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Proposed Architecture for Energy Efficiency and Comfort Optimization in Smart Homes

Smart Home Architecture for Energy Efficiency

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Abstract
In this paper a smart home controller proposal is formalized as a multi-objective integer linear programming problem that minimizes energy consumption and maximizes comfort. A comfort objective function is tested for several tariff scenarios including one with renewable sources as local off-grid micro-generation. The proposed model specifies best times to activate real household appliances based on energy consumption data, given load-limiting constraint and user preferences, by use of a weighted aggregation function. The proposed scenarios have shown excellent results for energy saving without a significant reduction in comfort.

Keywords Demand side management · Renewable sources · Operations research · Smart home

1 Introduction

Energy efficiency has matured from the technological fringe to daily reality. Smart appliances, smart grids and renewable energy converged to our homes putting pressure in our old habits in face of new sustainable environment. Energy management for home owners has become a de facto requirement for modern households, where smart home controller (SHC) offers the framework into which a sustainable and energy efficient house can be built upon, removing some of the burden from the user.

However, creating a SHC that adjusts human desires (like comfort) to grid responses (to achieve lower costs and better use of energy) is complex and, most of the time, conflicting. The technological advances in computers and communication networks enabled, in the last years, the increased opportunity to use optimization models in real (or *quasi* real) time applications.

In Di Giorgio and Pimpinella (2012) it is presented an optimization model using integer linear programming to minimize a single objective function (energy cost) and an event-driven SHC is then proposed. A more proactive control based in fuzzy and adaptive methods (adjust-based learning rules) for smart homes is proposed in Vainio et al. (2008). Similar studies using mono-objective optimization models can be seen in Kantarci and Mouftah (2011) and Lentini (2012).

Further developments in Antunes et al. (2002) proposed an integer multi-objective linear programming for cost analysis in planning, maintenance and operation of new power generators. Similar works from Fehrenbach et al. (2014), Shaikh et al. (2016) and Grandclment et al. (2015) expanded the multi-objective approach and presented energy efficiency optimization proposals using SHC for the management of electrical loads in changing political and technological sce-

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narios for temperature adjustments, being temperature the comfort variable.

Similar works like Cho (2013) and Casella et al. (2016) proposed different theoretical loads and tariffs models for an integer linear programming that optimizes demand in real time. In Rasheed et al. (2015) it is proposed a different load classification; related cost and comfort equations, loads operation time are discretized and all loads are considered within a single cycle, finally Bezerra Filho et al. (2015) proposed and compared the same load classification and scenarios as in Di Giorgio and Pimpinella (2012), adding further comfort variability.

Other related works like Corno and Razzak (2012) model a real-time load configuration scenario providing minimal energy consumption and satisfying users demand. In Kofler et al. (2012) a semantic representation based on web ontology language (WOL) is proposed to define energy consumption databases for control systems in smart homes. Solutions for ubiquitous home networks based on a network of active sensors for the intelligent home control system are proposed in SUH and KO (2008) and Hernndez et al. (2013). Authors such as Leite and Montovani (2015a) and Leite and Montovani (2015b) have proposed smart grid optimized architectures.

The remaining of this paper is organized as follows. In the second section the problem statement is presented, in the third section the architecture is proposed, in the fourth section results are discussed, and finally, some conclusions and recommendations for future research are given in the last section.

2 Problem Statement

The search for the optimal dispatch time for electrical loads in a controllable home environment using integer linear programming is a complex problem due to a high number of decision variables and constraints; nevertheless, several authors Di Giorgio and Pimpinella (2012), Cho (2013), Rasheed et al. (2015), Bezerra Filho et al. (2015) and Lai et al. (2015) have shown the potentials to this approach. The main goal, to many of these models, is to find the scheduling of loads with the lowest cost considering a restriction given by the user comfort, thus defining a multi-objective problem. For cost objectives the time-of-use (ToU) tariff model, as proposed in Brazil by the Resolution 773/2017 of the National Electric Energy Agency (ANEEL), is used in varying hours. Since comfort, in this paper, is defined as the minimal distance between the users chosen start time and the actual start time proposed by the SHC, the user inputs his preference using a variable weighted aggregation function.

Table 1 Symbols related to the objective functions

Symbol	Meaning
M	Number of loads
$\bar{\mathrm{P}}_m$	Mean power of mth load
$\hat{\mathrm{P}}_m$	Peak power of mth load
N_m	Duration, in samples, of mth load
I_{sm}	Minimal start time for mth load
I_{em}	Maximum end time for mth load
S	Sample for first planning instant
E	Sample for last planning instant
μ_{mi}	ith decision variable for mth load
P_k	Peak limit for kth time slot
C	Energy cost for given period
I_{bm}	Best start time for mth load
C_{lm}	Comfort level for mth load

2.1 Mathematical Formulation

These notations, as presented by Di Giorgio and Pimpinella (2012) and Bezerra Filho et al. (2015), are introduced to model the programming problem (Table 1).

In order to make reading easier, Eqs. (1) and (2) are proposed for cost and comfort, respectively.

$$f_1 = \sum_{c=1}^{C} \sum_{i=I_{\mathrm{sm}}}^{I_{\mathrm{em}}-N_m} \left(\sum_{n=i}^{i+(N_m+1)} \bar{P}_m[n-i] T_s C[n] \right) \mu_{mi} \tag{1}$$

$$f_2 = \sum_{m=1}^{M} \sum_{i=I_{\mathrm{sm}}}^{I_{\mathrm{em}}-N_m} \left(C_{\mathrm{lm}} \sqrt{\left(i - I_{\mathrm{bm}}^2\right)} \right) \mu_{mi} \tag{2}$$

