A Fuzzy Logic Controller for Demand Side Management in Smart Grids

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Abstract: Smart Grid Demand Side Management is the effective way for energy providers to encourage their customers on reducing their consumption during peak loads through several Demand Response programs. In this paper, An Artificial Intelligence approach based on a Fuzzy Logic control system is proposed for the home appliance scheduling problem. This is typically used in Home Energy Management Systems for the control of Heating, Ventilation, and Air Conditioning Systems (HVAC). The simulation results demonstrate the capability of the proposed model to manage and control of HVAC systems in a smarter way than traditional techniques. Furthermore, a reduction of 18.33% in total hourly energy consumption has been obtained after introducing a new parameter among the fuzzy input variables.

1 INTRODUCTION

As a consequence of recent advancement in smart grid communication and information systems, demand-side management (DSM) has become an efficient tool that can manage peak energy demand. DSM aims to peak load demand reduction, energy consumption optimization, reshaping the demand load profile and improving the grid sustainability by minimizing the total cost and carbon emission rates. Dynamic DSM (DDSM) has been ignored for a long time due to the inability of predicting users' performance, poor computational techniques, and complexity of consumption dynamics. Nowadays, DDSM has attracted great attention as Demand Response (DR) programs target the end-user customers' response by making changes to their normal load profile which could lead to lower electricity usage when it is required, hence improving the system performance, reliability and sustainability.

There are three main categories of DSM techniques, residential, commercial and industrial energy management (Khan *et al.*, 2016). One of the major sectors in consuming energy is the residential sector. It is also expected that the residential electricity demand will keep increasing through the upcoming decades(J. Conti, P. Holtberg, J. Beamon, A. Schaal, 2010). In order to manage energy consumption in the residential sector, Home Energy Management Systems (HEMS) have been implemented. HEMS can be classified under three main categories: dynamic pricing schemes like Time of Use (ToU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP), appliances scheduling and load forecasting.

The heating, ventilation, and air conditioning (HVAC) systems are considered an important target for HEMS due to their huge share of the annual total energy consumption in the world. In traditional Building Automation Systems (BAS), users have the capability to manage and control their load consumption schedules manually through a single application. Today, they do not need anymore to physically interact with the system because of having Internet Of Things (IoT) based operating systems. According to (*Emerson Climate Technologies*, no date), 33% of thermostats sold in 2014 were wifi-enabled and this percentage will jump to 75% in 2019. IoT has several benefits for HVAC systems such as: real-time monitoring, total controllability, remote diagnostics, inherent connectivity, system adaption, increased efficiency, continuous comfort and predictive maintenance. Monitoring systems play a vital role in smart grids as they help to keep the system supervised and controlled all the time. Thus,

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smart meters are commonly used for recording customers' energy consumption and send it as meter readings to be transmitted as electronic signals to the energy provider. Furthermore, using smart sensors, actuators and controllers would help internet-based systems to measure many parameters like temperature, humidity, and air flow and predict other external factors such as, weather forecast. Thus, IoT is mainly considered in forming the connection with objects and with each other. It is not only a connected system, it is a more intelligent environment involved in constant communication.

It is expected that the increasing number of smart HVAC systems will affect the pattern of the electrical grid. Thus, various techniques have been proposed in order to tackle related problems (Mirinejad *et al.*, 2008). In this paper, a DMS strategy is proposed for managing the HVAC systems in smart grids. In the proposed strategy, an appliance scheduling algorithm based on a modified fuzzy logic control system, that maintains the comfort level of end-use customers saturated, is introduced considering a new input parameter for the controller.

The rest of this paper is organized as follow. Section 2 represents the literature review. In Section 3, the model description of house heating system is presented. Section 4 introduces the proposed algorithm. Section 5 discusses the simulation results. Finally, conclusion and future work are explained.

