The fuzzy rules for adaptation are based on the possible combinations listed in Table 2. There totally exist 27 combinations for each element under observation. In Table 2, O_1 represents the first occurrence, O_2 stands for second, and O_3 indicates the third one. In addition, in this table L, M, and H represent Low, Medium, and High respectively.

The final value (adapted output) reflected from changing weights is computed based on the weights of occurrences. For example, if all three daily/weekly occurrences have had the same weights, the same fuzzy value of three daily/weekly elements is returned as adapted output (i.e., rules 1 and 14). Another example, if only the weights of first two daily or weekly occurrences of the particular vector elements are high while the weight of third one is low, the weight of adapted output is medium (refer to rule 25).

4.4. Implementation steps and routines of the fuzzy decision-making

The main sequences of the algorithm based on the proposed AFLM to implement an 'Adaptive Smart Thermostat' are shown in Fig. 9. In this flowchart each block has an associated number that is used to provide additional details as presented in the following.

(1) Load 'Data' file and generate a new 'data object' which contains read data to mimic all sensory information. Therefore, the generated file has different occupant's preference and/or schedule changes, different outdoor temperature, TOU and RTP prices, house and HVAC parameters for simulation of different scenarios. 'Data' file which is a CSV file contains fuzzy rules and fuzzy membership functions of system inputs and outputs.
(2) Initialize and fuzzify all inputs loaded from 'Data' file. For example, occupancy sensors can consist of different sensors such as motion sensors, door sensors, and PIR sensors and have different attributes in order to detect the user in the zones. Ultimately, the smart thermostat can receive presence or absence of the occupant at any time of the day in the zones. In this research the user status is loaded from a CSV file.
(3) The learning vectors presented in Eq. (5) are created and initialized for each day of week. This is conducted by collecting data from wireless sensor nodes in real platform. This information is gathered from 'Data' file. As shown in Eq. (5), the learning vectors contain information based on the interval of a day and have 8 elements for each zone. We also divide

Table 2
Fuzzy rules for adapting to pattern changes.

#Rule	O_1	O_2	O_3	Output	#Rule	O_1	O_2	O_3	Output
R_1	L	L	L	L	R_{15}	M	M	H	M
R_2	L	L	M	L	R_{16}	M	H	L	M
R_3	L	L	H	L	R_{17}	M	H	M	M
R_4	L	M	L	L	R_{18}	M	H	H	H
R_5	L	M	M	M	R_{19}	H	L	L	L
R_6	L	M	H	M	R_{20}	H	L	M	M
R_7	L	H	L	L	R_{21}	H	L	H	M
R_8	L	H	M	M	R_{22}	H	M	L	M
R_9	L	H	H	M	R_{23}	H	M	M	M
R_{10}	M	L	L	L	R_{24}	H	M	H	H
R_{11}	M	L	M	M	R_{25}	H	H	L	M
R_{12}	M	L	H	M	R_{26}	H	H	M	H
R_{13}	M	M	L	M	R_{27}	H	H	H	H
R_{14}	M	M	M	M					

