An Agent Based Fuzzy Control for Smart Home Energy Management in Smart Grid Environment

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Abstract- Energy management in Smart Home environment is one of the main topics adopted in Smart Grid research field. In this paper, we present a Multi-Agent System (MAS) for a Smart Home intelligent control. Such a solution was integrated in a smart meter in order to alter the shape of the residential load curve. The MAS is strong appropriate to solve complex distributed problems as home automation system. Our contribution consists in performing an algorithm for scheduling appliances tasks, and designing a model for a direct load control which may accommodate customer preferences. The direct load control is based on Fuzzy Logic Control (FLC) using new fuzzy power indicator. In order to successfully implement our solution, customer acceptance of the direct load control is vital. We aim to reach a compromise among habitant comfort and electric bills in addition of satisfying technological constraints of appliances. Simulation results have proved the effectiveness of the proposed solution in energy savings.

Keywords Energy Management, Fuzzy Logic Controller, Multi-Agent System, Smart Home Automation, Smart Grid, Smart Meter.

1. Introduction

Energy presents a powerful actor in our quotidian activities. Energy demand is ever increasing with population growth along with the technological growth and as a result the prices of energy will rise [28]. The rise of energy demand has brought ecological and economic problems in the modern world. According to estimation of International Energy Agency (IEA), the demand of energy in the world will dramatically increase in rate of 55% between 2005 and 2030 [1]. The balance between generation and demand in power grid will be more and more difficult to be achieved. Therefore, the energy management is considered as a major research topic for Smart Grids (SGs).

As the electricity market changes, several utilities have to be more motivated in the fact of, implementing load management programs. The load management aims to encourage consumers to change their behaviour in using energy, by offering solutions to reduce their electric bills. These solutions are based on using appliances at different times of day or to interrupt the operation of some appliances briefly.

Furthermore, the demand of residential electrical systems has grown continually in the last decades. Buildings represent the main power end-users, consume as much as 40% of the whole end-users energy in the world [2]. In the SG, the consumer has an important role in energy conservation [28]. It points to the importance of integrating a customer in the smart metering system [8]. Thus, to achieve energy savings from smart metering and information feedback, it depends on customer's awareness and acceptance. So, well-informed consumers are playing a more active role in managing electricity consumption. Indeed, to realize the specified efficiency enhancements, energy use ought to be measured in additional detail and in real time, to obtain an awareness of the consumers in their way of energy use. One of the proposed technologies by the SG, to facilitate the load management and billing service for the customer is an Automated Meter Reading (AMR) [7] based on a smart meter (SM). A SM [7] is an electronic meter based on AMR technology, with two-way flow of energy and information to enable monitoring home energy. The SM transforms the consumer into an active element in the control of his power consumption, and even become a "prosumer" when he decides to sell energy to the utility. In this way it is possible to manage the power consumption for energy optimization purposes, both in terms of cost and energy savings [7].

For building energy control, many studies have been done in the energy control in the building side. In giant buildings, domestic equipment as lighting, Heating, Ventilation and Air-conditioning (HVAC) systems are the major energy consumers, and the control of power demand is achieved by turning off/mitigation artificial lighting systems and HVAC systems [16]. Authors in [4] and [5] has presented an automatic lighting control in a commercial building, that reduces the operation time of lamps and this contributes to 40% and 20% reduction in energy respectively. In [26] authors developed a six control logics for a rational utilization of the electric loads and air conditioning systems in a residential building. The energy saving can reach a 22% using the Net-Service scenario. Authors in [27] give an existing research in the area of the optimized control systems and comfort management for smart sustainable buildings.

The conventional control systems in buildings is improved by the introduction of intelligent control system using artificial intelligence and a logical control as Multi-agent system and Fuzzy logic controller. Furthermore, current trends to control and monitor the residential power demand are however moving toward the use of an automated agent technology which is generally known as a Multi-Agent System (MAS) [12]. A MAS is a distributed computational intelligent technique, which is capable of making autonomous decision without human intervention [10]. Thereby, a smart home based MAS can be considered as a smart self-sustainable system. A self-sustainable system is any system that can be able to support itself in a period of time without the need of external contribution [20].

The development of a home automation system based MAS has been used by many scientists. Some researchers are concentrated only on the control of an intelligent building. Recognizing the distributed nature of building energy optimization, authors in [15] presented a MAS integrated in a smart home to manage energy use in an anticipatory and reactive way. Others researchers are interested in the users comfort without arguing the percentage of energy reduced by their methods. Authors in [16] presented a number of articles demonstrating that MAS provides an effective energy management in buildings as well as improved comfort of residents. Scientists in [17] have designed a Multi-Agent Home Automation system (MAHAS) and have concentrated in the user comfort without achieving a signification reduction in energy consumption. Developing MAS is not restricted to modelling intelligent building, but must contain a learning ability [24], and dynamically learning new behaviours [29], to suit the residential preferences. Moreover, some other studies are done based MAS to prove the importance of energy economy in a building side. Authors in [22-23] showed advanced control systems for energy and comfort management in residential environment in order to minimize energy consumption, and has demonstrated that an intelligent control systems using MAS is the key way of an effective control of indoor environment. A load agent was designed in [1] using renewable energy sources to provide the consumer’s needs for energy. Other literatures have used MAS to optimize the energy consumption with providing a minimum comfort to residential. An intelligent building control based MAS has been developed by scientists in [30], in order to realize a balance between the energy efficiency and occupant's comfort, but in this study, authors do not concentrate in the savings of energy as a main optimization objective. Researchers in [18] had reached a 12% of reduction in energy consumption and a 5% improvement in residential comfort, by implementing a multi-agent control system for building energy and comfort management.

To decrease power peak demand, utilities would like to reduce the level of their load curve as soon as possible. Therefore, they encourage consumers to shift the operation of some appliances from periods of high power demand to low demand periods. Some researchers have been done in this area using Fuzzy Logic Controller (FLC). Fuzzy Logic is very close to human reasoning and affords an easy and efficient control with minimum analytical developments. Studies are done in the control of building using FLC, but some of them are concentrated only on the control or energy consumption without providing comfort to their residents. Researchers in [33] have designed a smart LED lighting based FLC to save energy consumption. In [35-36] a fuzzy model based multivariable predictive control (FMBMPC) and a cooperative fuzzy model predictive control (CFMPC) were developed to control a HVAC system in a building. The FMBMPC system reach a 44% less energy consumption with a 78.14% performance and a 100.21% energy supply, unless the CFMPC system achieved a 100% in performance and energy supply. A HVAC system was controlled also by an adaptive hierarchical fuzzy controller with two level [34]. This hierarchical FLC aims to improve the resident comfort level within a thermal space control. In an earlier study [6], the authors have presented a four block fuzzy logic based demand side management strategy to control the electric water-heater. Each of three blocks had been controlled by a different fuzzy controller. But this strategy uses, for one appliance, a complex system and the mean of power demand is higher compared to uncontrolled water-heater system. Also, these FLC systems do not take in consideration the user comfort. Authors in [31] implemented a FLC for naturally ventilated homes, without generating the user comfort and without maximizing the energy consumption reduction.

