

Intelligent Home Heating Controller Using Fuzzy Rule Interpolation

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Abstract—The reduction of domestic energy waste helps in achieving the legal binding target in the UK that CO₂ emissions needs to be reduced by at least 34% below base year (1990) levels by 2020. Space heating consumes about 60% of the household energy consumption, and it has been reported by the Household Electricity Survey from GOV.UK, that 23% of residents leave the heating on while going out. To minimise the waste of heating unoccupied homes, a number of sensor-based and programmable controllers for central heating system have been developed, which can successfully switch off the home heating systems when a property is unoccupied. However, these systems cannot successfully efficiently preheat the homes before occupants return without manual inputs or leaving the heating on unnecessarily longer than needed, which has limited the wide application of such devices. In order to address this limitation, this paper proposes a smart home heating controller, which enables a home heating system to efficiently preheat the home by successfully predicting the users' home time. In particular, residents' home time is calculated by employing fuzzy rule interpolation, supported by users' historic and current location data from portable devices (commonly smart mobile phones). The proposed system has been applied to a real-world case and promising result has been generated.

I. INTRODUCTION

The advance of smart home appliance control plays a key role in improving the current environmental issues by reducing unexpected domestic energy wastes which have greatly contributed to excessive carbon emissions. Typical domestic energy wastes include heating unoccupied homes, washing very few clothes for too long, unnecessary low temperature for fridges and freezers, and lighting unoccupied rooms [7]. Noticing that home heating uses more energy than any other residential energy expenditure, including air conditioning, water heating, and appliances [5], research on the reduction of heating unoccupied homes is of great importance. Human motion sensors have been commonly used in home heating control to detect if a home is occupied or not. If the home is not occupied, the heating system will usually be turned off or keep a minimum temperature, and otherwise the system will be on.

Two important drawbacks have limited the wide application of sensor-based home heating controllers. Firstly, residents may suffer from low temperature if heating systems are simply controlled by motion sensors. This is because it takes time to heat the home to a certain comfortable temperature and the home can be very cold when the residents just arrive home. Another important limitation of the sensor-based systems is

that the sensors can only be triggered by human activities, which means they can only deal with situations that users are within the sensor's coverage. In order to address this, a number of programmable controllers for central heating systems have been proposed in the literature [8], [15], [17], [21], [24], which are usually developed based on the assumption that residents in a property have a fixed and simple living pattern. These systems have gained different levels of success by providing some intelligence to control home heating systems to minimise the wastes of heating unoccupied homes.

Fundamentally, the existing programmable heating controllers can be grouped in to two classes, which are schedule-based and learning-based [14]. Schedule-based controllers require pre-configured timetables made by home users [17], [19]. The heating system follows exactly the scheduled time which is independent with the users' current situation. As a consequence, the system will waste domestic energy by heating unoccupied home when no resident is at home or close to get home. Also, the residents may suffer if they arrive home earlier than scheduled. In this case, the residents may manually turn the heating system on, but they will still suffer for the period of time before the home is properly heated as it takes time to heating the home to a comfortable temperature. Learning-based controllers are able to automatically make a heating schedule by learning the users' habits, such as satisfied room temperature and regular daily routine for a period of time [15], [21]. Different with the schedule-based controllers, this type of controllers require a number of sensors to detect human's activities, and thus this system can be seen as a combination of sensor-based controller and schedule-based controller, which enjoys the advantages of both. However, it still cannot solve the problem of preheating homes for the situations of getting home earlier than the schedule.

This paper proposes a novel smart home heating control system by efficiently utilising the personal data captured in smart portable devices. It is able to successfully preheat the home by predicting when the residents will arrive home and thus to address the limitation of the existing heating controllers by using it as a complementary part of the existing ones. Noticing that fuzzy systems have been successfully applied to many real-world control problems, fuzzy inference system is also employed in this work. Given the complexity of the problem dealt with herein, a large number of fuzzy rules are expected if a traditional fuzzy inference system, such as Mamdani [16] or TSK [23], is utilised. Therefore, Fuzzy rule interpolation (FRI) [13], [10], [11] is selected in this work,

which can reduce the complexity of traditional fuzzy module by omitting those rules in the fuzzy rule base which can be approximated by their neighbors.

The rest of the paper is structured as follows. Section II introduces the theoretical underpinnings of fuzzy rule interpolation (FRI), with a focus on transformation-based FRI that has been used in this work. Section III presents the proposed intelligent home heating system in detail. Section IV applies the proposed system to a real world case for demonstration and validation. Section V concludes the paper and suggests a number of future work directions.

II. FUZZY RULE INTERPOLATION

Fuzzy rule interpolation strengthens the power of fuzzy inference. When given observations have no overlap with any rule antecedent values, no rule can be fired in classical inference systems. However, fuzzy interpolation through a sparse rule base may still obtain certain conclusions and thus improve the applicability of fuzzy models. Also, with the help of fuzzy interpolation, the complexity of an inference system can be reduced by omitting those rules which may be approximated with their neighbouring ones. Various interpolation methods have been developed [12], [18], which can be categorised into two classes with several exceptions (such as type II fuzzy interpolation [4], [25]).