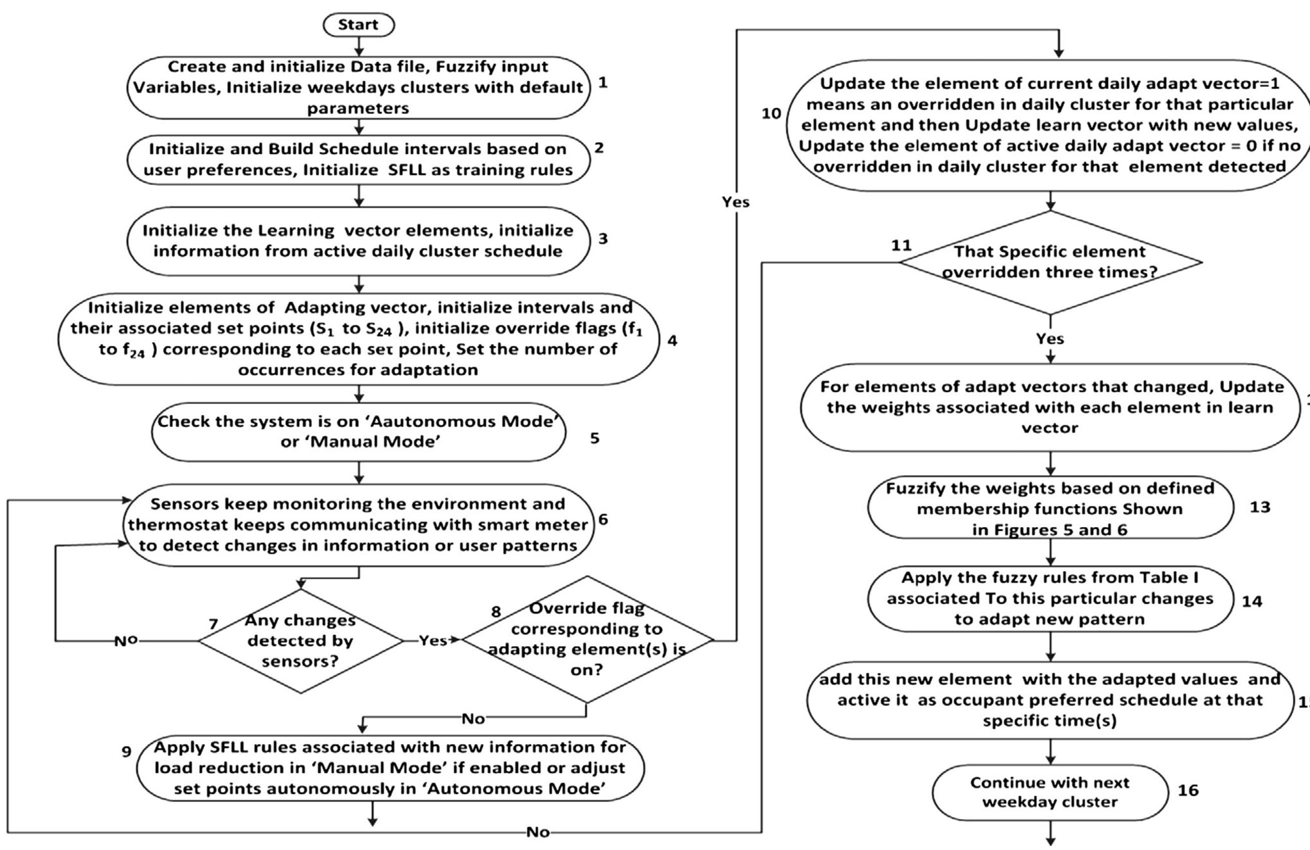

Fig. 9. Flowchart of implementation of AFLM.

a day of week into 6 time slots (intervals), thus, 6 elements for adapting intervals. Therefore, we have a size of 8 ∗ 6 that is 48 for each occurrence in a 'particular daily schedule' (i.e., number of elements in learning vector multiplied by number of elements in adapting intervals). Therefore, for 3 consecutive daily occurrences there will be 48 ∗ 3 that is 144 data available for each zone and ultimately 248 for both zones for three changes.

(4) Adapting vectors and their associated 'override flags' based on the learning vectors are created and initialized for each day of week. The value of 0 is assigned to each adapting vectors and their associated 'override flags'. This value shows that no change has happened to the set points in that specific interval. Adapting vectors are populated only after comparison with the learning vector data and '*adapt flag*'. The system also has an '*adaptdaily*' flag if three successive changes occur to each element in adapt vectors in three consecutive days of week. As mentioned in Eq. (7), the adapt vector structure for each set point of a day is as following: "*Heat SetPoint, Cool SetPoint, Start Time, and End Time*". We do not consider the '*override flags*' for adaptation. Adapt vector is extracted only after comparison with the learn-vector.

(5) At this stage, the AFLM detects the mode of operation. There are two modes of operation namely 'Autonomous Mode' and 'Manual Mode'. 'Autonomous Mode' works based on developed SFLL and consists of 'Economy Mode' and 'Comfort Mode'. In 'Manual Mode' all schedules and preferences such as time intervals of a day and set point values are defined and initialize by user.