Indeed, the attitude of consumers in energy consumption and their index of comfort have a serious impact on energy savings [27,5]. Authors in [19] have developed fuzzy control system architecture for maximizing the comfort level of habitants. The FLC and the comfort index have been developed only for temperature, air quality and artificial lighting. In [14] researchers affirmed that the designed FLC allows consumers to manage their electric power consumption based on their priorities, and this FLC may be implemented in a SM in order to make a system that saves energy up to 30%.

Moreover, many studies in the literature have been done on scheduling policies to regulate the operation of appliances. An appliance scheduling is one of the main parameters that take attention by many researchers. Furthermore, authors in [13] affirmed that the performance of a scheduling plan can be further enhanced through a pricing management scheme, and analysed an offline and an online scheduling policy. In both cases either power compression or request delay are tested, so as to reduce the residential power consumption [13]. In [25], authors proposed an optimal energy consumption scheduling algorithm for residential users is proposed to reduce the daily electricity cost. This scheduling algorithm is based on Binary Particle Swarm Optimization (BPSO) and Time-of-Use (ToU) pricing scheme. The BPSO technique is used to anticipate the optimal time for making the appliances to operate [25]. The ToU pricing furnishes to the customers the calendar of energy prices in a day, so it gives incentives to be part of DR program [25]. Furthermore, a power scheduling method is proposed in [37], which achieved peak demand reduction focusing on the elasticity of domestic operation duration.

Finally the presented literature review concerning the application of MAS and Fuzzy logic controllers has not sufficiently solving the problem in home energy management as the balance between the user comfort and the significant reduction in energy consumption. In that case we will show the novelty our work.

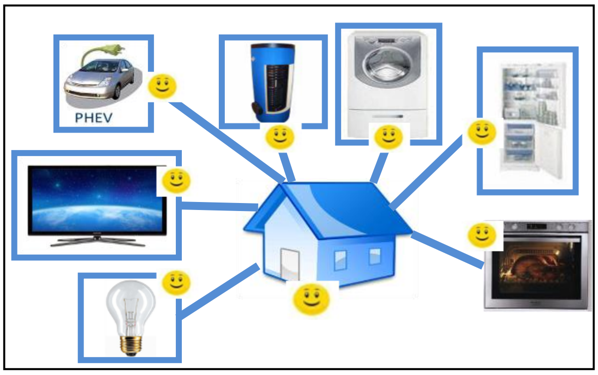

Fig. 1. Home appliances based-agent

In the present paper, we provide an adaptable local control and intelligent decision making for a home automation using multi-agent techniques. The implementation of solutions based on MAS, strong appropriated to solve distributed problems, such as an intelligent MAHAS [17]. The MAS consists of many agents embedded into appliances, seen in Fig. 1. Each agent uses the technique Fuzzy logic Controller (FLC) to manage the appliance's energy consumption. For the management of the whole smart home, we tend to use a scheduling policy algorithm executed by a cognitive agent called "AG_0". AG_0 makes joint decisions with respect to the user comfort and desire. Because the comfort level for users have a significant impact on energy savings. The user desire is represented in this paper by a Satisfaction Function (SF) for each appliance. So, our contribution resides on integrating a new solution AG_0 based-Fuzzy Logic Controller (AG_0-FLC) in the SM in order to provide a balance between the control, energy efficiency, and user comfort. Furthermore, we use a three type of fuzzy logic based control strategy in our work. Another advantage of our application is, in instance of writing this paper, there is no research based on three type of FLC taking in consideration all kind of residential load, this proves the novelty of our work. Another advantage of our work is that the algorithm can organize any added load and integrated to it an agent. So the operational times of this load can be shifted or curtailed according to their behaviour (temporary / permanent). And the main contribution of our solution AG_0-FLC, is that achieved a 58% less energy consumed in the building compared to other studies presented in the literature, and these proves again the novelty of the proposed application.

The remainder of this paper is organized as follows: section 2, describes the effectiveness of the proposed solution "AG_0-FLC" in the referred residential area. In section 3, we present the application of the proposed solution as well as a discussion of the comparative results. Section 4, highlights the main conclusion of this paper.

2. Home Automation Based AG_0-FLC

Home Automation Systems are very complicated items, identified by the presence of distributed equipment with different constraints and behaviour. For ensuring energy savings in residential building, a logic control of loads can be a solution [26]. In this section, we present the detailed description of load categorization on residential level [3] as well as smart appliances scheduling [9]. Moreover, we describe the architecture of a home automation system based on AG_0-FLC.

2.1. Load categorization

The proposed load model considers that each residential user have diverse kind of appliances that has different energy requests and different power demands and different functioning hours. We denote by A the set of appliances ($a \in A$). There are two load sub-categories, and each load model has their own features [3]. This sub-categorization is introduced as follows.

- Permanent load appliances (e.g., refrigerator, house heating, water-heater, electric water kettle, air-conditioner, etc.): This type of load is identified by its energy consumption/production which covers the whole time interval of the energy affectation plan [15].
- Temporary load appliances: This type of load is identified by the duration and the intended end time of the operation [15]. This sub-category can be divided in two sub-categories. The first one, "*the must run load*" (e.g. Television, lighting, cooking, hair drier, etc.) represents the users primary choice appliances. And then the functioning of such appliances cannot be deferred. The second one "*the shiftable load*" (e.g., laptop charger, washing machine, dishwasher, plug-in hybrid vehicles, etc). The latter sub-category is flexible to prioritize the user choice. The user is able to make changes according to his own preferences, in his appropriate SM through a panel installed at home to be used as a human machine interface (HMI).

2.2. MAS modelling

In this part, we present the MAS solution proposed to the home automation. A MAS is a combination of various agents react to their environment according to a set of predefined settlements [12]. An agent is an entity was generated to execute some tasks. Fig. 2 shows the design of an intelligent agent. An intelligent agent is an autonomous entity that perceives its environment through sensors and responds to the environment using actuators [12]. The agent asks himself questions at each cycle of its infinite loop, in order to maximize its expected utility.

The notion of control in MAS includes actions such as collaboration and discussion between agents to attain adequate solution, adding of new agents if necessary, and also delaying the turned off agents. Agent plays different roles in the electric power grid and it may have different purposes. The objectives of agents can be divided into global and local objectives.

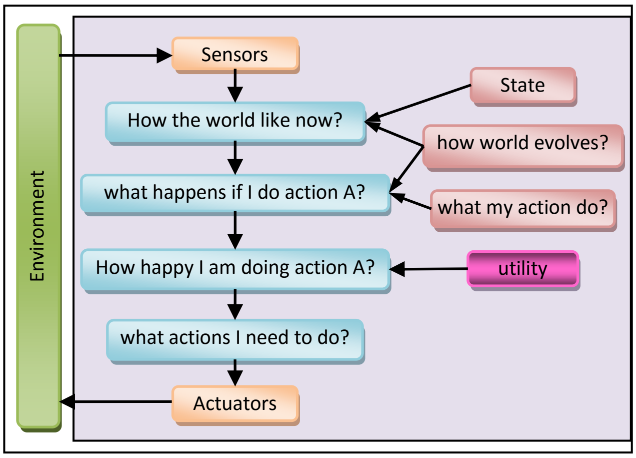

Fig. 2. Design of an intelligent agent

Regarding the electric power grid, the global objective of the proposed MAS takes into account the most important objective in the overall system, which is defined as "altering the shape of the utility load curve by reducing the end-users electric consumption". Inversely, local objectives are particular objectives to individual agents.