The first class of approaches are able to directly interpolate rules whose antecedent variables are identical to the observed. The most typical approach in this group is the very first proposed fuzzy interpolation[13], denoted as the KH approach, which was developed based on the Decomposition and Resolution Principles[20], [30]. According to these principles, each fuzzy set can be represented by a series of α -cuts ($\alpha \in (0, 1]$). Given a certain α , the α -cut of the consequent fuzzy set is calculated from the α -cuts of the observation and all the fuzzy sets involved in the rules used for interpolation. Knowing the α -cuts of the consequent fuzzy set for all $\alpha \in (0, 1]$, the consequent fuzzy set can be assembled by applying the Resolution Principle. Approaches such as[3], [9], [29] also belong to this group.

The second type of fuzzy interpolation is based on the analogical reasoning mechanism [2] and therefore, referred to as “analogy-based fuzzy interpolation”. Methods of this type work by first creating an intermediate rule such that its antecedent is as “close” (given a fuzzy distance metric) to the given observation as possible. Then, a conclusion is derived from the given observation by firing the generated intermediate rule through the analogical reasoning mechanism. That is, the shape distinguishability between the resultant fuzzy set and the consequence of the intermediate rule is analogous to the shape distinguishability between the observation and the antecedent of the generated intermediate rule. A number of ways to create an intermediate rule and then to infer a conclusion from the given observation by the intermediate rule have been developed in the literature, including[1], [10], [22]. In particular, the scale and move transformation-based FRI with triangle fuzzy sets has been employed in this work, this approach is introduced in detail as follows.

Suppose that two fuzzy rules R_i and R_j ($i, j \in \mathbb{N}$) are given as:

R_i : **IF** X_1 is A_{1i} and X_2 is A_{2i} and ... and X_m is A_{mi} ,
THEN Y is B_i
 R_j : **IF** X_1 is A_{1j} and X_2 is A_{2j} and ... and X_m is A_{mj}
THEN Y is B_j ,

where each fuzzy set A_{kl} , ($k = \{1, 2, \dots, m\}, l = \{i, j\}$) has a triangular membership function and conveniently denoted as (a_{kl}, b_{kl}, c_{kl}) . Given observations $(A_1^*, A_2^*, \dots, A_m^*)$, the calculation process of the conclusion using FRI is summarised as the following steps.

Step 1: Calculate the *representative value* of each given antecedent variable A_{kl} using Equation 1, and do the same for the given observation.

$$Rep(A_{kl}) = \frac{a_{kl} + b_{kl} + c_{kl}}{3} \quad (1)$$

Step 2: Calculate the *relative placement factor* λ_k , by Equation 2 based on the relative location of the observation regarding to the two antecedents, and then calculate the average $\lambda_{average}$ for later use.

$$\lambda_k = \frac{d(Rep(A_{ki}), Rep(A_k^*))}{d(Rep(A_{kj}), Rep(A_k^*))}, \quad (k = 1, 2, \dots, m) \quad (2)$$

Step 3: Based on λ_k calculated above, obtain the antecedents of the new intermediate rule A'_k by Equation 3.

$$A'_k = (1 - \lambda_k)A_{ki} + \lambda_k A_{kj} \quad (3)$$

Step 4: By comparing the size of A'_k and A_k^* , obtain the *Scale Rate* S_k using Equation 4.

$$S_k = \frac{c'_k - a'_k}{c_k^* - a_k^*}, \quad (4)$$

Step 5: Obtain the average of *Scale Rate* $S_{average}$ based on the $S_1 \dots S_m$ calculated above.

Step 6: Apply scale rate S_k to A'_k to obtain A''_k by Equation 5, 6, 7 ($k = 1, 2, \dots, m$).

$$a''_k = \frac{a'_k(1 + 2S_k) + b'_k(1 - S_k) + c'_k(1 - S_k)}{3} \quad (5)$$

$$b''_k = \frac{a'_k(1 - S_k) + b'_k(1 + 2S_k) + c'_k(1 - S_k)}{3} \quad (6)$$

$$c''_k = \frac{a'_k(1 - S_k) + b'_k(1 - S_k) + c'_k(1 + 2S_k)}{3} \quad (7)$$

Step 7: By comparing the shapes of A_k^* and A''_k , obtain *Move Transformation Rate* M_k , then calculate the average of move transformation rate $M_{average}$ for later use.

$$M_k = \begin{cases} \frac{3(a''_k - a_k^*)}{b''_k - a_k^*}, & \text{if } a''_k \geq a_k^* \\ \frac{3(a_k^* - a''_k)}{c_k^* - b''_k}, & \text{if } c''_k \leq a_k^* \end{cases} \quad (8)$$

Step 8: To compute B' from the rule consequences using Equation 3 based on the $\lambda_{average}$ calculated above.

Step 9: Finally, the fuzzy set B^* of the conclusion can then be estimated by apply $S_{average}$ and $M_{average}$ on B'

III. SMART HOME HEATING CONTROLLER

Most UK houses have a central heating system that uses a boiler to heat the water supply for heating. The boiler does not usually provide a user-friendly interface to adjust the output power, and thus the easiest way to adjust the rooms temperature is to control the time duration of the boiler burning. The proposed smart home heating controller in this work only concerns this type of house heating systems by deciding if the boiler should be on or off, though it can be readily extended for other types.