Such as both above equations could be used complementary as:

$$f_{\mathrm{cost}} = \alpha \times f_1 + (1-\alpha) \times f_2 \tag{3}$$

Subject to:

$$\sum_{i=I_{\mathrm{sm}}}^{I_{\mathrm{em}}-N_m} \mu_{mi} = 1 \tag{4}$$

$$\sum_{m \in M_k} \left(\sum_{i=k-(N_m-1)}^{k-(k-I_{\mathrm{em}}+N_m)} \hat{P}_m[k-i] \mu_{mi} \right) \leq P_k \tag{5}$$

$$\mu_{mi} \in [0, 1] \tag{6}$$

Energy cost is given in Eq. (1) as the minimization of cost. The comfort is given in Eq. (2) as the minimal distance from expected and real starting time. The optimization model employed was the minimization of the function formulated from the association of cost (Eq. 1) and comfort (Eq. 2)

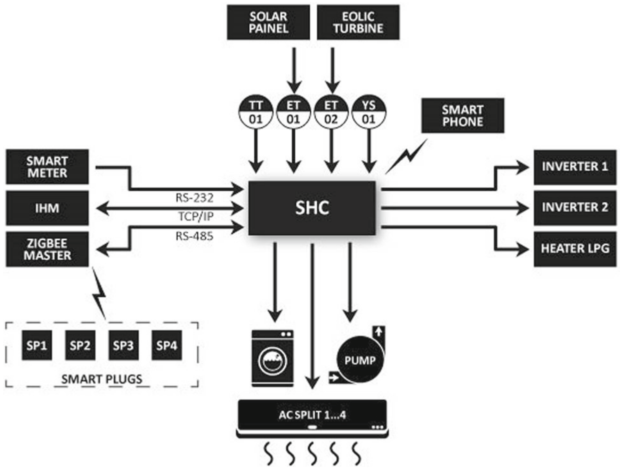

Fig. 1 System architecture model

objectives within determined weights as given by Eq. (3) (Di Giorgio and Pimpinella 2012; Bezerra Filho et al. 2015).

Constraint set (4) limits every load as having only one starting time, between the minimum start time (I_{sm}) and the maximum end time that would still allow the load to be run ($I_{sm} - N_m$). Constraint set (5) limits the overall loading for the entire SHC to be less than a peak limiting load from the *kth* start time and duration, to the last possible ending time plus duration. Constraint set (6) states that all decision variables are binary.

3 Smart Home Controller Architecture

3.1 Loads Definition

Loads, in this work, are characterized as:

– *Controllable loads (CL)* Loads that can be switched on/off for a certain period of time with or without degradation of service quality. These loads are connected to smart plugs (SP) or directly to the SHC. Examples of CL loads are air conditioners, pool filter pump, non-programmable washer, dishwasher, outdoor lighting;
– *Detectable loads (DL)* These are non-controllable loads that have estimated power consumption as the difference in energy measurement of the smart meter (SM) and all CL and SP. Examples of DL loads are audiovisual equipment; computer equipment; lighting; toasters, mixers.

3.2 Architecture

The architecture of the home automation system test scenario proposed in this paper is illustrated in Fig. 1. The SHC is responsible for the management of all loads and renewable energy generation. The SHC defines the operation of the loads by reading information from the measuring devices and outputs execution commands given by the programming after running the objective function optimization, as shown in SHC architecture (Fig. 1).

The SHC performs the following tasks:

1. Communicates with (smart plugs—SP) through the network coordinator (Zigbee manager) to acquire power consumption and send operating commands to the equipment connected using RS485 and MODBUS;
2. Receives the load operational status from the smart meter through RS232 and ABNT messaging protocol;
3. Receives load expectancy from the user through the human–machine interface (HMI) using TCP/IP—ethernet;
4. Directly schedules controllable loads by defining operating hours for each equipment;
5. Defines the way micro-generation equipment operates;
6. Activates, when necessary, the liquefied petroleum gas (LPG) heating system.

3.2.1 System Function

The system was validated through an industrial platform associated to the SP developed in lab, as previewed in Fig. 2.

To validate the SHC, a programmable logic controller (PLC) was used as slave to a supervisory control and data acquisition (SCADA) application installed in a personal computer (PC) SCADA server. In this case the PLC was used only as the master controller network coordinator (Zigbee Master), sensor reader and load logic controller.

The working logic is as follows:

1. Through the supervisory application (SA) the user inputs his preferences;
2. The SA generates a text file (Input.txt) that is used by the MATLAB code to optimize best times with weight based energy efficiency and comfort;
3. The MATLAB code outputs the answers in a text file (Output.txt) to the SA;
4. The SA shows the daily schedule for the home loads and sends it to the PLC using TCP/IP—ethernet;
5. The PLC programming, using the SA data, control loads directly connected and communicates with the Zigbee Master using RS 485 industrial protocol MODBUS-RTU sending action commands to SP and reading current response from loads connected to the actionable SP;
6. The PLC activates the solar and wind inverters (1 and 2) based on schedule and voltage condition (V1 and V2) for micro-generation of electricity. These inverters feed outside lights without priority status from the SHC. Also, depending on the temperature status of the TT01 sensor, the liquid petroleum gas (LPG) system is fired for heating water purpose;