2 REVIEW OF LITERATURE

Recent energy management systems aim to offer efficient advantages for both the customers and the utility. For the customer side, many studies based on applying DR program have been proposed. DR programs depend basically on motivating a customer to reduce his consumption during peak periods. On the other hand, it has to keep the level of customer comfort satisfied. (Paterakis, Erdinç and Catalão, 2017) presented a survey of technologies, programs, consumer response categories of DR and the corresponding benefits and barriers from DR programs application. Moreover, (Siano, 2014) proposed a review on DR classification and techniques regarding real case studies and research projects.

Customer response for such DR programs may differ according to customer profile. For residential customers, it is more appropriate to apply Direct Load Control (DLC) incentive-based and price-base DR programs. Recently, in (Shakeri *et al.*, 2018), an adaptive HEMS control system was proposed to manage and schedule the electric appliances in order to reduce the electricity consumption and corresponding cost. A TOU pricing model was implemented that resulted in a cost reduction of 14% with ensuring the user comfort. An intelligent algorithm that could help users to Handle their consumption rates was presented in (Fotouhi Ghazvini *et al.*, 2017). Both RTP and TOU DR programs were investigated in addition to an incentive-based program. The results showed that the incentive-base DR program can perform better than the RTP-based one under the pricing scheme of TOU strategy. Furthermore, in (Wang *et al.*, 2018), a multi-agent system was established to investigate several types of load demand in multi-agent household considering the price-based DR scheme. They concluded that shiftable loads outperform other loads in DR potential and cost saving, while the sheddable loads are better for energy saving. A structure of an HEMS with reference to the management process of thermostatically and non-thermostatically loads was introduced in (Paterakis *et al.*, 2015) under load shaping and day-ahead pricing DR strategies. Similarly, a classification of residential smart appliances was proposed in (Qu *et al.*, 2018). Moreover, an optimal control algorithm was submitted through day-ahead electricity prices and real-time incentive measures.

An HVAC system is considered to have a great attention of appliance scheduling systems due to their widely spread over the world. (Sala-Cardoso *et al.*, 2018) introduced a data-driven based model for the short-term load prediction of the HVAC systems in smart homes. In (Adhikari, Pipattanasomporn and Rahman, 2018), a hybrid algorithm based on both greedy and binary search algorithms was proposed to control and monitor HVACs. Their algorithm is based on DLC DR scheme by using IoT-based thermostats.

Fuzzy set theory was introduced by (Zadeh, 1965) to tackle uncertainties and vague problems, also it has been successfully applied to the field of control engineering. In particular Fuzzy Logic (FL) is a decision making-based tool which allows intermediate values to be defined between conventional evaluations like (True/False) and (High/Low) (Caggiano, 2014). Thus, it can be considered as an effective tool for appliance scheduling problem. In (Soyguder and Alli, 2009), an FL-based model was implemented for HVAC systems to maximize the performance of the controller in predicting the damper gap rate. Moreover, (Qela and Mouftah, 2014) proposed a fuzzy system approach to reduce the peak loads using the utility beak load data as the system inputs and the DR power reductions as the system output with different peak load scenarios and energy consumption patterns. (Chekired *et al.*, 2017) presented an FL-based technique to control a grid-connected photovoltaic home energy system by describing the related demand as load priorities to meet customer's need and comfort. In (Keshtkar *et al.*, 2015), an FL-based approach was implemented to control the initialized setpoints in HVAC systems by considering the appropriate load reduction that can be performed for energy saving and user comfort concerns. After that, an extension study has been introduced in (Keshtkar, Arzanpour and Keshtkar, 2016) to provide an adaptive model by training the initialized setpoints of thermostat over three different values of them. Furthermore, (Javaid *et al.*, 2017) investigated an extended approach considering both hot and cold regions through a world-wide adaptive thermostat model. However, those studies consider the degree of outside temperature or the relative humidity separately which does not emulate the real conditions. In this paper, a fuzzy controller for appliance scheduling is proposed. An equivalent value for outside temperature has been calculated with consideration of the relative humidity which is used to obtain the actual temperature that user feels over the day.