A. The Framework

A number of smart home heating controllers [8], [15], [17], [21], [24] have been developed to deal with the situations when the residents are at home; this work therefore only focuses on the development of decision making when home users are away. This is achieved by predicting if the heater should be turned on to preheat the home such that the home temperature can reach a certain comfortable level when the residents arrive home. Whether the resident is at home or not can be detected by checking if the resident's smart portable device is connected to the home Wi-Fi. The decision making procedure is triggered once the resident's portable device is disconnected from home Wi-Fi, and it terminates when the resident arrives home. The flow chart of the decision making procedure for the proposed home heating controller is illustrated in Fig. 1.

The controller first extracts the resident's location and moving information. There are four types of residents' location and moving information need to be considered: At Home, Way Back Home, Leaving Home, and Static (i.e. at Special Location). The users current location and moving states are obtained effectively using the GPS information provided by user's portable devices. From this, if the resident's current state is At Home, the algorithm terminates; and if the residents' current state is Leaving Home, that is the residents are moving away from home, the boiler is off and the system will check the resident's location and moving information again in a certain period of time. Otherwise, the time to arriving home (denoted as T_{AH}) is predicted and the time to preheat the home to a comfortable temperature (denoted as T_{PH}) is also calculated, based on the resident's current situation and the current environment around home. If T_{AH} is not greater than T_{PH} , the boiler will be turned on and the system will check this again in a certain period of time. The details of the important steps in this procedure are explained below.

B. Location Information Processing

As stated earlier, there are four different situations that a user normally has based on the location data. In particular, the situation of static represents that the user either is stuck in the traffic or at some special locations for particular activities, such as shopping in a supermarket or dining in a restaurant. In order to obtain the user's current state, a comparison algorithm, as shown in Fig.2, was developed to verify which situation the user currently belongs to. In the algorithm, the *Google Distance Matrix API* was employed here to calculate the real travel distance and time duration between user's current location and home. As different travel modes, including driving, walking and bicycling, will result in different travel

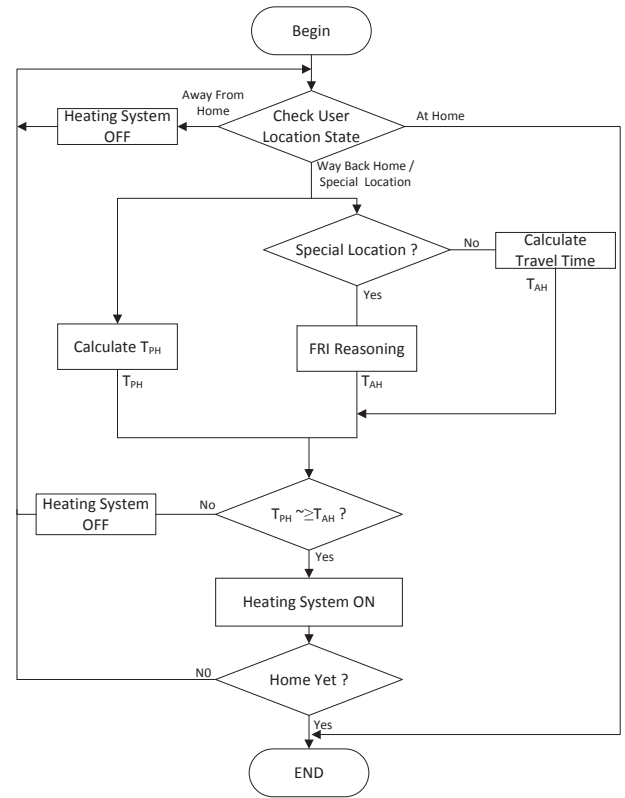


Fig. 1. The Overall Work Flow

distances and times, naive Bayes classifier [6] is applied to the current and past location information to obtain the user's current travel modes. Then the detected travel mode is used as a parameter passed to *Google Distance Matrix API* to estimate travel distance and time. The distance and duration will be recorded continuously based on an adjustable time interval to determine the users current state. In particular, when the current distance from home is continuously three times greater than the previous ones, the user state will be classed as Away From Home. Similarly, if the current distance from home is continuously three times less than the previous ones, it is believed the resident is on their Way Back Home. Otherwise, if the past four captured distances are roughly equal to each other, the system will then knowledge that the user is under a special event. At Home state can be verified based on the condition that either the distance is zero or the user's mobile device is connected to the home Wi-Fi.

The times spent on different locations can vary significantly, and also different residents usually spend different amount of times at the same special location as people have their own living styles or patterns. In order to predict the time that a particular resident is most likely to spend at a special location, the resident's historical GPS data can help. The historical GPS data either can be stored at smart portable devices, such as a mobile phone, or can be deliberately captured for the proposed system. Once the historical GPS data is obtained, data mining techniques can be used to extract the time spending information for different types of locations. For simplicity, this work assumes that the resident only go for shopping on their way back home, and all residents spend the same amount