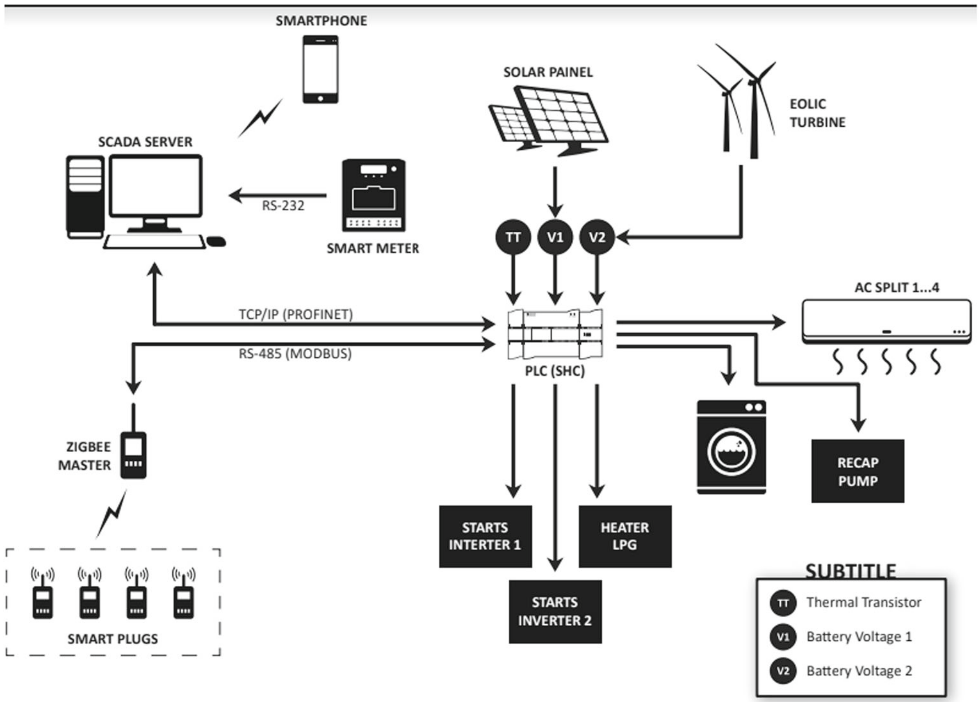

Fig. 2 System architecture implemented

7. As data are collected from all loads, the SA show actual and scheduled energy consumption in a status screen display;
8. With these data, including load current from SP and current reading from SM, the SA calculates DL for a realistic demand measurement in order to maintain peak shaving capacity. The communication between SCADA Server and SM is through a RS232 connection using ABNT (Brazilian association of technical norms) protocol.

4 Simulation Results

The IBM ILOG CPLEX, a benchmark solver in the academic and industrial areas, provides good performance even with many variables and can be used with user-written applications. MATLAB is a high-level language and interactive environment for numerical computation, visualization and programming. Real residential load simulations are tested for five scenarios in CPLEX using the cplexbilp. MATLAB is used for easier data management and communication with SCADA interface while providing a working embeddable framework for CPLEX.

4.1 Experimental Scenarios

Scenarios are presented with a common load-set and price tariff allocation. Thus, some real-load parameters are measurable: number and duration of stages/cycles and average and peak power load, while others are controllable by the SHC: their start time.

– Stage is the amount of time spent by a load performing a specific function, e.g., the time a washer spends only on the rinsing activity;
– Cycle is the period of time that encompasses all the stages of a load, e.g., the time a washing machine performs all its stages (washing, rinsing, drying).

Real loads used throughout this paper are presented in Fig. 3. The renewable source in scenario 4, being off-grid, is battery-enabled and supplies a relatively small load (outdoor lights 0.30 kW). It can be considered as always able to provide energy when demanded; this remains true since usual batteries in off-grid setups can provide energy for long periods with a single small charge.

Some loads are described in Table 2. All values were obtained from the smart meter with timed description and user preferences. The actual, expected and range of operating hours were also captured. Relevance for each load is also described.

Pricing is based on a estimated tariff (Table 3) where peak and off-peak are considered as well as mixed and conventional energy values.

4.1.1 Scenario 1

Time-of-use (ToU) tariff. Variable pricing on hourly basis.

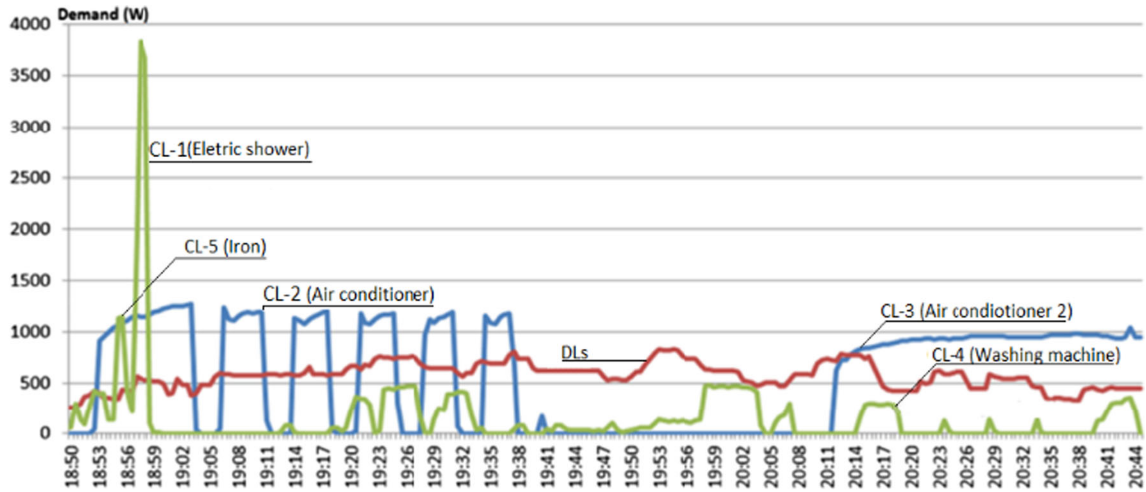

Fig. 3 Controllable and detectable loads (real representation)