To control and coordinate the message exchange and the decisions making among agents, it is necessary to have a coordinator agent. We use a coordinator agent in the proposed MAS, called "AG_0", integrated in the SM, which makes decisions with respect to the consumer luxury and ambition. Besides, other models of agents are used in the smart home automation: permanent agent and temporary agent. These agents are related to appliances and are different according to the load categorization. After the integration of the MAS in the house, agents had no knowledge about the environment and its equipment. For evaluation of the proposed method, we have performed several settings of AG_0, which are described in the following section.

2.2.1 AG_0 setting

The coordinator agent (AG_0) is a cognitive or Belief-Desire-Intention (BDI) agent. To take a good global decision at a precise time of the smart home, this agent must have a knowledge base and also must take into account its antecedent actions. Knowledge is a set of rules which is important for artificial agents because they permit successful attitudes. Knowledge Base (KB) is a set of sentences that can be updated using two tasks: (Tell and Ask) [32]. Each time, the AG_0 Tell the KB what it observes, and then asks the KB what action it must take. So to add new sentences in the KB, there are some settings should be configured by the end user. Using the interactive HMI of the SM, the AG_0 must be programmed according to the end user requirements by setting the following parameters:

- Select the Name of the new added appliance,
- Select its installation Time & Date,
- Select its Priority,
- Select the Comfort Zone,
- Select the Threshold of Consumption.

Indeed, according to these selected parameters, AG_0 have to execute five tasks which are described below.

For the initial task of setting, AG_0 checks if another appliance "bi" was added to the house. So following 24 hour of appliance's operation, the agent take in its conduct and distinguishes its type (permanent or temporary). Next, AG_0 include "bi" to the set of appliances (A) and updates its knowledge base, found in Fig. 3.

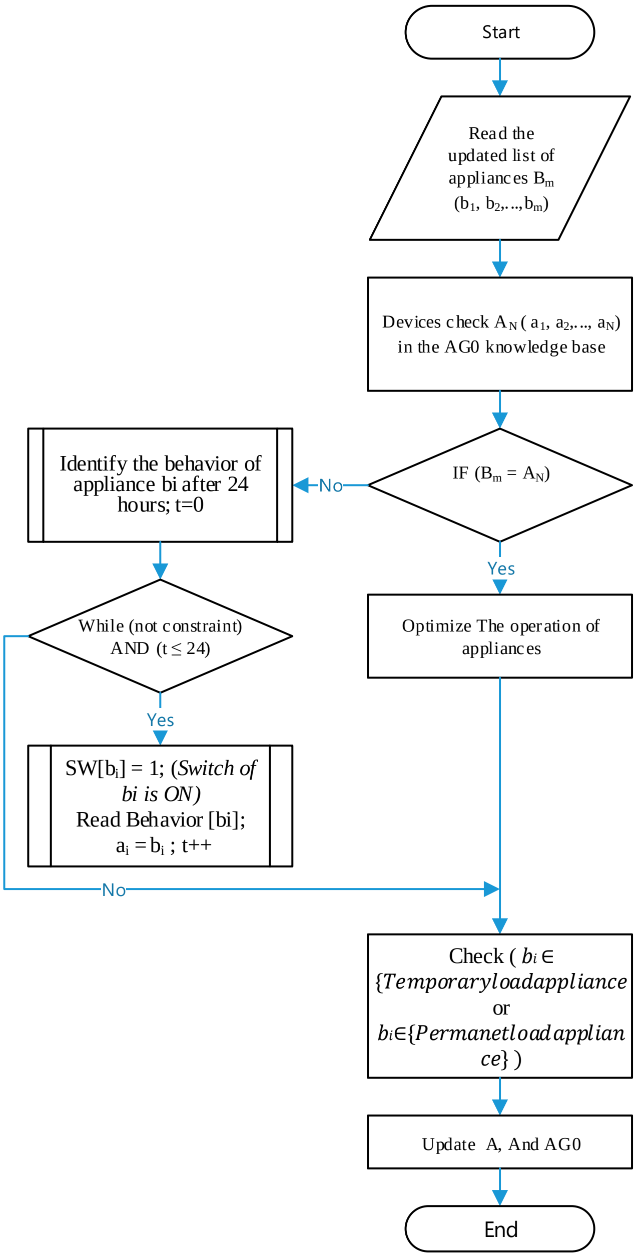

Fig. 3. The new added appliance by AG_0 algorithm

In the second task the AG_0 displays within the panel all the existed appliances in the home. So AG_0 asks the user to assign his list of priorities, appeared in Fig. 4. This list may be modified depending on the period (weekend, holiday, day, night, etc) and the requirement of the end user.

In the third task, AG_0 sets up the list of the most consuming appliances according to the appliance's characteristics and hourly energy consumed. This list will be used by the developed application based FLC system. The fourth task is resumed by the set of the user comfort zone, shown in Fig. 5. The agent asks the user to set his comfort zone for each appliance. In the case of permanent load, the comfort zone depends on the variables (min/max), otherwise it depends on time.

The fifth task of AG_0 is to ask the user to set his threshold within given bounds (TH≤ TH-max) to not be exceeded (Fig. 6), where TH-max is fixed by the utility according to prediction mechanism. The threshold will be represented in section 2.3 by the fuzzy threshold indicator. The consumption threshold value is calculated and chosen by the consumer according to his ability to pay and for which he intends to be aligned. This value is chosen by the consumer, from the range sent by the utility related to time-varying rate. The consumer can also take advantage from the feedback sent by the utility through a SM. So, the consumer can be notified of the dynamic unit price on the display device letting him know when higher rates are in effect. The utility receive every day user's consumption profiles from SMs. Thus, from the consumption history, utility can predict its peak power demand. Thereby, a specific threshold will be predicted for each home. In our solution, we program the AG_0 in order to reduce the total power consumption.