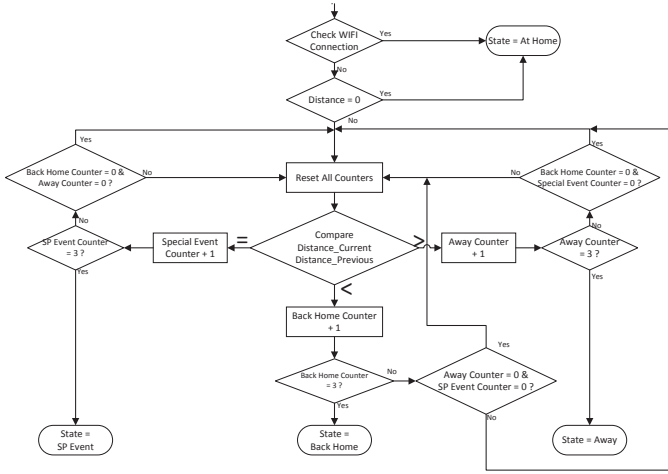


Fig. 2. Comparison Algorithm

of time at the same type of stores. *Google Place API* is applied herein to achieve the home user's current location. A systematic study of the time spent on different type of locations based on the demographic classification may greatly improve the performance of the controller, which remains as future work.

C. Time to Home Estimation

Due to the difficulty to model the residents' behavior using traditional mathematical modeling led by uncertainty and complexity, fuzzy inference systems is employed in this work to predict the time duration before residents getting home. By using fuzzy inference systems, residents' behavior pattern can be modeled as fuzzy rules, which can be readily transferred from natural language description. The fuzzy inference engine takes five fuzzy inputs and produces one fuzzy output which is the estimate of the time to getting home.

$x_{Location}$: The time spent in stores will directly affect the time to getting home. In this work, Tesco store system is used to represent different types stores: Superstore, Extra, Metro, and Express, which are represented as triangular fuzzy sets. In other words, the 4 types of Tesco stores are used in this system to represent the domain of variable location.

x_{Days} and x_{Time} : Time spent at the same location will normally be different during different times of the day, and different days of the week. For example, people usually spend longer at supermarket on the weekends than that on week days. 7 fuzzy sets have been pre-defined to partition the domain of variable x_{Days} to represent seven days a week (Monday to Sunday), and 13 fuzzy sets are defined for the domain of variable x_{Time} to represent a day.

x_{Spent} : The amount of times has already been spent on the location is another factor to affect the time of travel to home. In this work, 13 triangle fuzzy sets are designed for this input variable to represent real time value between 0 and 60 minutes. It is simply fuzzified from crisp data which are obtained by personal portable devices.

x_{Travel} : This input variable is used to identify the travel time between user's current location and home based on the

current traffic situation. It is fuzzified from a crisp data which is returned by *Google Distance Matrix API*. 13 fuzzy sets are designed for this fuzzy input variable to represent between 0 and 60 minutes, as most of the properties can be preheated within an hour.

x_{AH} : The proposed fuzzy inference engine is to predict the time span from the moment of the prediction made to the residents getting home. This variable domain is partitioned by 13 different linguistic values which represent the time period of 0-120 minutes. During defuzzification, the linguistic values (T_{AH}) are converted to a crisp value using the center of gravity. The domain partition of input and output variables are shown in the Fig. 3. Based on the above description, 61,516