Table 2 Loads' full description

ID	Description	Stages	Δt(min)	$\bar{P}$(kW)	$\hat{P}$(kW)	UP	Scheduled		R_n
						Start	Start	End	
01	Booster pump	01	20	2.00	3.00	08:00	07:00	17:00	0.1
02	Filter pump	01	120	0.75	1.75	08:00	07:00	17:00	0.1
03	Clothes iron	01	120	1.00	1.20	16:00	14:00	17:00	0.3
04	Washing machine	08	10 10	0.13 0.51	0.70 0.51	08:00	07:00	17:00	0.5
			4 6 2	0.30 0.26 0.15	0.30 0.26 0.15				
			2 2 7	0.15 0.15 0.22	0.15 0.15 0.30				
05	Outdoor lights	01	270	0.30	0.30	18:00	17:00	23:55	0.3
06	Indoor lights	01	270	0.15	0.30	18:00	17:00	23:00	0.7
07	Office AC	14	10 5 …	1.30 …1.30	1.70 1.30 …	20:00	17:00	23:55	1.0
08	Suite AC	07	30 20 5	2.00 2.00 2.00	2.10 …	20:00	17:00	23:55	1.0
			5 5 5 5	2.00 …2.00	…2.20 2.00				
09	Single AC1	01	240	1.10	1.20	20:00	17:00	23:55	1.0
10	Single AC2	07	10 10 5	0.90 0.90 0.90	1.10 …1.10	20:00	17:00	23:55	1.0
			5 5 5 5	0.90 …0.90	1.10 …1.10				
11	Dishwasher	05	5 10 15	0.03 1.76 0.03	0.03 1.76 0.03	21:00	18:00	22:00	0.3
			5 10	1.76 0.03	1.76 0.03				

Table 3 Daily cost-of-use values

Tariff	Period	Price ($cents/kWh)
Conventional	[00:00–23:59]	22.50
ToU: off-peak	[00:00–17:59] and [23:00–23:59]	11.25
ToU: intermediate	[18:00–18:59] and [22:00–22:59]	33.75
ToU: peak	[19:00–21:59]	45.00

4.1.2 Scenario 2

Time-of-use (ToU) tariff. SHC for mono-objective optimization, cost only.

4.1.3 Scenario 3

Time-of-use (ToU) tariff. SHC for multi-objective optimization, cost and comfort simultaneously.

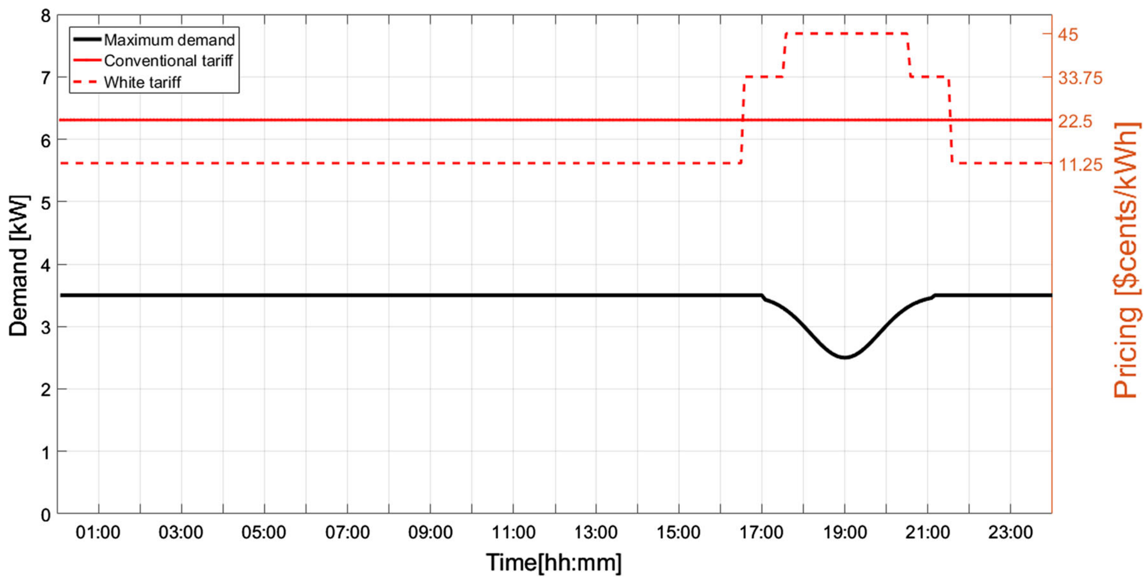

Fig. 4 Load-limiting threshold and tariffs

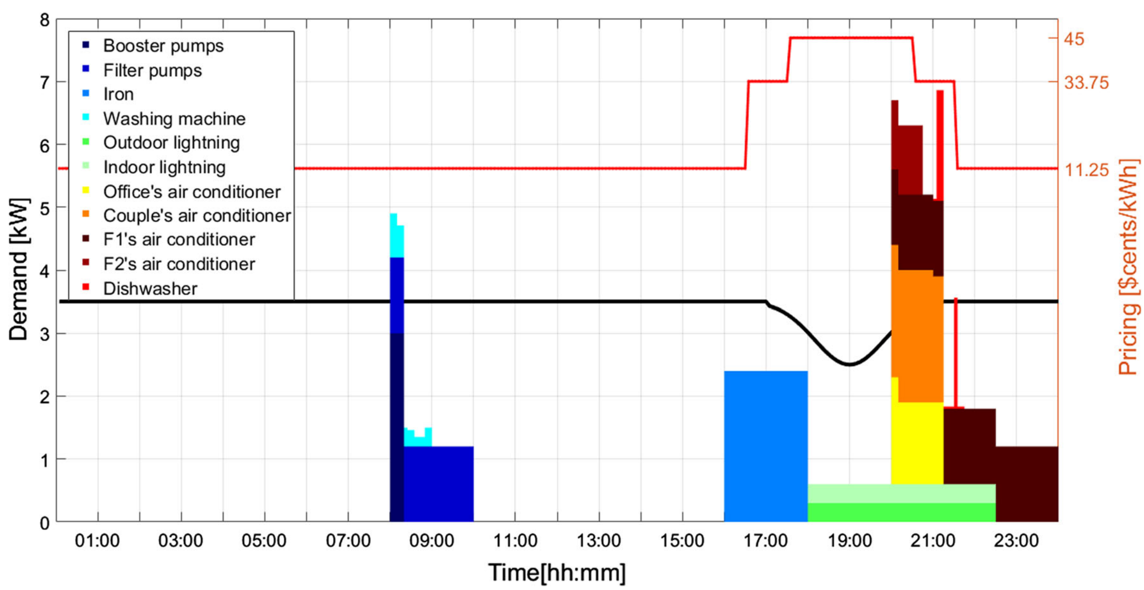

Fig. 5 Scenario 1: ToU tariff without SHC

4.1.4 Scenario 4

Local micro-generation and time-of-use (ToU) tariff. SHC for multi-objective optimization, cost and comfort with added use of off-grid renewable power source.