(6) Based on step 5, the thermostat equipped with AFLM was set on 'Autonomous Mode' or 'Manual Mode'. However, the received information and the sat schedule and preferences are not permanent and may vary over time or overridden by user. Therefore, in this step the system keeps monitoring and receiving new information from environment. If any change was detected then goes to step 7.
(7) Upon any change was detected by 'smart thermostat', the system checks to realize that the occurrence is due to changing in environmental conditions (i.e., outdoor temperature) or the decision initialized by user or SFLL has been overridden.
(8) If the 'override flag' is 'on', it shows the decision made by SFLL or the schedules sat by user (step 5) has been canceled by user, then it goes to step 10.
(9) In the event of changing in environmental conditions, AFLM measures, fuzzifies, and applies the particular rules associated with these changes using SFLL.
(10) In this step adapting procedure is applied for each day of week by creating three temporary vectors with a limit of 24 elements (refer to steps 3 and 4). AFLM updates those elements that have changed in learning vector with value of '1', and if no change detected update with value of '0'.
(11) Verification is performed for each element and specific day occurrence in order to assure if the change is persistent. Therefore, if the number of changes related to each element in adapting vector meets the limit, it is considered for adaptation. If not, it goes back to step 6 for next hours/days.
(12) The weights of elements that have overridden for three consecutive times are updated. To do so, the active daily file is read; all data added in a '*weightread*' list for future actions. In addition, all the necessary data is stored into a '*decisionweight*' vector (size of 48 elements). Then, another '*learnweight*' vector exploits the data from the specific learning vector of the daily cluster in order to compare with the '*decisionweight*' vector. It does the above routine for all the elements of interest in learn-vector

$$\langle H_{k_{zm}} cij, C_{k_{zm}} cij, S_{k_{zm}} cij, E_{k_{zm}} cij, W_{H_{k_{zm}}} cij \rangle \tag{8}$$

Finally, it performs a weight check for each day/week (first, second and third), while all the data elements from the '*decisionweight*' and '*learnweight*' are compared.
(13) From AFLM description we already defined three different weights which can be allocated to any daily vector based on its shift from the initial value for three consecutive occurrences of a particular day. Then, the difference between new value and existing value is fuzzified by membership functions shown in Figs. 5 and 6.
(14) The fuzzy rule-based decision-making based on the rules shown in Table 2 is applied in order to adapt to new preference changes. Each time that the weight check process is performed, the result is assigned to that particular element of the daily cluster schedule.
(15) The AFLM checks the new pattern if it is not in daily cluster, this new preference is updated as new knowledge.

5. Simulation results and performance of the developed algorithm

The simulations are run for several scenarios in order to verify the performance of the developed algorithm with respect to energy saving as well as its functionality for adapting to user preference changes. The AFLM approach is verified for both "Manual Mode" and "Autonomous Mode".

5.1. Manual mode

The thermostat sat on "Manual Mode" is a PCT equipped with AFLM. In this way more intelligence has been added to existing PCTs in order to address lack of learning and adapting to user preference and schedule changes in these thermostats (i.e., resulting in an adaptable PCT). As pointed out, in "Manual Mode" all schedules, preferences, and set point values are initialized by users.

5.1.1. Energy saving and load reduction using SFLL enabled

The first case is dedicated to verify the functionality of decision-making with and without enabling SFLL in "Manual Mode". In this case the importance of input parameters in energy saving is considered as well. It is assumed that the initialized schedules set points and intervals do not change during simulation. In addition, the initialized settings for the simulation such as user schedules and their associated set points values for weekdays and weekends and house parameters are listed in Tables 3–5 respectively. TOU rates used for the simulation are taken from Hydro One utility in Ontario, Canada and are in effect in 2014 for winter season shown in Table 6. The weather data for outdoor temperature is taken from the Canada's National Climate Archive for winter 2014.