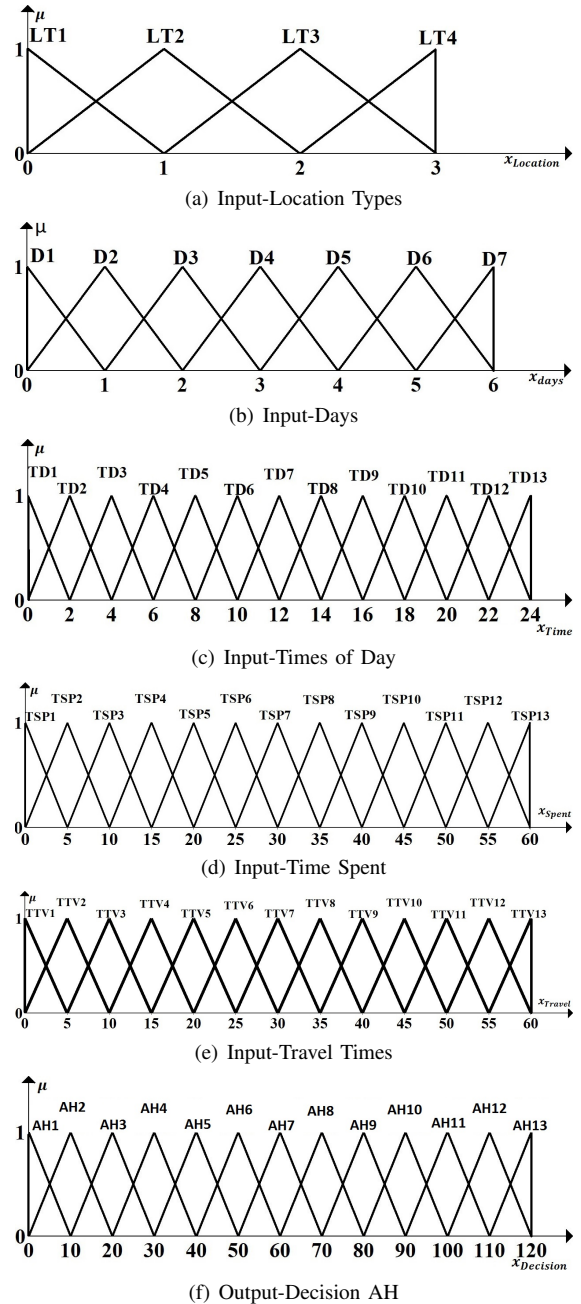


Fig. 3. Fuzzy Variables

rules are needed to fully cover all the situations. In order to simplify the system and to preserve the transparency of fuzzy inference systems, fuzzy rule interpolation is employed in this work thanks to its ability in reducing system complexity by omitting those rules which can be represented by their neighbors. Therefore, 72 of the most important rules have been selected for fuzzy rule interpolation, which are listed in Table I. In this table, *LT* represents Location Types; *D* represents Days; *TD* represents Times of Day; *TSP* represents Time Spent; *TTV* represents Travel Time; and *AH* represents the Final Decision AH. The numbers in the table represent the corresponding fuzzy variables as illustrated in Fig. 3. Given the robustness and generality of the scale and move transformation based fuzzy rule interpolation approach, it is employed in this work to predict the time of getting home.

No.	IF					THEN	No.	IF					THEN
	LT	D	TD	TSP	TTV	AH		LT	D	TD	TSP	TTV	AH
1	1	1	1	1	1	2	37	4	1	1	1	5	
2	1	1	1	1	13	8	38	4	1	1	13	13	
3	1	1	1	13	1	1	39	4	1	1	13	1	
4	1	1	1	13	13	7	40	4	1	1	13	13	
5	1	1	10	1	1	3	41	4	1	10	1	6	
6	1	1	10	1	13	9	42	4	1	10	1	13	
7	1	1	10	13	1	1	43	4	1	10	13	1	
8	1	1	10	13	13	7	44	4	1	10	13	13	
9	1	1	13	1	1	2	45	4	1	13	1	5	
10	1	1	13	1	13	8	46	4	1	13	1	13	
11	1	1	13	13	1	1	47	4	1	13	13	1	
12	1	1	13	13	13	7	48	4	1	13	13	13	
13	1	5	1	1	1	3	49	4	5	1	1	5	
14	1	5	1	1	13	9	50	4	5	1	1	13	
15	1	5	1	13	1	1	51	4	5	1	13	1	
16	1	5	1	13	13	7	52	4	5	1	13	13	
17	1	5	10	1	1	4	53	4	5	10	1	7	
18	1	5	10	1	13	10	54	4	5	10	1	13	
19	1	5	10	13	1	1	55	4	5	10	13	1	
20	1	5	10	13	13	7	56	4	5	10	13	13	
21	1	5	13	1	1	3	57	4	5	13	1	5	
22	1	5	13	1	13	9	58	4	5	13	1	13	
23	1	5	13	13	1	1	59	4	5	13	13	1	
24	1	5	13	13	13	7	60	4	5	13	13	13	
25	1	7	1	1	1	2	61	4	7	1	1	5	
26	1	7	1	1	13	8	62	4	7	1	1	13	
27	1	7	1	13	1	1	63	4	7	1	13	1	
28	1	7	1	13	13	7	64	4	7	1	13	13	
29	1	7	10	1	1	3	65	4	7	10	1	6	
30	1	7	10	1	13	9	66	4	7	10	1	13	
31	1	7	10	13	1	1	67	4	7	10	13	1	
32	1	7	10	13	13	7	68	4	7	10	13	13	
33	1	7	13	1	1	2	69	4	7	13	1	5	
34	1	7	13	1	13	8	70	4	7	13	1	13	
35	1	7	13	13	1	1	71	4	7	13	13	1	
36	1	7	13	13	13	7	72	4	7	13	13	13	

TABLE I. FRI RULES

D. Preheat Time Calculation

The rate of home temperature increasing (i.e., the time takes for the house to heat up by 1°C) is not linear and several factors can affect it such as the weather, the outside temperature, the efficiency of radiator, the insulation of walls, and the output power of the home boiler. A higher current inside temperature will lead to a much longer increasing rate. For simplifying, this work assumes that the boiler, radiators, and the wall insulation are selected and installed based on the UK standard, and other factors such as the weathers and the outside environment will not be considered in this work. This assumption has been commonly used in the literature. For example, a Heating Gain Table has been created based on the collected temperature data in the house over 3 days in the work of [21]. This work adapts a similar approach and creates a heating gain table based on a 4-bedrooms detached house with a total floor area of 100 m² and a ceiling height of 2.4 meter. The heating gain table, as shown in Table II, was created based on the collected data over 3 days by employing the average principal.

Temperature Range	Time Required
Boiler initialise / pre heat	5 Minutes
15°C-16°C	8 Minutes
16°C-17°C	8 Minutes
17°C-18°C	8 Minutes
18°C-19°C	12 Minutes
19°C-20°C	17 Minutes
20°C-21°C	28 Minutes

TABLE II. HEATING GAIN TABLE

E. Decision Making

A final ON/OFF decision for boiler can be made by comparing the time to getting home (T_{AH}) and the time needed for preheating home (T_{PH}). In particular, when $T_{PH} \geq T_{AH}$, the boiler will be on based on the current situation. The system will continue checking the user's and home's states and making decisions for the home heating system in a certain frequency until At Home state is triggered. From this, all the GPS location checking will be temporarily stopped until the state of user's mobile device disconnected from home Wi-Fi network again. Surely, if the user is far away from home, the FRI system will keep home heating system staying on OFF position to save the energy usage.