3 THE HOUSE HEATING MODEL

Wireless sensor networks and smart thermostats development offer many opportunities for HEMS in smart grids. Wireless sensor networks are groups of separately distributed sensors that are connected via the internet, and typically used for depicting and monitoring the environmental conditions, as well as integrated data collection. On the other hand, smart thermostats are fully-internet connected devices that can be responsible for controlling the load of any residential HVAC system.

A control system consists of a plant, controller, and environment. For the house heating system these components are a heater, smart thermostat, and room respectively. It is a simplified model of a heat gain and cool loss system that can observe the impact of outdoor temperature variations on the indoor temperature. Additionally, it is adaptive to add more smart capabilities on the control system.

In a heating system, the thermal specification of the house and the heater should be defined as well as a thermostat for the heater management, also both the indoor and outdoor environments must be determined. Upon those settings, the smart thermostat will switch the heater ON/OFF according to how much the outdoor temperature differs from the room temperature. When the heater is ON, the thermal energy is gained to the room by convection of the heated air. As a result of the process of conduction that occurs through walls and windows, a thermal energy loss is developed. The rate of temperature change in the room ($\frac{dTr}{dt}$) is calculated as:

$$\frac{dT_r}{dt} = \frac{1}{m_{ha}.c_a}\left((M_{ha}.\ c_a.\ (T_h - T_r)) - \left(\frac{(T_r - T_o)}{R}\right)\right) \quad (1)$$

Where m_{ha} is a mass of air in the room or heater , c_a is the specific heat capacity, T_h is the constant air temperature from heater, T_r is the air temperature of room, M_{ha} represents the constant rate of air mass passing through the heater. The thermal resistance is represented as (R) and T_o is the outside temperature.

4 THE PROPOSED FUZZY LOGIC BASED CONTROLLER

The proposed FL control system is based on load reduction that determines a reasonable reduction value of the initialized set point in order to minimize the energy consumption without causing inconvenience for households. The controller consists of fuzzy variables, membership functions and a set of IF-THEN rules. Figure 1 shows the general mechanism of the proposed control system. As it can be observed, the fuzzification process is applied to convert the real scalar values of the measured inputs into fuzzy values using several types of fuzzifiers called membership functions. After that, the defuzzification process produces a crisp value of the fuzzified load reduction (LR) output value using the centre of gravity technique. By doing so, the new set point and the corresponding energy consumption will be calculated.

4.1 The Fuzzy Variables and Their Related Membership Functions

The proper selection of fuzzy input variables results in accurate output solutions. They should be selected based on a precise description of the problem conditions and the fuzzy inference system (FIS) complexity.

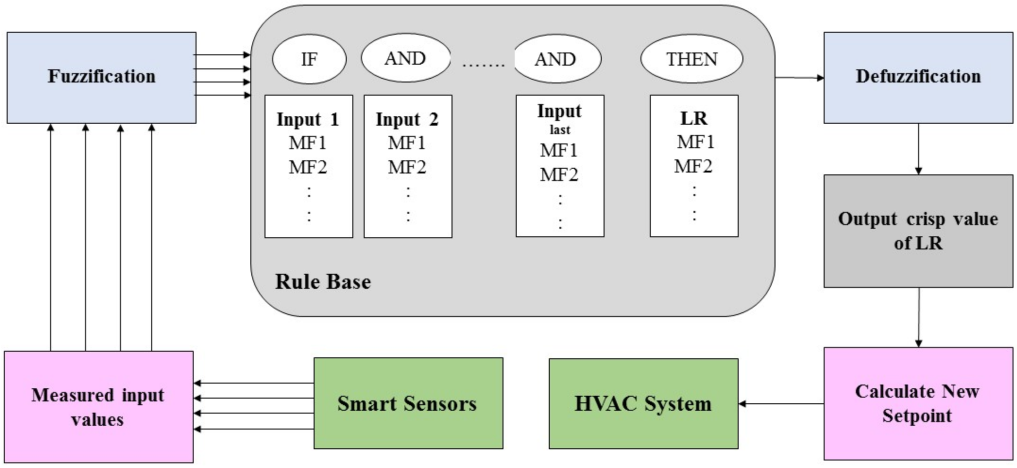

Figure 1: The general mechanism of the Fuzzy Logic controller operation.