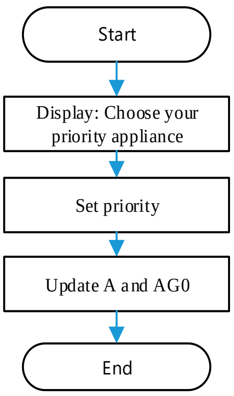

Fig. 4. Efficient policies for assigning priorities algorithm

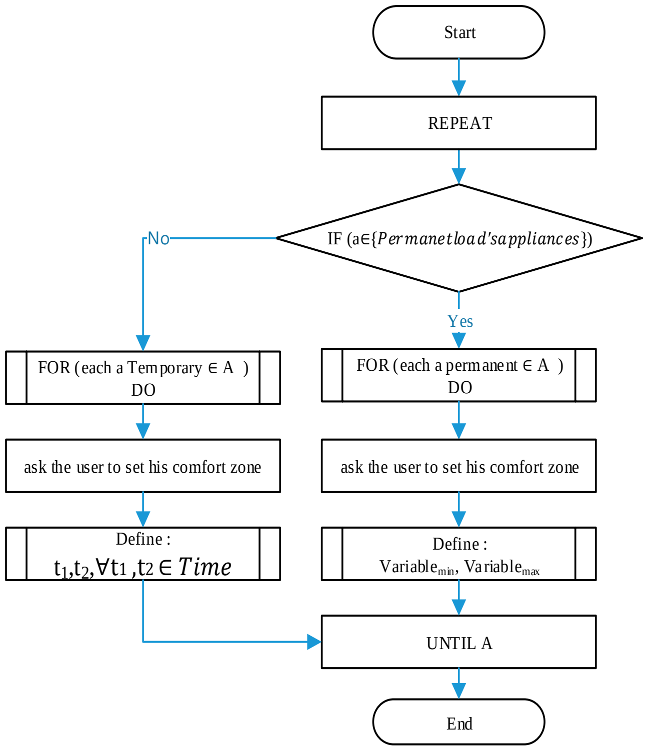

Fig. 5. User comfort zone algorithm

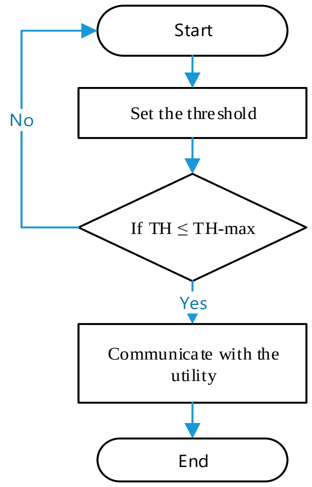

Fig. 6. The threshold setting algorithm

In home automation, "user comfort" presents an important factor to take into account [15]. Then as a sixth step, AG_0 represent the user comfort using a satisfaction function. A SF characterizes the user's desire with respect to the operation requirements of the appliances. The SF defines over an interval [0..100]% where zero is inadmissible and 100% is superb [17]. The agent verifies its level of contentment over every cycle of its infinite boucle. The AG_0's task and the SF will be explained in the following section.

2.2.2 The coordinator agent tasks

Given a set of appliances, i.e. $A = \{a_1, a_2,..., a_N\}$, where each appliance has their proper energy consumption. For each $a \in A$, we define energy consumption vector Y_a as follows:

$$Y_a \triangleq [y_a^1 .. y_a^H] \quad (1)$$

Where: H=24 hours, H is the scheduling range that indicates the number of hours in a day can take the operation of appliance $a \in A$. The scheduling range H is taken into account by the coordinator agent for decision making in the energy consumption scheduling. y_a^i $(i \in \{1..H\})$, represents the energy consumption of an appliance "a" for one hour.

For each $a \in A$, the user preset his zone comfort α_a , $\beta_a \in \mathcal{H}$, $(\alpha_a < \beta_a)$, as the starting and end of a time allowed gap to schedule energy consumption for appliances. But $(\beta_a - \alpha_a)$ must be larger than the time required (t_a^{req}) to finish regular process of an appliance "a", as described in Eq. (2).

$$\beta_a - \alpha_a \geq t_a^{req} \quad (2)$$

We also define the total daily energy consumption for each appliance $a \in A$ as:

$$EC°_a = \sum_{h=\alpha_a}^{\beta_a} y_a^h \quad (3)$$

It is expected that $y_a = 0$ for any $h > \beta_a$ and $h < \alpha_a$.

We define the lower and upper limit constraints of y_a, in which we take into account on the energy consumption scheduling vector selection:

$$\delta_a^{min} \leq y_a \leq \delta_a^{max} \quad (4)$$

Where: δ_a^{min} is the minimum stand-by power level, and δ_a^{max} represents the maximum power level.

For each residential SM, the total energy consumption at each hour must be inferior or equal to the predefined hourly energy threshold (E^{max}), That is:

$$EC°^{Total} = \sum_{a \in A} y_a^h \leq E^{max}, \quad \forall h \in \mathcal{H} \quad (5)$$

Where: E^{max} and $EC°^{Total}$ will be used in the a future subsection as an input/output to the FLC, as a Fuzzy Threshold Indicator, and a Home's Power Demand respectively.

Gathering the constraints Eq. (2), Eq. (3), Eq. (4) and Eq. (5) we determine all valid choices for the energy consumption scheduling vectors. Thus, we can establish a possible scheduling collection Y for all feasible y_a, as:

$$Y = \begin{cases} y \mid EC°_a = \sum_{h=\alpha_a}^{\beta_a} y_a^h, \forall a \in A, \beta_a - \alpha_a \geq t_a^{req} \\ \delta_a^{min} \leq y_a \leq \delta_a^{max}, \forall a \in A, h \in [\alpha_a, \beta_a], \\ y_a^h = 0, \forall a \in A, h \in \mathcal{H} \setminus [\alpha_a, \beta_a], \\ \sum_{a \in A} y \leq E^{max} \end{cases} \quad (6)$$

Where: $y \triangleq (y_a; \forall a \in A)$ represents the energy consumption scheduling vector which contains all variables for all appliances. So, a vector y is valid only if $y \in Y$.

2.2.3 Permanent Agent modelling

Permanent agent is related to each permanent load's appliance. In this sub category, the loads are running regularly, depending on the internal temperature of its appliance. In this case, the comfort zone depends on the upper and the lower temperature levels $[T_{ac}^{min}, T_{ac}^{max}]$. The permanent agent tries to maximize the SF of each permanent load's appliance.

- User comfort

The SF of a permanent load appliance depends on its characteristic variable (e.g. air conditioner service depends on its Temperature (T), seen in Fig. 7). For example, a user will be satisfied if the temperature in his sitting room is between 20°C and 22°C.

$$SF = \left\{ T \middle| \begin{matrix} SF(T) = SF(T_{ac}^{min}) = SF(T_{ac}^{max}) = 100, \\ \forall T \in [T_{ac}^{min} .. T_{ac}^{max}] \end{matrix} \right\} \quad (7)$$

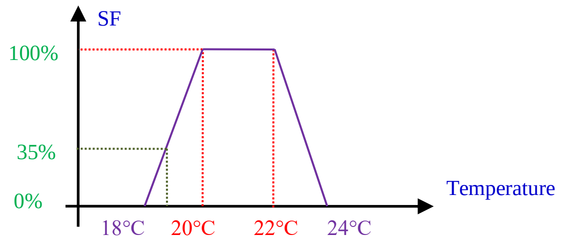

Fig. 7. Air conditioner satisfaction function

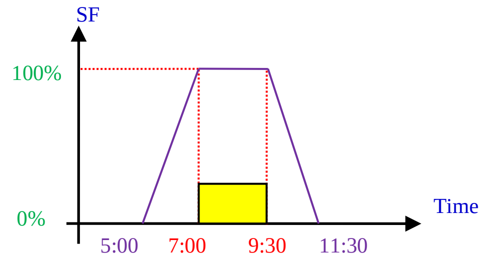

Fig. 8. Washing machine satisfaction function

➢ Permanent load's appliances scheduling

To avoid peak load demand without affecting the comfort of user, the permanent agent uses the method of scheduling operation, which is described in Eq. (4) and Eq. (5). The flexibility of this service comes from the possibility of modifying the energy quantities consumed/produced throughout all the periods. So the agent decreases or increases y_a with given bounds $[\delta_a^{min}, \delta_a^{max}]$ of each appliance.

2.2.4 Temporary Agent modelling

Temporary agent is related to each temporary load's appliance. The *must run load* starts at the moment a user wants (e.g. hair drier). As the power consumption is fixed and there is no other option to adjust its operation in normal power demand, those tasks do not need to be scheduled. But in high power demand periods of utility, agent will be obliged to use the global FLC to control the operation of the must run load, explained in section 2.3.2. The *shiftable load* starts its task at the moment a temporary agent wants (e.g. dishwasher) with respect to the comfort zone $[\alpha_a, \beta_a]$ of the user, and the constraint Eq. (2) of the operation of each appliance.