Fig. 10 shows the energy consumption for different configuration for one month simulation. As shown in Fig. 10, the potential energy saving for the entire house with SFLL enabled versus entire house with SFLL disabled is 386 kW h. In addition, the first right bar in Fig. 10 represents energy consumption of house for one month simulation when the effect of electricity prices is not taken into account as system input in decision making process by SFLL. In this case, the energy consumption of house increases about 185 kW h due to lack of considering electricity prices. Hence, designing price-responsiveness devices in current and future smart grids is necessary. Based on results shown in Fig. 10 the improvements in terms of energy management and saving with and without SFLL during one month simulation are apparent. This is because SFLL keeps evaluating information received from wireless sensors and electricity prices and changes the set point values to save energy without sacrificing thermal comfort. Fig. 11 depicts a one day sample scenario that the SFLL responds to input parameters for demand-side management. As it can be observed from Fig. 11, from 5:00 P.M. to 7:00 P.M. that the electricity price is on-peak and the home is occupied, the "Manual Mode" thermostat equipped with SFLL reduces the set point temperature from 22 °C to 19 °C (3 °C) to participate in DR programs by applying specific fuzzy rules.

5.1.2. Learning and adapting to user preference changes and relative energy saving

In this section multiple changes are applied to user schedules and preferences in order to validate the performance of the developed AFLM with respect to learning and adapting to new user's habits while "Manual Mode" is the preferred mode. The objective of considering the problem from this aspect is to demonstrate that AFLM can be embedded into existing PCTs as well.

Table 3
Schedules and set point values for weekdays.

SP	Time of day (Start time to End time)	Heat SP (°C)	User status
SP_1	00:00–06:00	21	Sleep
SP_2	06:00–08:00	23	Home
SP_3	08:00–11:00	17	Away
SP_4	11:00–17:00	18	Away
SP_5	17:00–19:00	23	Home
SP_6	19:00–24:00	21	Home

Table 4
Schedules and set point values for weekends.

SP	Time of day (Start time to End time)	Heat SP (°C)	User status
SP_1	00:00–08:00	21	Sleep
SP_2	08:00–14:00	23	Awake
SP_3	14:00–19:00	17	Away
SP_4	19:00–24:00	18	Away

Table 5
House parameters for simulation.

Parameters	Values	Unit
House length	15	m
House width	8	m
House altitude	5.5	m
Number of windows	6	
Window length	1.5	m
Window height	1	m
Windows thickness	0.01	m
Walls thickness	0.3	m
Wall thermal coefficient	0.038	W/m K
Window thermal coefficient	0.78	W/m K
Initial house temperature	0	°C

Table 6
TOU rates for winter 2014.

Time of day	Price ($)	Description
00:00–07:00	0.077	Off-peak
07:00–11:00	0.129	On-peak
11:00–17:00	0.109	Mid-peak
17:00–19:00	0.129	On-peak
19:00–24:00	0.077	Off-peak

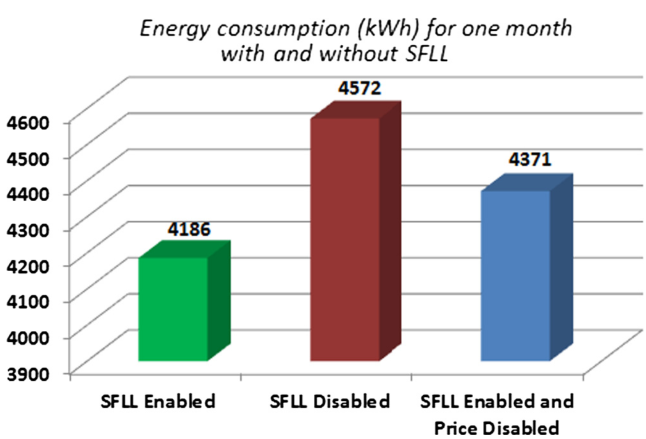

Fig. 10. Energy consumption for one month with SFLL.

To do so, the first three weeks are dedicated to training the thermostat for learning user schedules, preferences, etc. This means the system only compares the changes related to similar weekdays (Monday to Monday, Tuesday to Tuesday, etc.). A scenario for participating in demand response programs is emulated in order to predict pattern changes of user with respect to the 'set point start time', 'set point end time', and 'heat set points of weekdays'.