Based on this concept, the proposed approach discusses two different scenarios. The first scenario considers the outside temperature, while the second one considers the humidity percentage, as the first input. Both scenarios have the same remaining parameters. Furthermore, the membership functions for all fuzzy variables have been implemented by the triangular geometric pattern.

4.1.1 Outside Temperature (*Tout*)

Continuous variation in weather conditions can directly affect the energy consumption. Thus, the outside temperature is an important input to reflect the pattern of demand load profile. It can be measured by a wireless temperature sensor. As presented in Figure 2, it has four membership function: very cold, cold, cool, and natural.

4.1.2 Equivalent Temperature (*Teq*)

Thermal comfort evaluation is affected by various parameters, such as relative humidity. In particular, a one hundred percent of relative humidity refers to that the air is fully saturated with water vapor. So, in this case, the human skin cannot lose its moisture. Thus, the user can feel warmer in low temperature if the humidity is high. For example, if the current Tout equals 23° C and the relative humidity is equal to 100%, we would feel that the current *Tout* is 26.6° C. on the other hand, it would be felt like 20.5° C in case of 0% relative humidity is depicted. It is necessary to have an input variable to describe the *Teq* which have the same membership functions as *Tout*.

4.1.3 Electricity Price (*EP*)

The main reason that can force users to reduce their consumption is a lower electricity bill. Thus, keeping them aware of RTP values can significantly help to manage demand load profile. The *EP* membership functions are shown in Figure 3.

4.1.4 User Presence (*UP)*

The presence of an occupant can greatly help in saving energy. If an occupant is absent, it is essential to reduce the consumed load automatically. Smart sensors are used to provide the fuzzy logic system with occupancy information over the time. *UP* is divided to two membership functions, Present (P) or Absent (A) as introduced in Figure 4.

4.1.5 Initialized Setpoint (*Tsp*)

It is important to take the initialized setpoint (*Tsp*) into account as one of the fuzzy input variables. It assists to keep on the comfort level. For example, if *Tsp* is already set to be low then the load reduction must be low whenever the user is in the controlled area. Figure 5 depicts the related membership function of *Tsp*.

4.1.6 Load Reduction (*LR*)

The proposed fuzzy control system has one output variable. The Mamdani-type of defuzzification is proposed. Figure 6 presents the *LR* membership functions.

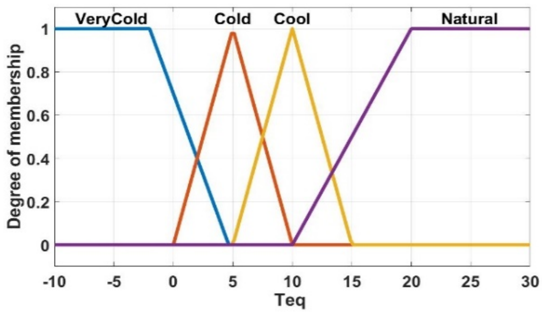

Figure 2: Teq Membership Functions.

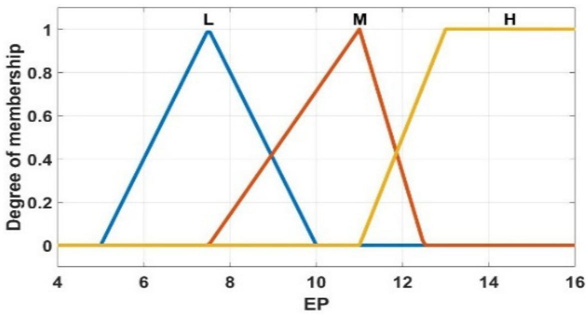

Figure 3: EP Membership Functions.