4.2 Experimental Results Analysis

The SHC optimization for each scenario has a load-limiting threshold of 3.5 kW which represents the maximum demand allowed for the user by the grid operator. Detectable charges (DL) are presented as an inverted Gaussian centered at 19:00 with amplitude of 1.0 kW that decreases the load-limiting threshold. In Fig. 4 the load-limiting threshold and tariffs applied to the various scenarios are presented.

Comfort, as described in Eq. (2), is simply a distance from an expected start time and an actual start time given by the SHC, most comfort being obtained as loads starting-up when the user expects them to.

Multi-objective function deals with the simultaneous minimization of cost and maximization of comfort Eq. (1) where a parameter α weights cost–comfort responses; for maximum comfort we have that $f_2 = D_{\max}$ and the relative comfort is given by:.

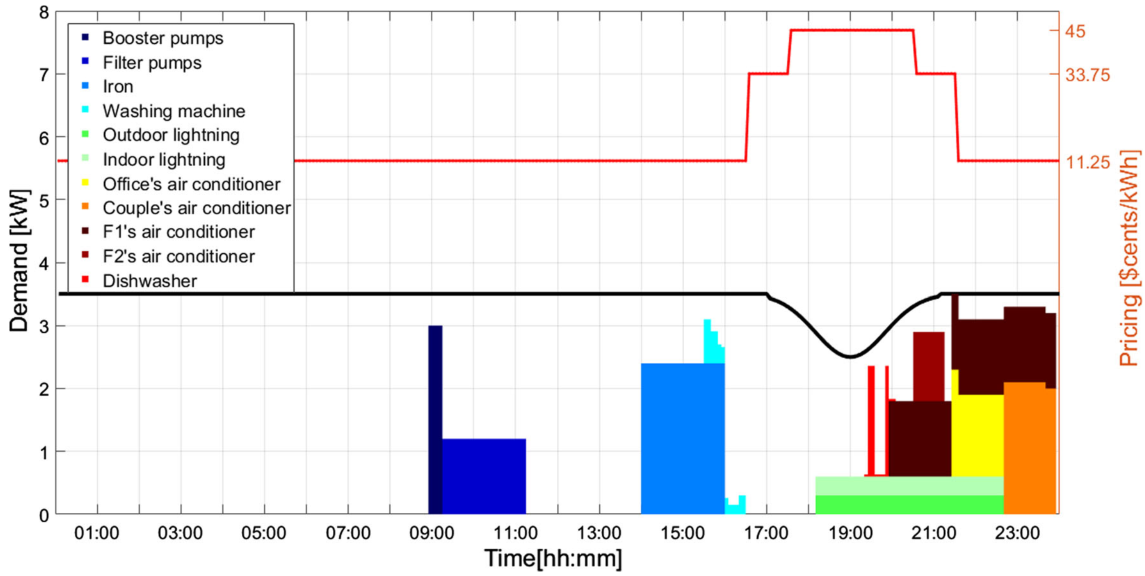

Fig. 6 Scenario 2: ToU tariff with SHC cost optimization

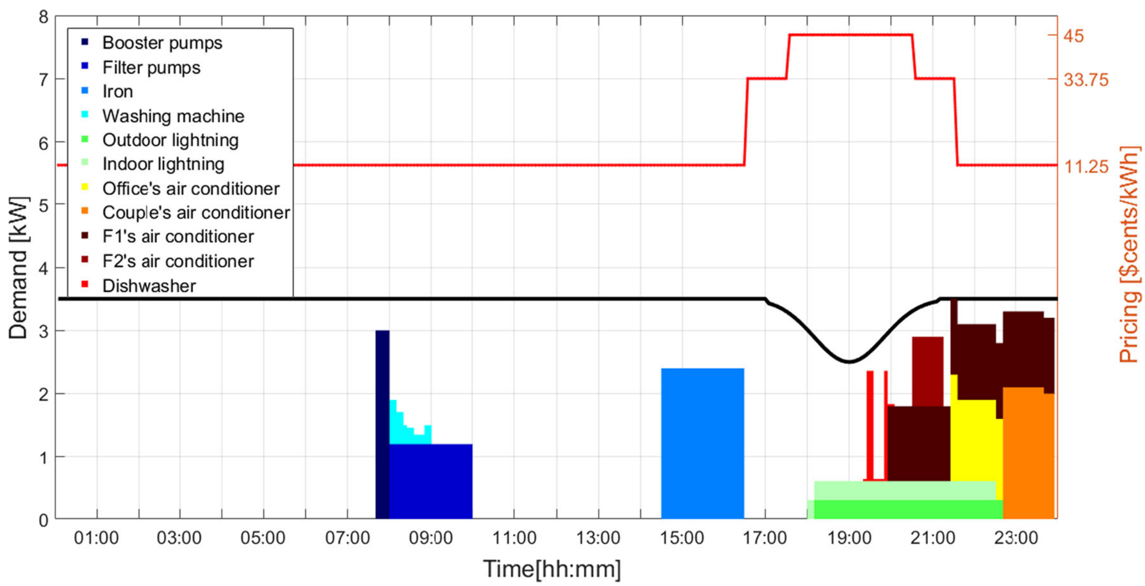

Fig. 7 Scenario 3: ToU tariff with SHC multi-objective optimization (α 0.55)

$$\text{Relative}_{\text{comfort}} = \frac{\text{Comfort}_c}{D_{\max}} \times 100 \tag{7}$$

When all loads are allocated at the time requested by the user, the relative comfort value will be equal to 1.0 (maximum). On the other hand, when all loads are allocated furthest from the time requested by the user the relative comfort will be equal to 0.0 (minimum).