As shown in Table 7, the SP_5 has been initially set by occupant on 23 °C between 17:00 and 19:00 for all weekdays (refer to Table 3), where the price and load demand are normally high at this period of day. In order to predict consumer patterns after three successive changes in SP_5, a scenario is considered as follows:

In the first week the user reduces SP_5 from 23 °C to 21 °C (heat set point) from 16:30 (start time) to 18:30 (end time). In the next week SP_5 is reduced to 22 °C from 17:30 (start time) to 18:00 (end time). Finally, the set point temperature (SP_5) is decreased to 20 °C from 18:00–19:00 in the third week.

The thermostat equipped with AFLM detects three consecutive changes corresponding to all elements of SP_5 in all weekdays cluster (Monday to Friday). Therefore, the new preferences must be considered for adaptation. The outputs of AFLM that indicate the adapted values after three weeks of learning are shown in Table 7 (last row). As a matter of fact, the thermostat detects the changes associated with each element in learning and adapting vectors, and then compares initial values with new values (overridden by user), and finally fuzzifies these changes (weights) based on Figs. 5 and 6. Since three successive changes have been detected in the elements of learning vectors; AFLM applies the corresponding fuzzy rules shown in Table 2 in order to predict new pattern, while considering energy conservation aspects.

Comparing the two last rows of Table 7, it can be observed that the adapted values using AFLM after the third occurrence for 'start time' is different from the adapted values using averaging approach. The adapted 'start time' value using averaging is 17:20, while it is 17:08 using AFLM. This demonstrates that AFLM adapts to the value that is closer to initial (17:00) occurrences where applying tuned fuzzy rules shown in Table 2.

In addition, as shown in Table 7, in comparison to using averaging approach with respect to energy conservation; AFLM participates in DR programs 12 min earlier (start time 17:08) and this engagement in DR lasts 11 min longer (end time 18:42). This functionality of AFLM can improve energy saving while maintaining user thermal comfort. In addition to this, the adapted 'heat set point value' is 1.15 °C lower compared to averaging approach (21 °C). As a result, AFLM adapts to the value that is near to user's third pattern (20 °C) detected during new preferences, and at the same time leads to better energy saving.

Furthermore, in order to validate the functionality of AFLM in terms of energy management and conservation, a two months simulation is conducted. The simulation is run for the same changes related to SP_5 explained in Table 7. Therefore, the new preferences take effect from the fourth week of simulation (first three weeks for training system). Hence, the thermostat sets the SP_5 on 19.85 °C in the interval of 17:08–18:42 from the fourth week until the end of two months of simulation. The result shows the relative energy saving for adapting to a very limited time (1 h and 42 min) in SP_5 compared to non-adapting is 73.54 kW h.

5.2. Autonomous mode

This section is dedicated to verification of the functionality of AFLM with respect to learning and adapting to new preferences of user when the thermostat is set on "Autonomous Mode". In order to compare different cases, we provide similar conditions for similar days of the month. Hence, some assumptions are taken. We assume the variations of outdoor temperature for similar days of month are identical during the one month simulation (i.e., outdoor temperature of all Mondays are similar). The variations of load demand and dynamic pricing are similar and assumed not to change for similar days of month during the simulation (i.e., load demand of all Tuesdays are similar). In addition, the settings used for daily intervals and their associated set points are depicted in Tables 8. Therefore, the adjusted set points for different days of the first week based on information received from wireless sensor nodes and electricity prices are shown in Fig. 12. In fact, these are set points S_1 to S_{24} distributed within 6 intervals listed in Table 8. However, the robustness of the system might be one of concerns based on above-mentioned assumptions. To do so, we considered the robustness of system by changing parameters in the fuzzy controller and house parameters such as buildings mass, hear trans-