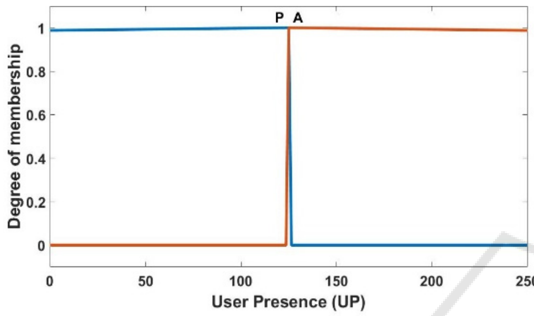

Figure 4: UP Membership Functions.

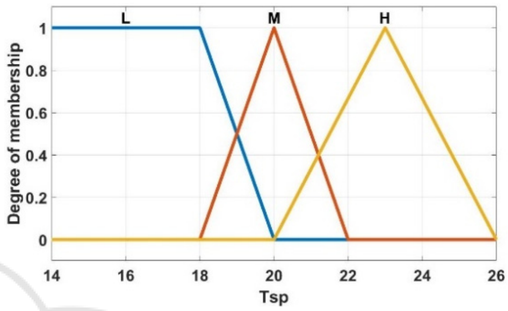

Figure 5: Tsp Membership Functions.

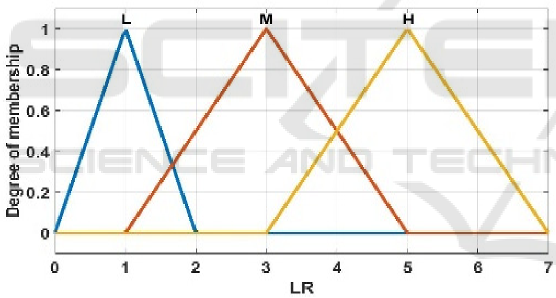

Figure 6: LR Membership Functions.

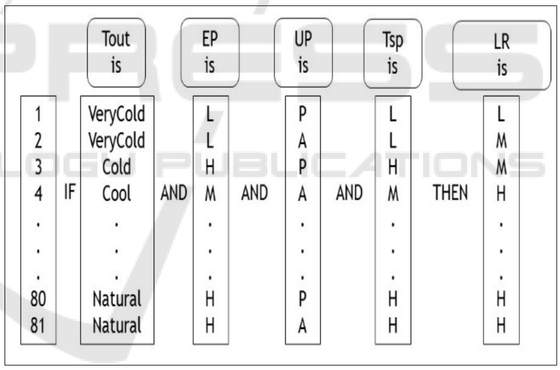

Figure 7: A summary of 81 fuzzy IF-THEN rules.

4.2 Fuzzy Rule Base

The process of creating a fuzzy IF-THEN rule is logically based on the reduction degree of the *Tsp*. For example, to decide *LR* value, each of *Tout* or *HP*, *EP*, *UP* and *Tsp* should be measured. In this paper, the proposed two scenarios have four inputs and one output. Thus, there is a set of 81 IF-THEN rules in the rule base. A summary of the proposed fuzzy inference system 81 rules of the first scenario is presented in Figure 7. For example, the first rule expresses that a low load reduction is needed if the outside temperature is very cold, the electricity price is low, the user is present at home and the scheduled setpoint is low.

5 SIMULATION RESULTS

This section contains the simulation analysis of the results obtained from the proposed fuzzy logic control system.

The proposed FL-based control system is compared with the model in (Keshtkar *et al.*, 2015) with the new concept of combining both output temperature and relative humidity through an equivalent temperature. It can be declared that this new concept would bring more logic to the model. Almost the same data are used in simulation to demonstrate the proposed algorithm significance except for those that are missed or added. The weather conditions such as outside temperature and humidity percentage for the simulated day were adopted from (*Weather in Canada*, 2014). Figure 8 shows the relative humidity over the simulated day.