IV. EXPERIMENTATION

The proposed system has been applied to a real-world situation for the purposes of validation and evaluation. Suppose that the residents are on their way back home by driving from location A at 12:00PM on Wednesday, as shown in Fig. 4. As location A is far away from home, the current heating is OFF. During the traveling, user's GPS location data will be obtained and sent back to the heating control system by the mobile device in every two minutes. Based on returned information, user traveling time and estimated time of arrival could be obtained by the designed algorithm as shown in Fig. 1. The testing house environment is a new built 4-bedroom detached house, and the total heating area is about 100 m² with 2.4 meter ceiling height. The output power of the heating boiler is 15KW. The home temperature at was 16°C, and user's satisfied temperature has been set up to 20°C. Based on Table II, T_{PH} can be calculated which is $T_{PH} = 50$ minute. Five different time points during the traveling have been selected to demonstrate the working progress of the system.

A. Time Point 1

Based on the GPS data in the user's portable device, the comparison algorithm shown in Fig. 2 is used to detect home user's state, that is currently on the way back home. Then, the returned strings from *Google Place API* are checked to see if the user has gone for shopping, and in this case the user does not go for any shops. As no special location event occurred, the time getting home (T_{AH}) is the same as the travel time which is provided by *Google Distance Matrix API*. In this case, $T_{AH} = 60$ minutes. As mentioned above, the T_{PH} has already be calculated based on the current situation of the home and its environment, which is $T_{PH} = 50$ Minutes. It is obvious in this case that $T_{AH} > T_{PH}$. Therefore, the system turned the home heating system off and waited for the next cycle of location checking and decision making. The decision making process is summarised as follows:

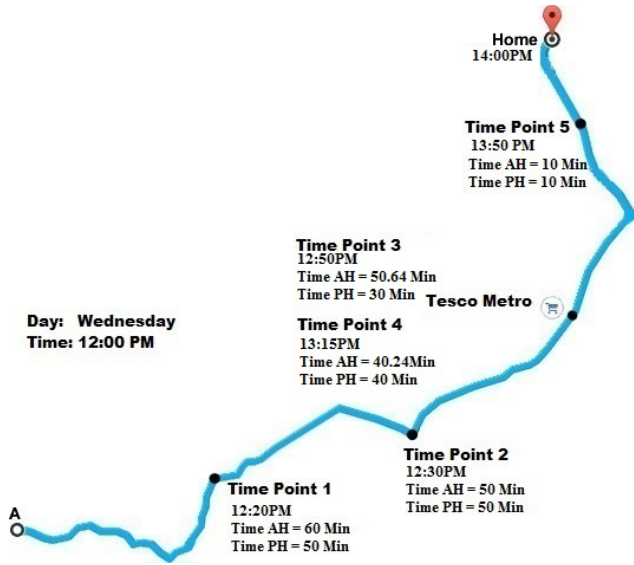


Fig. 4. The Map Used in the Experimentation

- 1 User State → Way Back Home
- 2 Special Location ? → No
- 3 Calculate T_{AH} → $T_{AH} = 60Min$
- 4 Calculate T_{PH} → $T_{PH} = 50Min$
- 5 Compare T_{AH}, T_{PH} → $T_{AH} > T_{PH}$
- 6 Heating → Turn OFF

B. Time Point 2

During the traveling, the users were getting closer to home. At the time point 2, the returned $T_{AH} = 50Minutes$, which is equal to T_{PH} . the system will then decide to turn the home heating system on to per-heat the room, the progress shows below.

- 1 User State → Way Back
- 2 Special Location ? → No
- 3 Calculate T_{AH} → $T_{AH} = 50Min$
- 4 Calculate T_{PH} → $T_{PH} = 50Min$
- 5 Compare T_{AH}, T_{PH} → $T_{AH} = T_{PH}$
- 6 Heating → Turn ON
- 7 Home Yet ? → No

C. Time Point 3

The system keeps running to check user's location data during the traveling, and in a particular time point 3, the system detected that the user went to a shop which equivalent to Tesco Metro, based on the returned location information by *Google Place API*. The system timer shows user has stayed in for 5 minutes. In this particular case, the transformation-based FRI was employed to estimate the home time. In particular, the observation is ($A_1^* = (1, 2, 3)$, $A_2^* = (1, 2, 3)$, $A_3^* = (10, 12, 14)$, $A_4^* = (0, 5, 10)$, $A_5^* = (25, 30, 35)$), which does not overlap with any rule antecedent. The two closest neighbouring rules used for interpolation are $A_{11} \wedge A_{21} \wedge A_{31} \wedge A_{41} \wedge A_{51} \Rightarrow B_1$, $A_{12} \wedge A_{22} \wedge A_{32} \wedge A_{42} \wedge A_{52} \Rightarrow B_2$, as shown in Fig. 5. In this case, based on Equation 2, the relative placement factors can be calculated: $\lambda_1 = 2.5$, $\lambda_2 = 0.83$, $\lambda_3 = 1.89$, $\lambda_4 = 15.5$, $\lambda_5 = 1$, and the average $\lambda_{ave} = 4.34$ was used to calculate the intermediate rule result B' . Then,