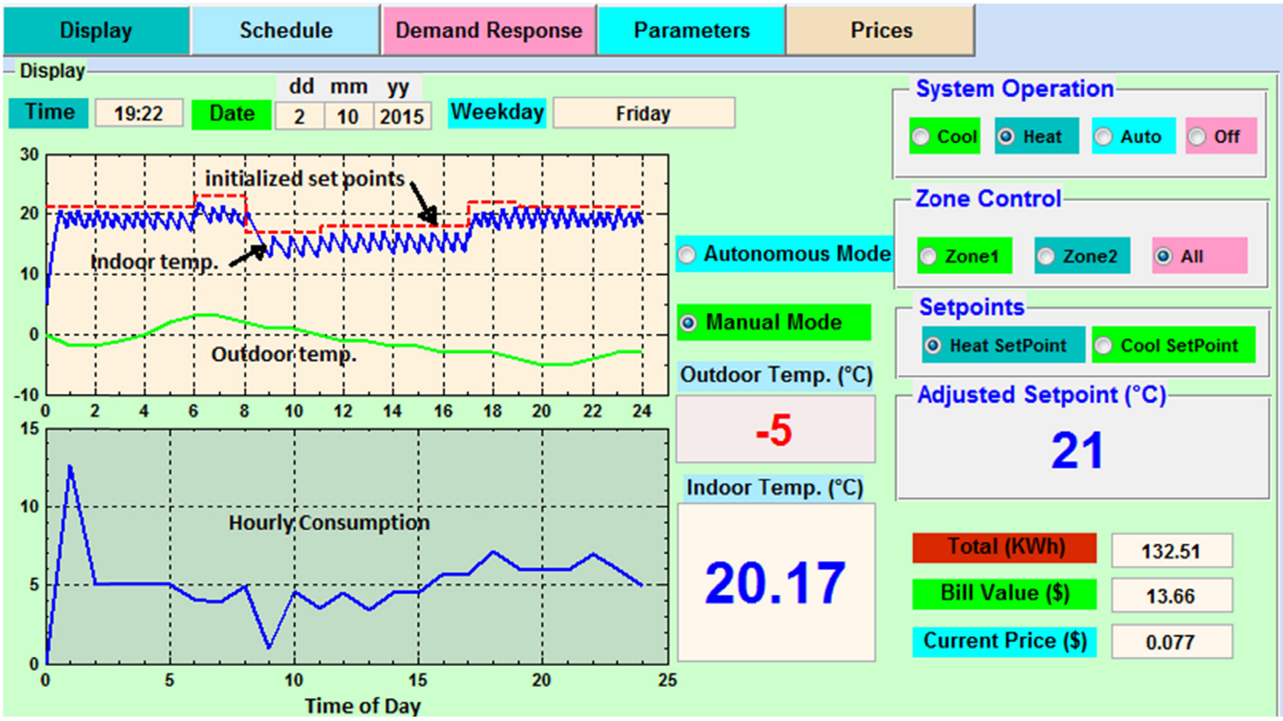

Fig. 11. Load reduction using SFLL added to "Manual Mode".

Table 7
Adapting to user pattern changes in "Manual Mode".

Occurrence	Start time value			End time value			Heat SP value (°C)		
	Initial	New	Weight (min)	Initial	New	Weight (min)	Initial	New	Weight
First week	17:00	16:30	−30	19:00	18:30	30	23	21	3
Second week	17:00	17:30	30	19:00	18:00	60	23	22	5
Third week	17:00	18:00	60	19:00	19:00	0	23	20	4
Average adapted value	17:20			18:31			21		
AFLM adapted value	17:08			18:42			19.85		

mission coefficient, etc. based on several real data which a part of them has been shown in Table 5.

In order to validate the performance of AFLM, the period of learning and adaptation of system is set on three successive days. This means if any element(s) in learning vector changes for three consecutive days, it is considered for adaptation as new habit of user. The first week is also dedicated to training system as well as initializing all information described in AFLM decision-making process.

As shown in Table 9 multiple changes are applied to decisions made by autonomous thermostat in order to validate and analyze the functionality of AFLM algorithm statistically. Hence, the decisions made by autonomous thermostat (i.e., set point values and their associated 'start and end times') are overridden to mimic user's pattern changes for three consecutive days; Monday, Tuesday, and Wednesday clusters of the second week.