➢ User comfort zone

The SF of a temporary load's appliance depends on the shift time in service $[\alpha_a, \beta_a]$ offered in relation to the end time desired by the user, as illustrated in Eq. (8). For example, one user will be satisfied if his clothes will be clean at 9:30 am, seen in Fig. 8.

$$SF = \left\{ t \;\middle|\; \begin{matrix} SF(t) = SF(\alpha_a) = SF(\beta_a) = 100, \\ \forall\, t \in [\alpha_a .. \beta_a] \end{matrix} \right\} \quad (8)$$

➢ Deferred operation of Temporary load's appliances

The temporary agent uses the existed list of priority prepared by AG_0 and then uses a three type of fuzzy logic based control strategy, as an efficient solution to shift the residential appliances power demand from periods of high demand of utility for electricity to: "low demand", "low-rising", and "low-falling" periods.

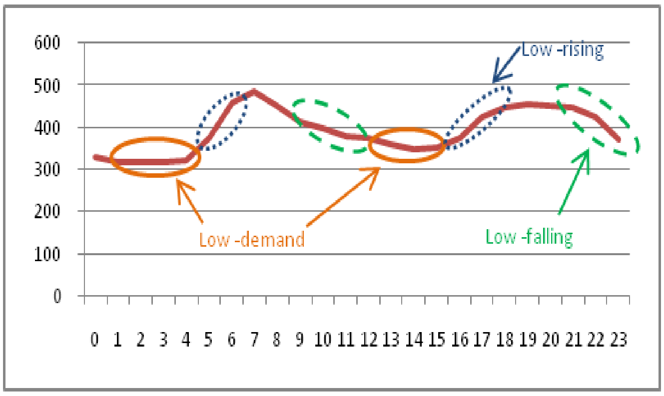

Fig. 9. Daily average total utility demand (MWh)

Fuzzy controllers are more performance than conventional techniques, in status where the mathematical model of the problem was unknown or when the attitude of the process varies non-linearly [11]. The use of FLC presents a powerful way to minimize and facilitate management of home's energy. In this paper, we design the first FLC_1 to shift high power to "low-demand", representing the low-demand zones of the total demand profile with slope close to zero. The second FLC_2 shifts the high power demand to "Low-rising", representing the low-demand zones with positive slope, and the third FLC_3 shifts the high power demand to "Low-falling", representing the negative slope, shown in Fig. 9 [38].

2.3. Fuzzy Logic Controller based home automation

In this part, a PC based-LABVIEW was used to implement a FLC to smart home. We analyze the results of the global FLC programmed by the AG0. FLC comprise a fuzzifier, inference engine, and defuzzifier. FLC is used to reduce uncertainty in measurement of non-linear inputs variable of appliances. The input variables of the controller are: (Fuzzy Utility Power Demand Indicator (FUPDI), Fuzzy Threshold Indicator (FThI)). The controller picks up the two crisp input values, fuzzifies them in term of membership function of linguistic expressions. Then, it affects a fuzzified control signal to regulate the voltage applied to the appliance based on the settled rules and membership functions. So this mapping from input to output relies on a robust rule-based inference engine. Hence, the rule's setting depends on the expert knowledge and his logical reasoning. Finally, after the appropriate control, it deffuzzifies the outputs to crisp values,

(Fig. 10). The output variables are "Home's power demand in W (PD)" and "closing most consumed appliances (CMCA)". The fuzzy membership functions (MFs) and rules will be explained in next two sections.

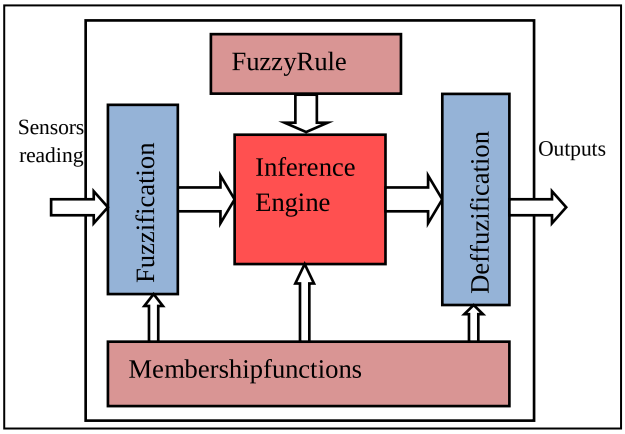

Fig. 10. Fuzzy logic control system

2.3.1 Membership functions

In order to define linguistic rules that manage the relationship between inputs and outputs, a fuzzy membership function is needed. Each of input/output variables is divided into a range of three states. We use the GAUSSIAN (shape) MF because it is well suited to fuzzy input power demand variables. For the outputs we use the TRIANGLE shape. Fig. 11 represents the MF of inputs/outputs of the fuzzy control system.

2.3.2 Fuzzy Rules of global FLC

The fuzzy rules are very critical task in the development of FLC. Fuzzy rules present a helpful connection between the inputs and the outputs of the system. Fuzzy rules are a series of linguistic statements that describe how the decision is made by the fuzzy controller.

The rules in the global FLC aim to show the user his present behaviour by a lighting indicator in the SM. So, when FUPDI = "High", and FThI = "Normal/Expensive" the light in the SM will be red. And in this case, AG_0 sends the appropriate fuzzy control to FLC, and the latter closes the most/highest consuming appliances using the fuzzy output variable CMCA. Table 1 shows the nine fuzzy rules.

➢ Developed interface FLC based LABVIEW

An interface fuzzy was developed for control and monitoring. The software used is LABVIEW which is a graphical development environment that allows creating modular application (VI) a scalable for application design, control, and test. The LABVIEW program has two main components:

- A Front Panel: represents the Graphical User Interface (GUI) of the FLC, which enables the user to monitor current value parameters (FUPDI and FThI),
- A Block Diagram: contains code program of FLC