based on the calculated $\lambda_i, i = (1, 2, 3, 4, 5)$, the obtained scale rate for each variables (Equation 4) are $S_1 = 0.5$, $S_2 = 0.92$, $S_3 = 1.57$, $S_4 = 1.67$, and $S_5 = 0.46$. The average of scale rate is $S_{ave} = 1.02$, works together with the combined move ratio, which is 0.87 (the average of the five move ratios (0.70, 0.27, 1.40, 0.62, 1.37)), are employed to achieve the final result B^* , which is $B^* = (40.64, 50.64, 60.64)$. The center of gravity principle was used to defuzzify the generated result, then $T_{AH} = 50.64 minutes$ has been generated. This value is then compared with T_{PH} . Because the home heating system has been turned on at Time Point 2 for a while, T_{PH} was re-calculated which is currently $T_{PH} = 30$, and thus $T_{PH} < T_{AH}$. The system then turned the home heating system off immediately and returned to beginning to prepare for next prediction cycle.

- 1 User State → Way Back
- 2 Special Location ? → Yes
- 3 FRI Reasoning → $T_{AH} = 50.64Min$
- 4 Calculate T_{PH} → $T_{PH} = 30Min$
- 5 Compare T_{AH}, T_{PH} → $T_{AH} > T_{PH}$
- 6 Heating → Turn OFF

D. Time Point 4

At the Time Point 4, 25 minutes ($T_{Spend} = 25Minutes$) has been spent in the shop, and T_{PH} has changed to 40 minutes as the heating did not turn on for $T_{Spend} = 25Minutes$. At this time point, the generated result from FRI reasoning was 40.24 Minutes, which is less than the T_{PH} . The system therefore turned the heating system back on. Table III summaries the results of FRI reasoning. As the user was still in the shop, the system will check about the users' state until they return home.

- 1 User State → Way Back
- 2 Special Location ? → Yes
- 3 FRI Reasoning → $T_{AH} = 40.24Min$
- 4 Calculate T_{PH} → $T_{PH} = 40Min$
- 5 Compare T_{AH}, T_{PH} → $T_{AH} \sim T_{PH}$
- 6 Heating → Turn ON
- 7 Home Yet ? → No

Antecedents		Observation
$A_{11} = (0, 0, 1)$	$A_{12} = (2, 3, 3)$	$A_1^* = (1, 2, 3)$
$A_{21} = (0, 0, 1)$	$A_{22} = (3, 4, 5)$	$A_2^* = (1, 2, 3)$
$A_{31} = (0, 0, 2)$	$A_{32} = (16, 18, 20)$	$A_3^* = (10, 12, 14)$
$A_{41} = (0, 0, 5)$	$A_{42} = (55, 60, 60)$	$A_4^* = (20, 25, 30)$
$A_{51} = (0, 0, 5)$	$A_{52} = (55, 60, 60)$	$A_5^* = (25, 30, 35)$
$B_1 = (10, 20, 30)$	$B_2 = (50, 60, 70)$	
Results		$B^* = (30.24, 40.24, 50.24)$

TABLE III. FRI REASONING FOR TIME POINT 4

E. Time Point 5

The home users traveled again after the shopping. At Time Point 5, the system detected that the user is on the road traveling back home, and T_{AH} is 10 minutes. T_{PH} is also updated to 10 minutes in this case. Therefore, after the comparison, home heating system is still on and users' current state does not meet the at home state yet. The system continue making decisions until the users return home.