As it can be observed from Table 9, the first change is for Monday cluster of the second week, where the user overrides the set point $S_3 = 22\,°C$ and reduces it to 21 °C (overridden value) at 2:30 A.M. (start time). Hence, the set point stays on 21 °C until the user increases it (21 °C) to 23 °C at 4:30 A.M. (end time). Based on these changes, the 'override flags' F_3 and F_5 associated with set points S_3 and S_5 become 'on' (shown in Table 9). Therefore, the associated weights for all elements within interval 'I_1' [0:00 A.M.–6:00 A.M] after comparing with initial values are recorded.

Table 8
Intervals and associated set points in "Autonomous Mode".

Intervals	Time of day	Occupancy	Associated SP
I_1	00:00–6:00	Occupied	S_1, S_2, S_3, S_4, S_5, S_6
I_2	6:00–8:00	Occupied	S_7, S_8
I_3	8:00–13:00	Unoccupied	S_9, S_{10}, S_{11}, S_{12}, S_{13}
I_4	13:00–17:00	Unoccupied	S_{14}, S_{15}, S_{16}, S_{17}
I_5	17:00–21:00	Occupied	S_{18}, S_{19}, S_{20}, S_{21}
I_6	21:00–24:00	Occupied	S_{22}, S_{23}, S_{24}

For example, in this case (Monday) the weights associated with 'heat set point' (S_3) and 'start time' are 1 °C and 150 min (2:30 A.M.–0:00 A.M. = 2:30) respectively. In addition, the weights associated with S_5 and 'end time' are 2 °C and 90 min ($6:00 - 4:30 = 1:30$) respectively. Similarly, the other changes applied to the system for Tuesday and Wednesday clusters of the second week are shown in Table 9.

As shown in Table 9, AFLM adapted value after the third occurrence is not the average value of three successive changes. The adapted values of AFLM after one week training fall within the interval of the 95 percent 'fuzzy confidence interval' of the sample mean values [42]. Fuzzy confidence interval will assure whether or not the AFLM adapted values are in the appropriate interval after three consecutive occurrences. Hence, it implies that AFLM conform to the value that is near to frequent habits. Referring to

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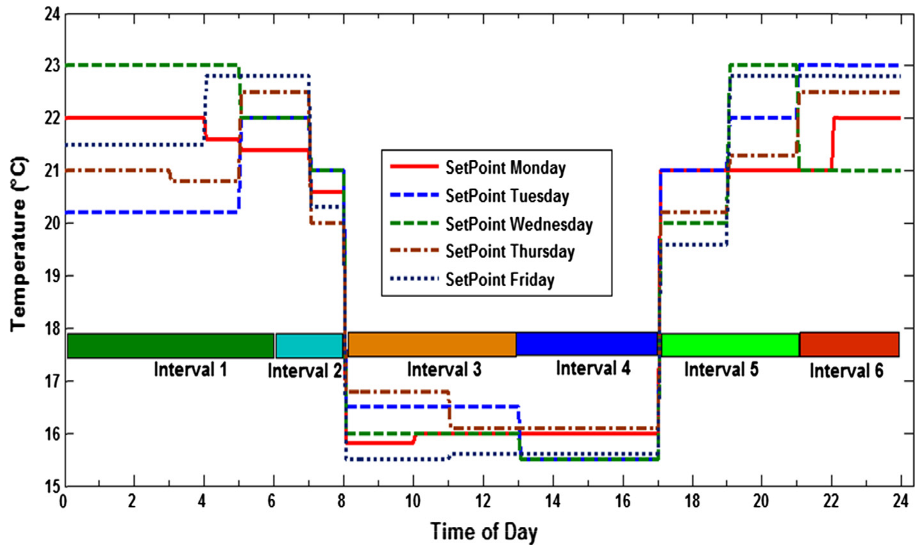

Fig. 12. Adjusted set points for different days of week in 'Autonomous Mode'.