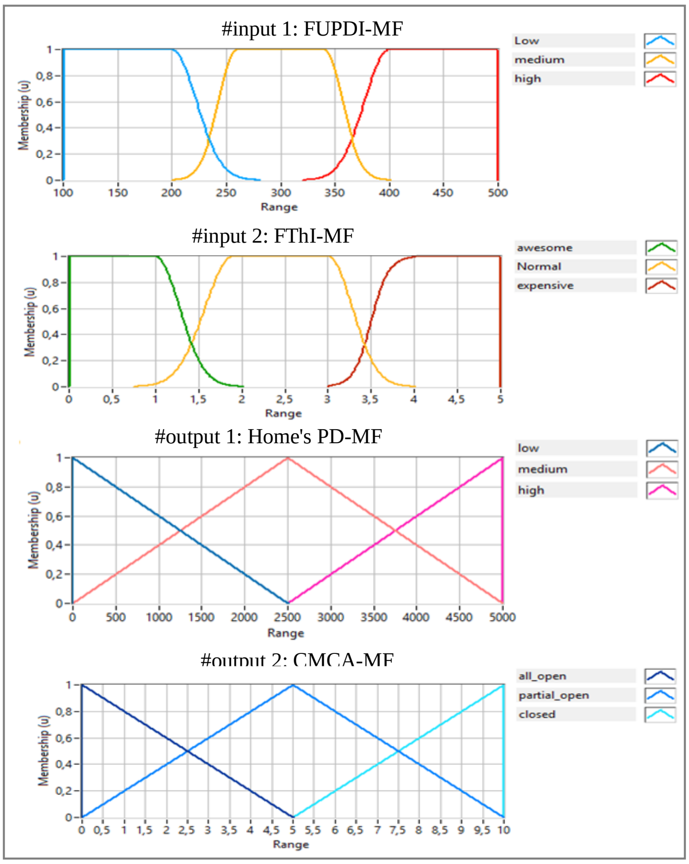

Fig. 11. Fuzzy membership functions

The Virtual Instrument (VI) using LABVIEW was designed to accurately control in real-times. The GUI of the developed solution is shown in Fig. 13. Fig. 13 shows the waveform of the input/output variables of the fuzzy system. So with the variation of FUPDI and FThI, there will be significant change in the range of Home's Power Demand as well as in the number of appliances the most consumed. Moreover, we notice that the waveforms of the two output variables are opposite and it is explained in Table 1. (When the Home's PD is "High" ∈ [2500..500], so the CMCA is all-opened ∈ [0..5]).

Table 1. Fuzzy Rules of Global FLC

Rules	IF FUPDI (MW)	AND FThI	THEN PD	AND CMCA
1	Low	Awesome	High	All-opened
2	Low	Normal	High	All-opened
3	Low	Expensive	Medium	Partial-opened
4	Medium	Awesome	High	All-opened
5	Medium	Normal	Medium	P-opened
6	Medium	Expensive	Low	Closed
7	High	Awesome	Medium	P-opened
8	High	Normal	Low	Closed
9	High	Expensive	Low	Closed

In the next section we will describe the fuzzy rules of the three used Fuzzy systems (FLC_1, FLC_2, FLC_3) then in the flowing section we will present their fuzzy rules.

The implementation of the three FLC systems is done using MATLAB software. MATLAB has been used because it is extensively used in electrical engineering, and it provides a very practical MATLAB fuzzy logic toolbox [21].

2.3.3 Fuzzy Rules of FLC_1 (shifting peak demand to low-demand period)

We incorporated 4 inference rules that conclude to four IF-THEN rules, seen in Table 2. Fig. 12 shows the fuzzy inference rules. The output decision of PD-of-appliance y= 1.45, arising from the input value of the FUPDI x_1 = 186 and from the input value of the Period x_2 = 0.295. The output decision is represented by blue coloured areas in PD-of-appliance column.

The MF "L-medium" represents the region of transition from low demand to high demand represented in Fig. 9.The MF "H-medium" represents the region of transition from high demand to low demand of power.

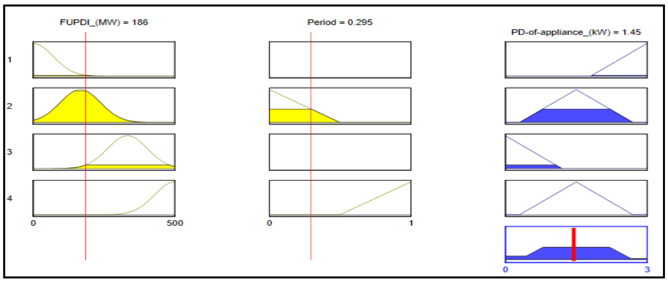

Fig. 12. The inferred output of the FLC_1 system

2.3.4 Fuzzy Rules of FLC_2 (shifting peak demand to low-rising period)

Mathematically low-rising period is expressed as:

$$y_{l-r}(x) = \begin{cases} 55x + 55, & 3 < x < 5 \\ 36.5x + 236.17, & 15 < x < 17 \end{cases} \quad (9)$$

Where: x represents the number of hours in a day.

For evaluation of the FLC_2, we included 4 inference rules, seen in Table 3. Fig. 14 shows the fuzzy inference rules. The output decision of PD-of-appliance y= 2.1, arising from the input value of the FUPDI x_1 = 186 and from the input value of the Period x_2 = 0.295.

Table 2. Fuzzy Rules of FLC_1

Rules	IF FUPDI (MW)	AND Period	THEN Power demand of appliance
1	Low	-	High
2	L-medium	Low-rising	Average
3	High	-	Low
4	H-medium	Low-falling	Average

Table 3. Fuzzy Rules of FLC_2

Rules	IF FUPDI (MW)	AND Period	THEN Power demand of appliance
1	Low	-	Average
2	L-medium	Low-rising	High
3	High	-	Average
4	H-medium	Low-falling	Low

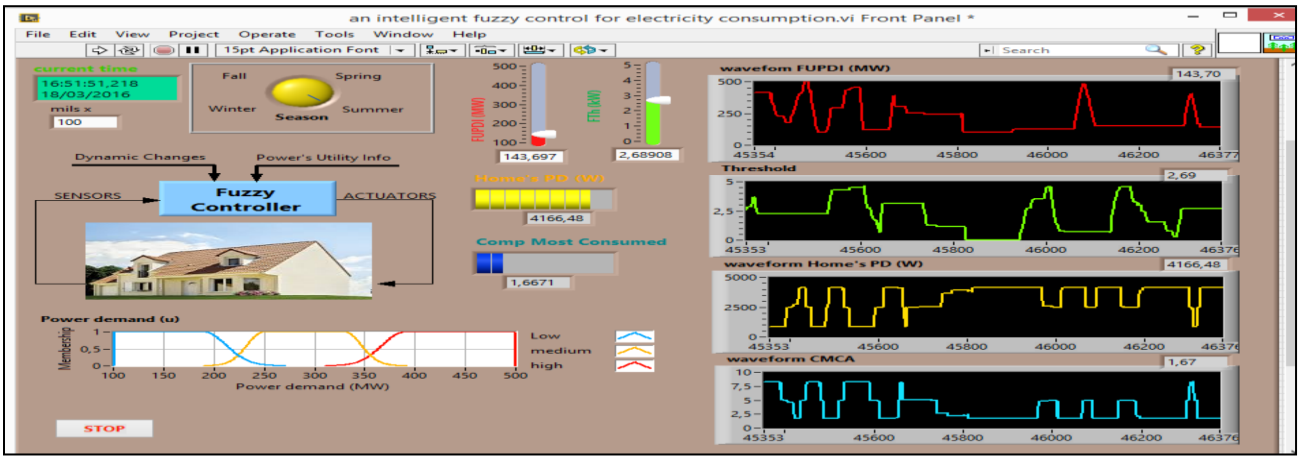

Fig. 13. GUI for Fuzzy Logic Control Based MAS

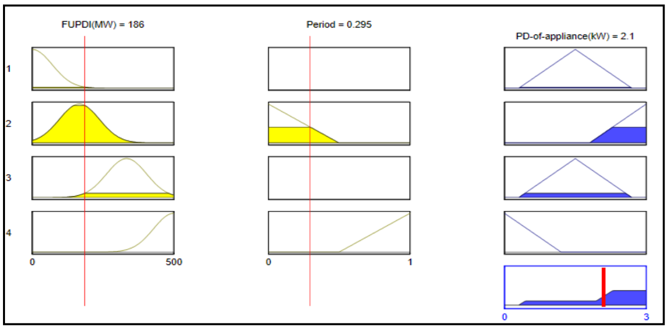

Fig. 14. The inferred output of the FLC_2 system

2.3.5 Fuzzy Rules of FLC_3 (shifting peak demand to low-falling period)

Mathematically low-falling period is expressed as:

$$y_{l-f}(x) = \begin{cases} -12.5x + 535, & 10 < x < 12 \\ -37x + 1266.7, & 21 < x < 23 \end{cases} \quad (10)$$

Table 4 represents the fuzzy rules of FLC_3. Fig. 15 shows the fuzzy inference rules. The output decision of PD-of-appliance y= 0.903, arising from the input value of the FUPDI x_1 = 186 and from the input value of the Period x_2 = 0.295.