4.2.1 Scenario 1: ToU Tariff Without SHC

For this pricing scenario a different peak, an intermediate and off-peak tariffs (3) are used. The cost is $4.50, obtained for the configuration requested by the user, as presented in Fig. 5. The load-limiting threshold and the tariff are not used for optimization purposes as presented in Fig. 5. The configuration requested by the user exceeds the load-limiting threshold.

In this scenario the pricing scheme causes a greater penalty to cost as tariffs increase in peak times that are coincident to the peak load demand (Fig. 5) setup by the user.

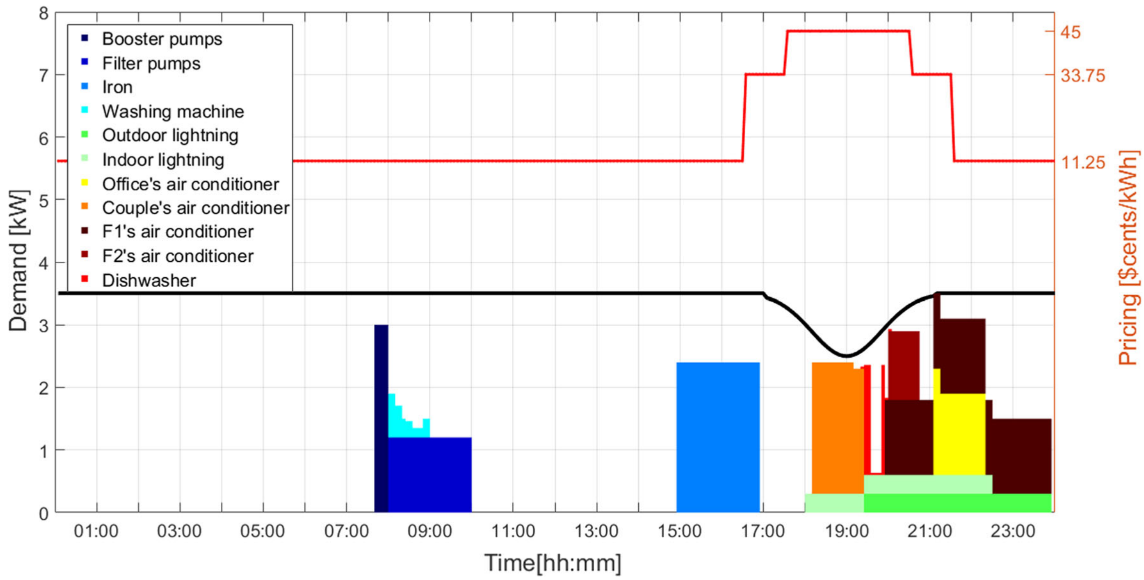

Fig. 8 Scenario 3: ToU tariff with SHC multi-objective optimization (α 0.00)

4.2.2 Scenario 2: ToU Tariff with SHC Cost Optimization

Cost optimization is used in the SHC (objective function f_1). The cost obtained in this scenario is $3.06 (32% cost reduction when compared to scenario 1). In Fig. 6 the SHC load allocation is presented. In this case loads are relocated so as not to exceed the load-limiting threshold, in addition the SHC seeks to allocate the loads at off-peak periods at the same time aiming for cost reductions.

When cost is implemented in the SHC optimization algorithm by use of a ToU tariff model, the result is delayed loads (air-conditioning and dishwasher) to less demand-intense periods. Thus, the peak load restriction and price optimization can be attained simultaneously and comfort could be extremely penalized in such an optimization scheme.

4.2.3 Scenario 3: ToU Tariff with Multi-objective Optimization

Cost and comfort optimization is used in the SHC (objective functions f_1 and f_2), and the cost obtained in this scenario is dependable in the alpha value selected from $3.06 to $4.03 (up to 32% economy when compared to scenario 1). In Fig. 7 the SHC load allocation is presented. In this case loads are relocated so as not to exceed the load-limiting threshold in addition to both seeking off-peak times for cost and least distance from users input for comfort.
Unlike scenario 2 the washing machine (given the relatively low influence to comfort) has moved drastically in time, showing that the SHC input wasn't trying to penalize much comfort from higher ranked loads.

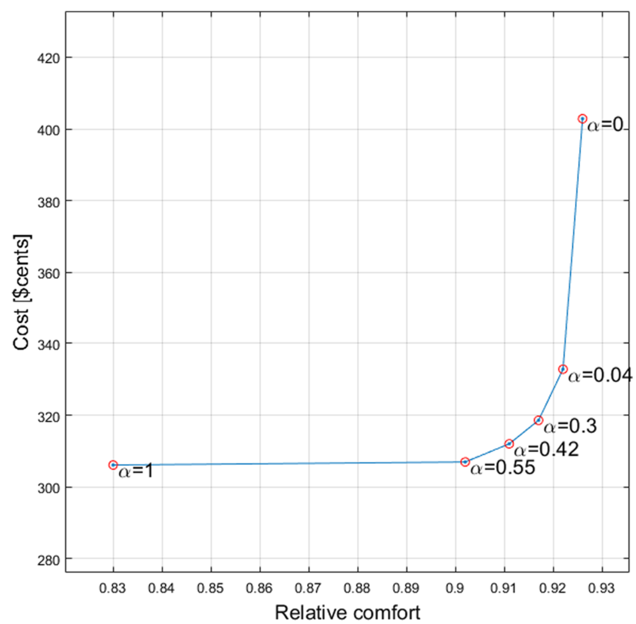

Fig. 9 Cost and comfort relationship on scenario 03

Further improvement can be found when comfort is the exclusive goal. As objective function f_2 becomes relevant with low-valued alpha (Fig. 8) the loads are relocated as not to exceed the load-limiting threshold, but very aggressively allocate higher ranking loads (comfort wise).