Table 9
Adapting to User Pattern Changes in "Autonomous Mode".

# Weekday cluster	Affected flags	Affected set points	Initial value (°C)	Overridden SP value (°C) [start]	Start time	Overridden SP value (°C) [end]	End time
Monday	F_3, F_5	S_3, S_5	22	21	2:30	23	4:30
Tuesday	F_2, F_4	S_2,S_4	20.2	18	1:45	21	3:30
Wednesday	F_1, F_3	S_1, S_3	23	19	00:30	23	2:45
Average	N/A		21.66	19.33	1:25	22.33	3:15
Fuzzy confidence	N/A		N/A	(17.5, 21.3)	(0:18, 2:43)	(20.4, 23.6)	(2:31, 4:46)
Adapted values	N/A		N/A	18.46	1:06	20.8	3:30

Table 9, the AFLM adapted value for set point temperature after three times overriding of the made decisions for next daily clusters is 18.46 °C. As it can be observed it is closer to the patterns that occurred on the second and third day. Hence, AFLM does not accommodate to the average value of three daily occurrences (19.33 °C). In this way we can save more energy, while the adapted set point is still in thermal comfort interval ($18 \leqslant$ PPD $\leqslant 19.5$ °C). Furthermore, referring to Table 9, the AFLM adapted value for the days after Wednesday cluster (start time of set point changing) is 1:06 A.M. which, in fact is closer to the habits on second and third days. Hence, AFLM does not adapt to the average value of three daily occurrences, which is 1:25 A.M.

As a result, the 'start time' is not affected by a change of pattern on first day of occurrence 2:30 A.M. the AFLM adapts to the value that is closer to the typical user preferences observed during the first and third occurrence, and at the same time leads to energy saving because it reduces the adapted set point 19 min earlier than average value.

Furthermore, the AFLM adapted value for 'end time' for next days is 3:30 A.M. while the average value is 3:15 A.M. Therefore, the 'end time' is not influenced by a change of pattern on the third day 2:45 A.M. AFLM accommodates to the value that is closer to frequent user preferences recorded during the first and second occurrence. In addition, the adapted set point related to 'end time' is 20.8 °C. Hence, the set point is not influenced by the changes of preferences on the first and third habits which are 23 °C. Therefore, the adapted values for 'end time' and its corresponding set point value result in more energy saving because the set point remains longer on the adapted value that is lower than overridden set points (last two columns). Furthermore, one of the main advantages of the developed AFLM was that the user thermal comfort was not threatened during the process. Instead, occupant's preferences were maintained, while energy savings were achieved.

6. Conclusion

This paper presented an implementation of adaptable autonomous approach utilizing fuzzy logic and wireless sensors capabilities in smart grids to develop an 'adaptable smart thermostat' for residential energy management. The result of SFLL performance added to the thermostat for load reduction with respect to energy saving for one month simulation was around 21.3%, where any interaction on user side for modifying the set points in response to input parameters was not required.

Furthermore, in the cases that the user overrode the initialized set points both in 'Manual Mode' and 'Autonomous Mode', an AFLM was developed in order to adapt to new user's habit changes. In order to verify the functionality of AFLM with respect to adaptability and energy saving; multiple changes were applied to user schedule and preference changes. The results from a two months simulation with and without enabling AFLM showed that the relative energy saving for only adapting to a very limited time compared to without enabling AFLM was 1.03% saving, while the learning and adapting process was taken place as well.

Moreover, it was observed when the 'Autonomous Mode' was the user preferred mode; the thermostat equipped with AFLM was able to adapt to new schedules and preferences after three consecutive changes applied to elements of learning vectors. In this case, the adapted values of AFLM after one week training fell within the interval of the 95% 'fuzzy confidence interval' of the sample mean values. Thus, it implied that AFLM adapted to the value(s) which is close to frequent habits, while the adapted set point(s) was in thermal comfort-zone. In addition, the adaptable autonomous thermostat reduced the adapted set point earlier than average approach, and in this case the thermostat also remained longer on the adapted set point which resulted in more energy saving and conservation.

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