Table 4. Fuzzy Rules of FLC_3

Rules	IF FUPDI (MW)	AND Period	THEN Power demand of appliance
1	Low	-	Average
2	L-medium	Low-rising	Low
3	High	-	Average
4	H-medium	Low-falling	High

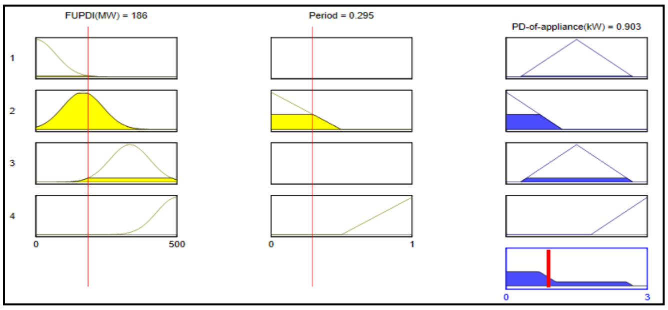

Fig. 15. The inferred output of the FLC_3 system

3. Application of the Proposed Solution

3.1. A cooperative mechanism based MAS

In this part, we explain the effectiveness of the proposed method used to reduce power demand for a smart home based "AG_0-FLC". A cooperative mechanism that reduces complexity problem has been detailed in Fig. 16.

For the simulation, PC based-LABVIEW was used to implement a FLC, to regulate the temperature of permanent load by making decisions based on difference between set-point and measured inputs variables. Also, FLC was used to shift the operation of some temporary appliances.

Therefore, each load category is correlated with a scheduling policy in order to reduce the energy use through the compression of power demand or the deferral of power requests [13]. We analyze the behaviour in the control of power demand of some appliances and the type of control used.

- The electric water kettle has the first priority (P1) so its operation cannot be stopped because its use is unpredictable. This is an uncontrolled appliance.
- The refrigerator and freezer can be interrupted for a little period, with a condition that the temperature is maintained in a given range. The agent can predict their energy need for the next time by observing the parameters T and door-open time. Permanent Agent use the scheduling policy with respect to comfort zone $[T_{ref}^{min}, T_{ref}^{max}]$.
- Washing machine and dishwasher are devices which, once commenced, could not be halted, although the user may choose to start them later. SM provides to the user the time-of-use electricity pricing sent by utility, he can take advantages of washing overnight where the cost is cheap. Temporary Agent predicts its consumption and therefore uses FLC_3 to control the operation of washing machine, and FLC_1 to control the dishwasher. For example the user expects the dishes to be ready to use by dinner, so α_a = 2 PMand β_a = 6 PM.
- TV set is a device where their level of power is manoeuvrable. TV set has three functions with different levels, so temporary agent use the scheduling policy in the case where the threshold would be reached soon, and there are operating appliances that could not be stopped, so the agent adjusts the function of TV to ambient light or stand-by power level with $y_a = \delta_a^{min}$.

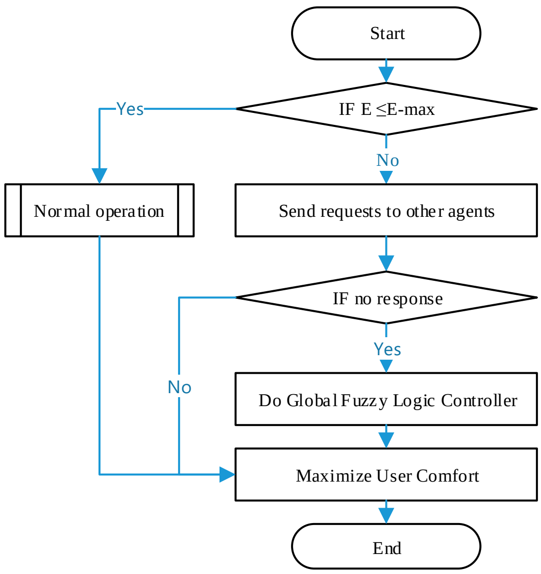

Fig. 16. A cooperative mechanism based MAS in home automation

- Water heater has a primary importance, in the situation of the user want to take his bath immediately. However, a user programmed the time of his bath, so the agent could heat up the water before the organized time. Besides, an agent can cut off the power from a boiler for one hour without ruining the comfort of the user. Permanent agent controls the water heater daily energy need using scheduling policy and in case to prevent power peak demand it uses FLC_2.

In this part we analyze the control of power consumption of three types of appliances in the case of a peak power demand (Fig. 17). The simulation spans hours in a day divided in quarter-hourly slots and represented by a set of time slots $t \in$ Time, where Time={1, 2, 3, ..., etc}. The maximum of power of appliances used in our strategy is as follows: refrigerator (140 W), TV set (300 W), water heater (1800 W), space-heater (1500 W), and washing machine (2000 W). In the mentioned period [0,1] the total home energy need has to respect the equation (4), with $E^{max} = 3000W$.

$$EC^{ototal} = \sum_{a \in A} y_a^{h=1} = 140 + 300 + 1800 + 1500 + 2000 = 5740\ W > E^{max} \quad (11)$$

So the agent predicts this power peak and takes/performs in advance some tasks. The operation of washing machine will be shifted overnight. The TV set will operate normally. The refrigerator can be disconnected for one hour as long as the door is closed. The agent checks the SF of water heater and space heater, and schedules their operations and in case of peak power demand the agent disconnects the appliance that has the highest SF level. Finally the scheduling policy used by the agent is illustrated in Fig. 18.

The quantitative energy savings (ES) can be obtained by:

$$ES\,(\%) = \left(1 - \frac{EUAfterSchPolicy}{EUBeforeShPolicy}\right) * 100 \quad (12)$$

Where EUAfterSchPolicy presents the energy usage after scheduling policy algorithm, and EUBeforeShPolicy presents the energy usage before scheduling policy algorithm.

Indeed, the energy savings of the building is defined as the ratio of the energy usage difference before and after implementing the scheduling policy algorithm, during the same period, as illustrated in Eq. (12).

We calculated the quantitative energy savings in two intervals. In interval [0,1] the total energy consumed is then calculated: $EC^{ototal} = 300 + 1500 = 1800W$. In this case, we reduce power up to 69%. In the interval [1,2], $EC^{ototal} = 140 + 300 + 2000 = 2440W$, we reduce power up to 58%. On the two intervals we respect the constraint Eq. (5). Fig. 19 shows the total power demand before and after the scheduling policy algorithm, where the x-axes is expressed in 1/4 hour.