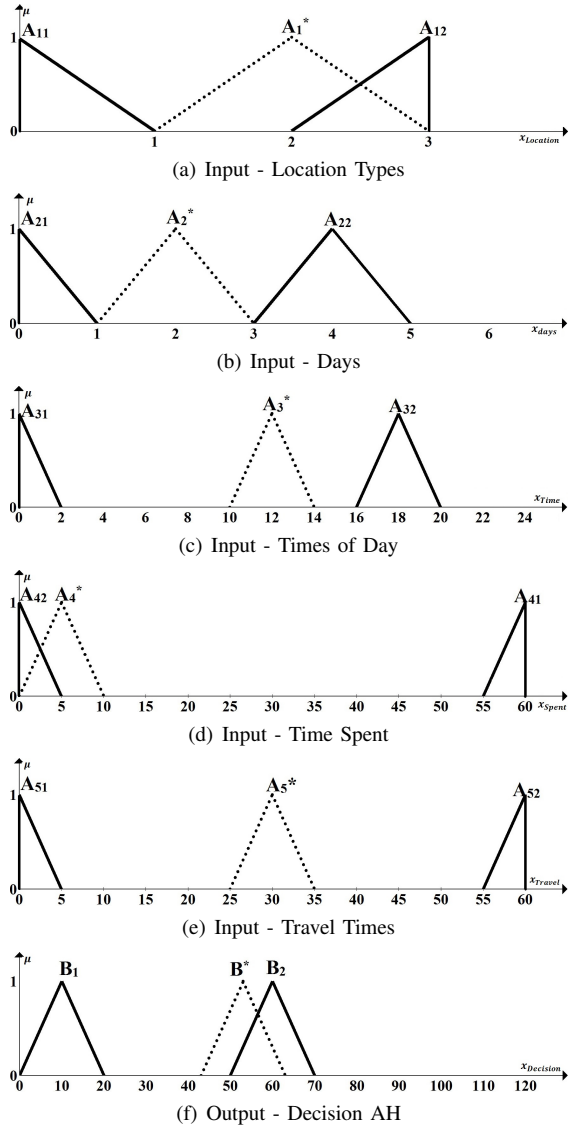


Fig. 5. Example of Fuzzy Rule Interpolation

- | | | | |
|---|--------------------------|---|-------------------|
| 1 | User State | → | Way Back |
| 2 | Special Location ? | → | No |
| 3 | Calculate T_{AH} | → | $T_{AH} = 10Min$ |
| 4 | Calculate T_{PH} | → | $T_{PH} = 10Min$ |
| 5 | Compare T_{AH}, T_{PH} | → | $T_{AH} = T_{PH}$ |
| 6 | Heating | → | Turn ON |
| 7 | Home Yet ? | → | No |

At 14:00PM, the users finally reach the At Home state as the mobile device was connected to the home Wi-Fi system. In the above case, the users came back home about 40 minute later than their normal schedule because of shopping. Although home heating system has been turned on at Time Point 2 for about 20 minutes, it was turned off for about 15 minutes immediately after a special location event was detected at Time Point 3. When users arrived home, the house temperature has just been pre-heated to the desired temperature which is 20°C. The system let the users benefit from warm home but avoid energy waste.

F. Discussion

Most of the home heating controllers in the UK are schedule-based, and they do not have any learning method to acquire users' occupancy activity. Home heating system are controlled by the scheduled time period. Once ON/OFF time periods have been scheduled, users do not normally re-configure it again even some scheduled times have slightly changed. For the environment for the experimentation, a schedule-based system is also used. In particular, the schedule-based controller has been set to turn the heating On between 12:30PM and 13:20PM every day to increase house temperature as the users normally came back at 13:20. The different operations between schedule-based controller and the proposed system are listed in Table IV.

Time	Description	Schedule Based Operation	Proposed System Operation
12:00	Set Off	OFF	OFF
12:20	Time Point 1	OFF	OFF
12:30	Time Point 2	ON	ON
12:50	Time Point 3	ON	OFF
13:15	Time Point 4	ON	ON
13:20	Between TP4 and TP5	OFF	ON
13:50	Time Point 5	OFF	ON
14:00	At Home	OFF	OFF

TABLE IV. COMPARISON WITH SCHEDULE BASED CONTROLLER

The schedule-based heating controller is able to control the home heating system based on the pre-scheduled time table. In the above situation, home heating system has been turned on for 50 minutes in total by schedule-based controller. However, the home heating system was turned off 30 minutes before user came back home and heated unoccupied house for about 30 minutes. As a result, the home temperature did not reach the desired temperature when user came back home as the heating loss in the cold environment. The users have to manually turn the heating on for extra 15-20 minutes to reach the satisfied temperature when they came back home.

By the proposed system, although the heating has been turned on between Time Points 2 and 3 for 20 minutes, the proposed system managed to turn it off immediately when a special event has been detected. FRI system helps the proposed system to make the correct decision. Although the total heating time duration is 65 minutes which is longer than the perfect situation, home temperature can be just pre-heated to the desired temperature when user came back home and the total heating time is not longer than the schedule-based controller which discussed above.

A number of learning-based smart home central heating system controllers have been proposed, which are usually combined with some novel features such as schedule learning, remote access, and occupancy sensing with auto-away mode. Although the proposed system does not provide any of the above three functionalities, the proposed system is able to successfully predict the user's home time based on the data captured through portable devices, and thus to effectively and efficiently pre-heat the home, which may not be possible by other approaches.

V. CONCLUSION

This paper presented a smart home heating controller, which is able to control the heating system to preheat the property before home users getting home. The controller is developed by adapting fuzzy rule interpolation, supported by location information through portable devices. In particular, the system first predict the time before home users getting home; then the time to preheat home is approximated. If the predicted time to getting home is not greater than the time to preheat home, the heating system will be switched on. As shown in the demonstrative example, the proposed system is able to automatically provide a solution to preheat the home when there is a need, but not leaving the heating system on all the time resulting in energy waste. Therefore, by applying such a system, home users can enjoy the benefit of energy saving, but without sacrifice the quality of life by suffering from cold home during the home heating processes as most of properties with existing home heating controllers do.

The work can be further improved despite of its promising results. Pre-defined rule base with no learning ability may not be perfectly suitable for all users' situations, which may be solved by allowing dynamic and adaptive rule base generation based on users personal data. A big reduction in complexity of the fuzzy model (from 61,516 rules to 72 rules) has been achieved by employing fuzzy rule interpolation approach in proposed system. Further research could be made to compare the system efficiency between the traditional fuzzy model and proposed model. Also, it is possible that the home heating system does not turn on when user comes back or the heating system has been turned on too early, as the proposed system does not have any error correction function to solve such issues. Adaptive fuzzy interpolation approach [26], [27], [28] could be used to track the error back and modify the faulty part when incorrect results are generated. Finally, it would be very interesting to integrate the proposed controller into the NEST system to improve its performance.

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