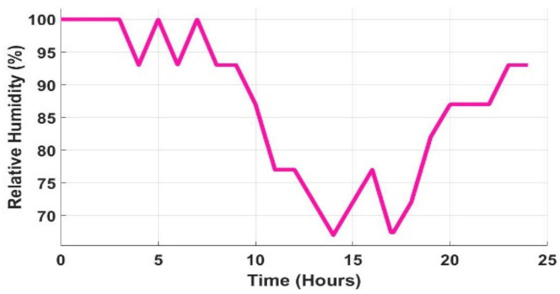

Figure 8: Relative Humidity.

Moreover, Table 1 presents the initialized Setpoints (*Tsp*) and User Presence periods over one day. In addition, the TOU Electric Price (*EP*) is illustrated in Table 2.

Table 1: User schedules for the simulated day.

Time of day	Tsp	UP
00:00–08:00	21	Present
08:00–12:00	18	Absent
12:00–17:00	19	Absent
17:00–20:00	22	Present
20:00–24:00	23	Present

Table 2: TOU prices for the simulated day.

Time of day	EP
00:00–07:00	7.2
07:00–11:00	12.9
11:00–17:00	10.9
17:00–19:00	12.9
19:00–24:00	7.2

For model evaluation, four different scenarios are introduced.

5.1 Scenario I

In the first scenario, *Tsp* is assumed to be fixed at value of (21 °C) with no DR existence. In such a case, the user is not allowed to control his setpoint or use a smart thermostat. Figure 9 shows the difference between *Teq*, fixed setpoint (*Tsp_f*), and room temperature (*Troom*).

5.2 Scenario II

The second scenario discusses the situation in which the DR is being applied through TOU pricing scheme where *Tsp* is scheduled according to time of use variations without any smart decisions taken. Figure 10 depicts the difference between *Teq*, *Tsp*, and *Troom*.

5.3 Scenario III

In this scenario, the proposed FL-based algorithm is simulated with selecting *Tout* as the first input. Figure 11 illustrates the difference between *Tout*, *Tsp*, and resulted room temperature when the proposed FL Control system is implemented (*Troom_FL*).

5.4 Scenario IV

Considering the *Teq* rather than *Tout* over a simulated day can have another impact on load reduction. Thus, this scenario includes the *Teq* as the first input of the proposed FL-based model to figure out this reflection. As shown in Figure 12, the *Teq*, *Tsp*, and room temperature when scenario II is implemented using *Teq* (*Troom_FL*) are plotted.

As it can be seen in scenario I and II, before implementing FL, there are a response just to the changes in predetermined setpoint patterns without any intelligence decision. By contrast in scenario III and IV, FL decision making tool results in a dynamic response over the day which could save energy consumptions more than the stable environment. On the other hand, adding the relative humidity through *Teq* in scenario IV increases the model reliability. For illustration, a comparison between the hourly energy consumption of the four discussed scenarios is given in Figure 13. It can be observed that scenario IV represents the best performance with a total hourly energy consumption of 140.48 KWh. It is worth mentioning that the result of the third scenario, which is equal to 142.32 KWh, is not so far from the best one. However, the main purpose is to clarify the importance of considering *Teq* generally.

On the other hand, performing the proposed model without including the FL concept results in the largest total hourly energy consumption of 172.06 and 166.94 KWh in scenario I and II, respectively. Moreover, scenario III and IV improve the system performance with total reduction in energy consumption of 17.26% and 18.33%, respectively.

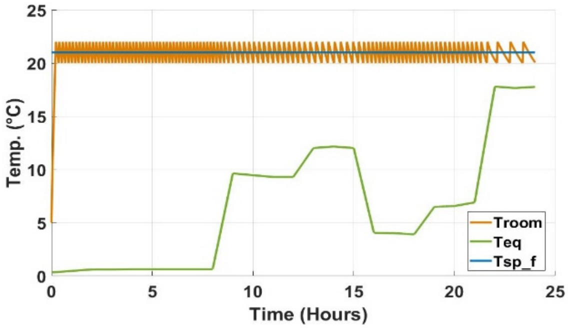

Figure 9: Scenario I result.