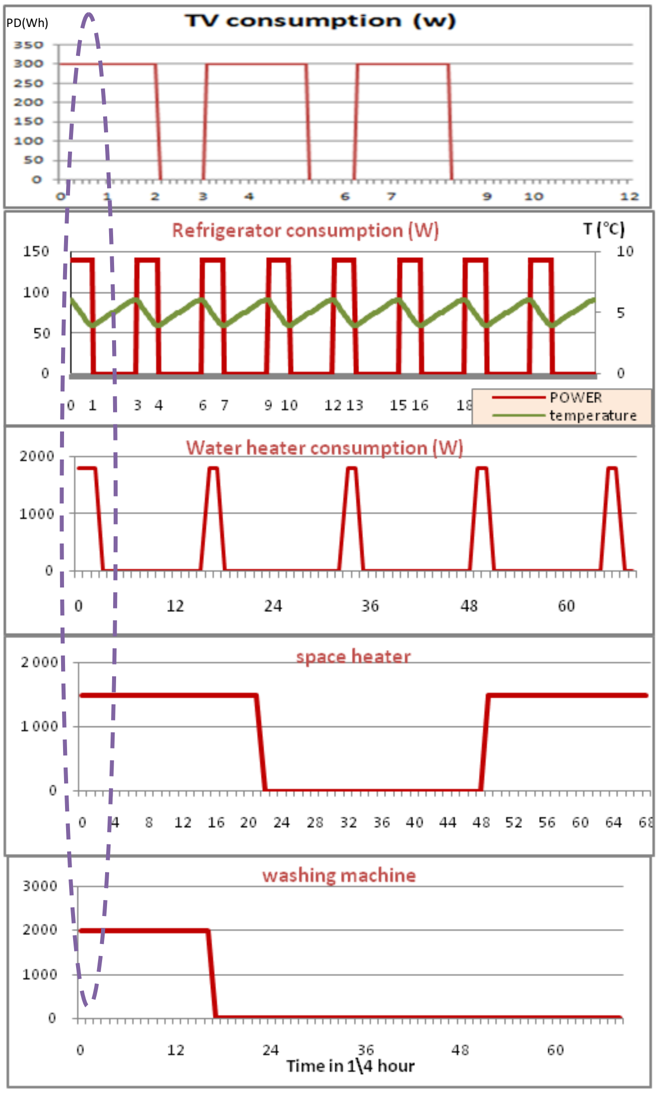

Fig. 17. Appliances power demand based AG_0-FLC

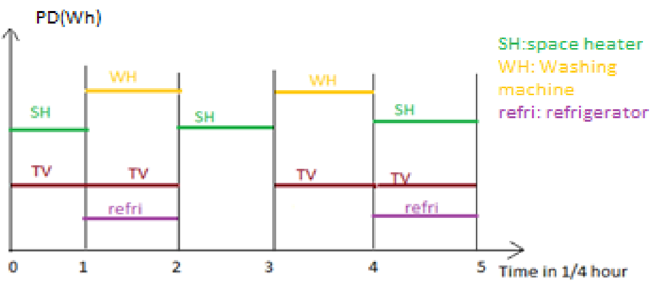

Fig. 18. Managing appliances power demand with adaptive scheduling method

3.2. Discussion and comparative results

In this section, we will compare our proposed technique AG_0-FLC to others studies in the case of the percentage of energy reduction in a building.

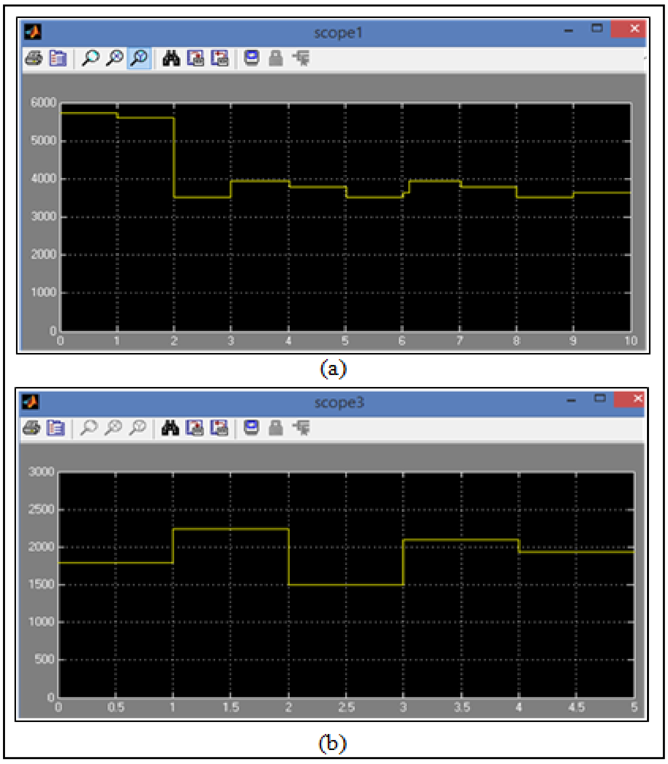

Fig. 19. The total power consumption (a) before scheduling policy, (b) after scheduling policy

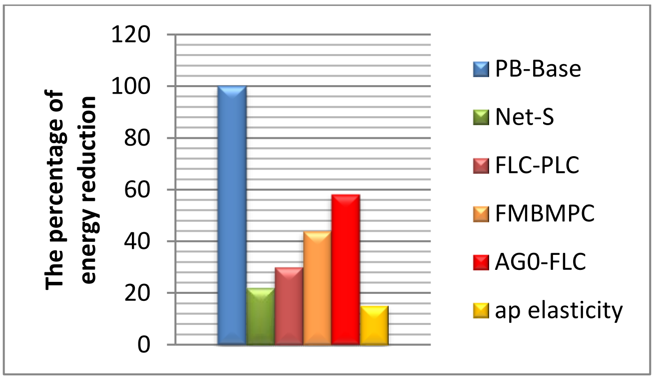

Fig. 20. A comparative studies done in the field of energy reduction

We compare different studies, to prove that the proposed solution AG_0-FLC has the highest reduction in power demand (58%). The different studies are explained in section 1, and these studied are the Net-S (22%) [26], FLC-PLC (30%) [14], FMBMPC (44%) [35] and appliance elasticity (15%) [37]. Fig. 20 illustrates comparative simulations of the percentage of energy reduction of the different studies with a reference a basic power demand (PB-Base: 100%). The y-axis is expressed in percentage of energy reduction.

The presented studies in Fig 20 are concentrated only on the control of energy consumption without providing comfort to their residents. But the proposed solution AG_0-FLC has significantly reduced the power demand without sacrificing comfort to much. So, in future work, we aim to develop an application to load control in overall electrical grid.

4. Conclusion

In the present paper we developed a strategy for a Home Automation system which reaches a compromise between the maximizing the habitant comfort and minimizing the electric bills in addition of satisfying technological constraints of appliances. Furthermore, the smart home responds quickly to the demand of the electrical grid compared to conventional one. The developed solution AG_0-FLC has been successfully altering the shape of the load curve and test results shows that the energy savings ups to 58% of the total residential energy consumption in the period of utility high power demand. This percentage of energy reduction has been compared to other studies in the literature as using the Net-Service, PLC-FLC, FMBMPC, PLC-FLC, and appliance elasticity methods, which has a percentage of energy reduction of 22%, 30%, 44%, and 15% respectively. So, AG_0-FLC shows an efficient reduction in power demand compared to other studied done in the same field. The performance of the use of Multi-Agent paradigm as a distributed artificial intelligence is the self-control of residential energy by the SM.

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