In Fig. 9 a Pareto front approximate representation, created from several scenarios, is presented that shows the effect of varying α in the solution associated with a changing cost and comfort. One can observe that the variation of comfort with respect to cost does not occur in a linear way. It is possible to choose α values that offer greater comfort than

Table 4 SHC time allocation for scenario 4 and different α

ID	Expected	$\alpha = 0.55$		$\alpha = 0.00$	
		Actual	Δ	Actual	Δ
01	08:00	08:55	55	07:40	20
02	08:00	09:15	75	08:00	0
03	16:00	14:00	120	14:30	90
04	08:00	15:30	450	08:00	0
05	18:00	18:10	10	18:10	10
06	18:00	18:10	10	18:00	0
07	20:00	21:25	85	21:25	85
08	20:00	22:40	160	22:40	160
09	20:00	19:55	5	19:55	5
10	20:00	20:30	30	20:30	30
11	21:00	19:20	100	19:20	100

the optimal configuration in cost without drastic increases in its value. For example, values 0.55 and 0.00 for α were selected for comparison purposes shown in Figs. 7 and 8 where load allocations for these two configurations are presented.

Given the time, load-limiting and peak tariff constraints for each load, the main differences between the configuration of Fig. 7 and the one presented in Fig. 6 (equivalent to the configuration of $\alpha = 1$) are the displacements of loads 1–4 which show starting times closer to those requested by the user. In Fig. 8 $\alpha = 0$ means that only the comfort function is considered. It can be observed that the SHC ignores the peak tariff rate aiming to allocate the loads in the most faithful way to user request without exceeding the load-limiting value. In Table 4 the results obtained for values of $\alpha = 1$ and $\alpha = 0.55$ are compared.

From Table 4 it can be observed that load allocation for $\alpha = 0.55$ was very close to the user preference. Note that, despite the comfort increase (α ranging from 1 to 0.55), the cost remained almost constant.

4.2.4 Scenario 4: Local Micro-generation and ToU Tariff Using SHC for Multi-objective Optimization

Loads 5 and 6 (indoor and outdoor lights) were considered battery-supplied and connected to in-situ micro-generators (wind and solar photovoltaic hybrid system). The optimization settings are limited to the remaining 9 loads.

Like scenario 3, the washing machine (given the relatively low influence to comfort) has moved drastically in time, at the same time the air-conditioning (higher ranked load) moves slightly from different alpha values tested.

Figure 13 shows the cost and comfort variations with variable α values. In both cases the comfort analysis is relative to α. In Fig. 13 several scenarios are simulated and a compilation of the trade-off between the cost in cents and the relative comfort of the configuration was presented, showing that values of α of each situation. It can be observed that with a small variation of α (from 1 to 0.98) it is possible to obtain a configuration with greater comfort without increasing the cost.

The same data are used to elaborate Fig. 13. In Fig. 14 the evolution of both cost (expressed in cents) related to energy (dotted line) and the relative comfort (filled line) with respect to α values is presented. The SHC load allocation in this scenario is presented in Figs. 10, 11 and 12 for the respective

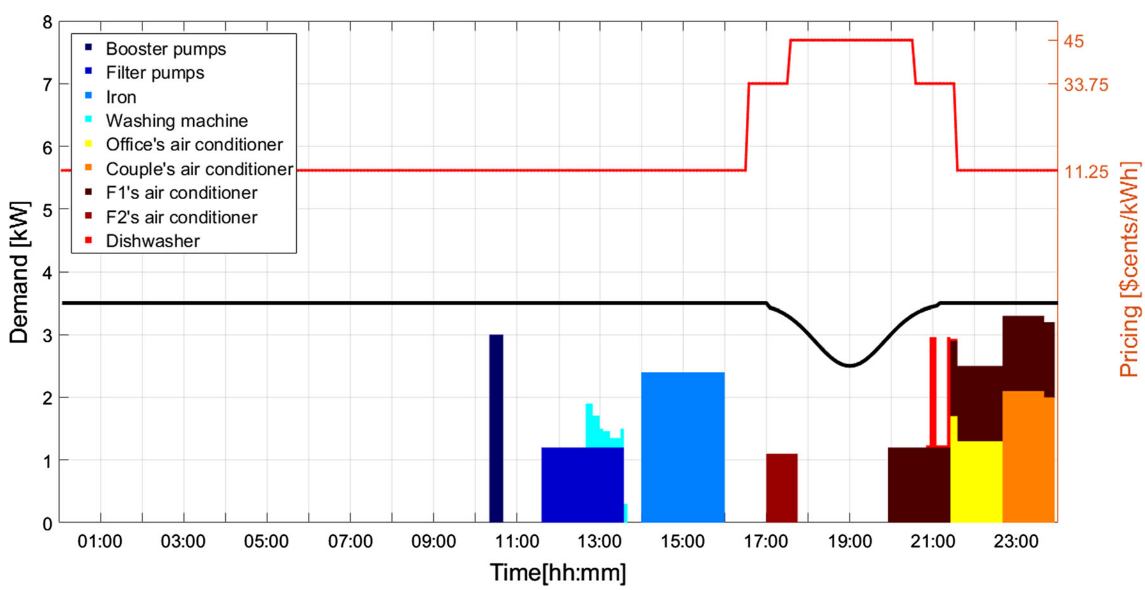

Fig. 10 Scenario 4: Local micro-generation and ToU tariff using SHC for multi-objective optimization ($\alpha = 1$)