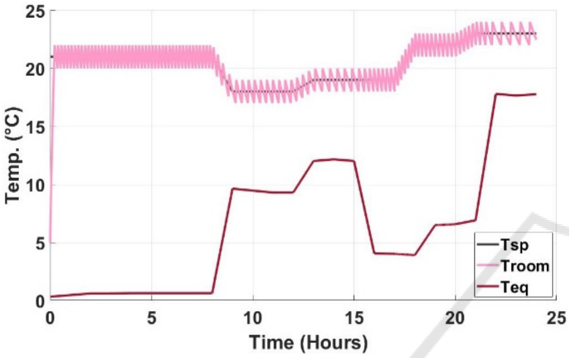

Figure 10: Scenario II result.

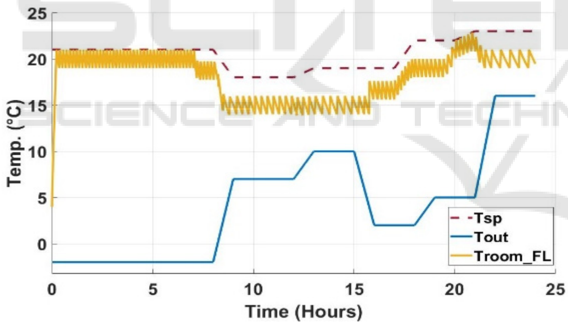

Figure 11: Scenario III result.

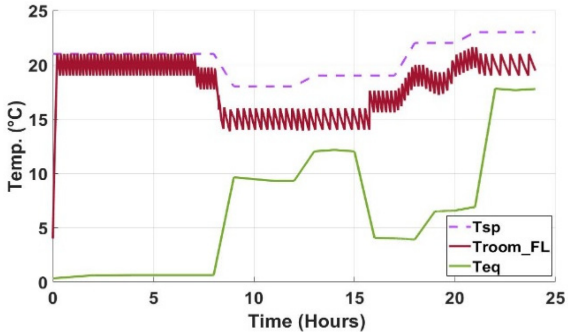

Figure 12: Scenario IV result.

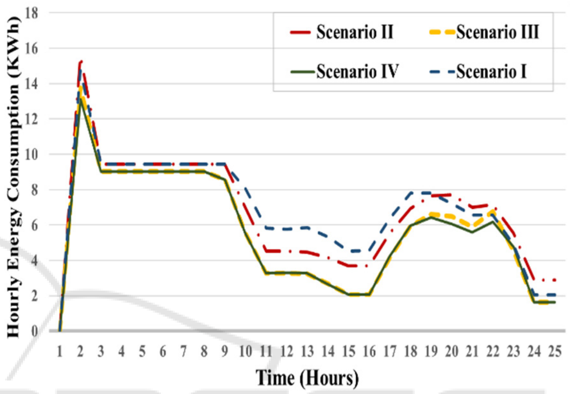

Figure 13: Comparison of the four scenarios.

6 CONCLUSIONS

Providing the energy customer with real-time information about his consumption pattern and the current electric price would certainly encourage him to manage his consumption more efficiently. In addition, providing a smart thermostat that could be able to make smarter decisions automatically would absolutely increase the system sustainability. Fuzzy logic control system can efficiently help in making such smart decisions in reasonable time. From this premise, this paper proposed a modified FL-based control system which is implemented with introducing a new input parameter of equivalent temperature, to express both the outside temperature and the relative humidity, instead of considering each of them separately. The proposed model has been compared with four different scenarios. The simulation results illustrate the model efficiency with a total improvement of 18.33% in the system performance. Other parameters of the FIS may be investigated in further researches to achieve higher performance in HVAC systems.

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