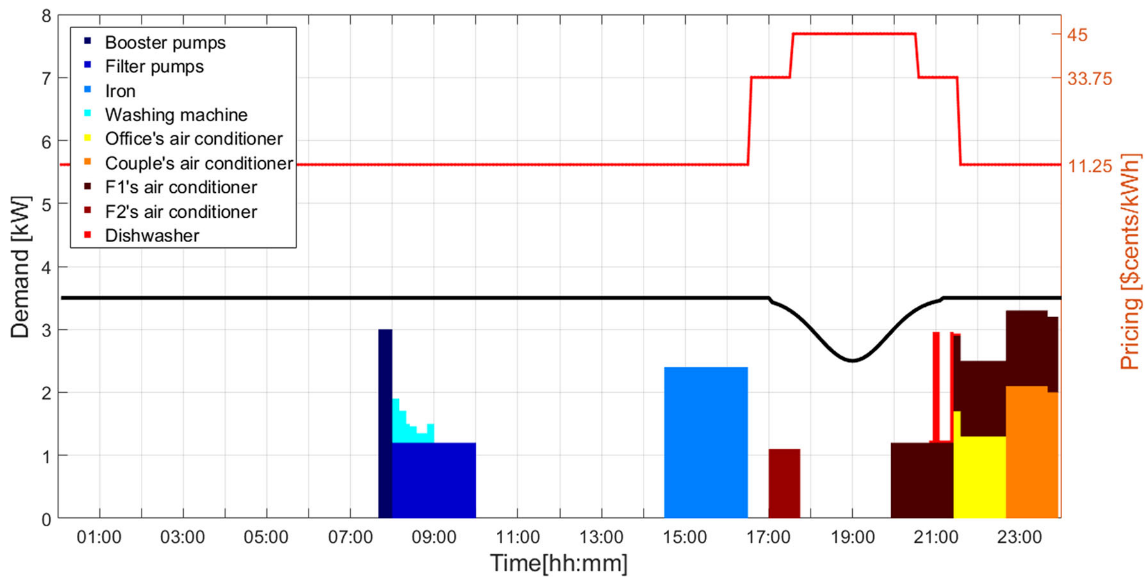

Fig. 11 Scenario 4: Local micro-generation and ToU tariff using SHC for multi-objective optimization ($\alpha = 0.98$)

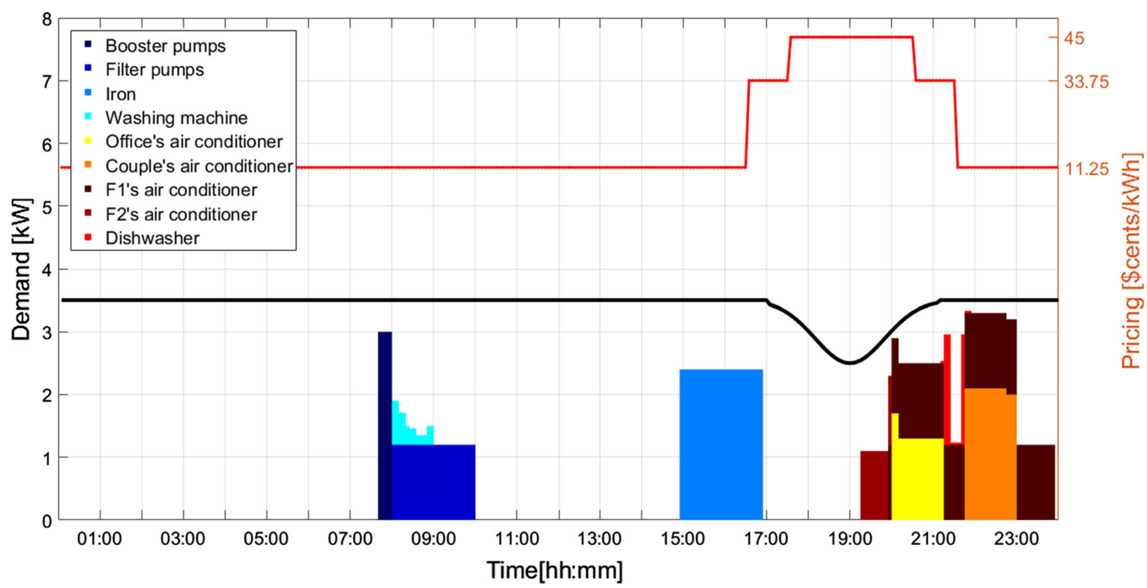

Fig. 12 Scenario 4: Local micro-generation and ToU tariff using SHC for multi-objective optimization ($\alpha = 0$)

values of α (1, 0.98 and 0) (Fig. 13). It can be seen from Fig. 14 that, for α values between 0.4 and 0.98, a considerable 32% reduction in cost is achievable for a 10% reduction in relative comfort.

In Table 5 the results for values of α equal to 1 and 0.98 are compared. From Table 5 and Fig. 9, it can be observed that the configuration with $\alpha = 0.98$ presents a configuration with greater comfort than that of $\alpha = 1$, although both have the same cost.

4.3 Results

Table 6 shows all cost, economy and comfort values for each simulated scenario. The columns UP cost and UP comf address the cost and comfort of the user preferences. In Table 6 one can observe that in scenarios 2 and 3 a reduction (economy) of 32% occurs and when the micro-generation is used the economy is even higher (38%). Scenarios 2

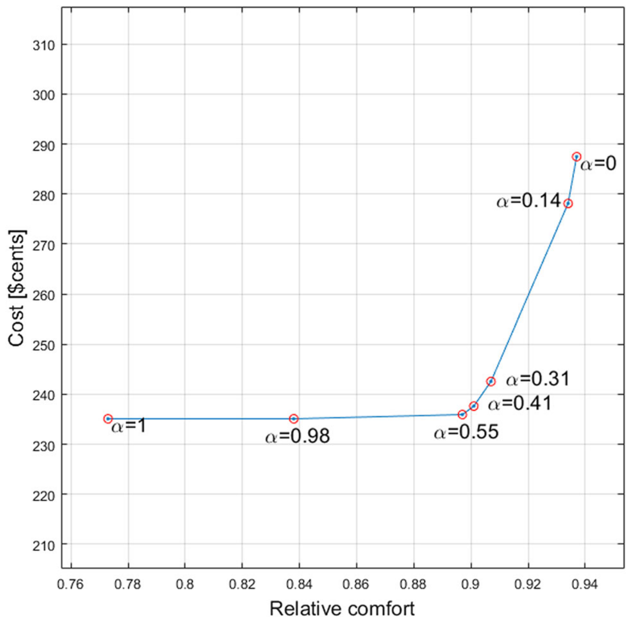

Fig. 13 Cost and comfort relationship on scenario 04

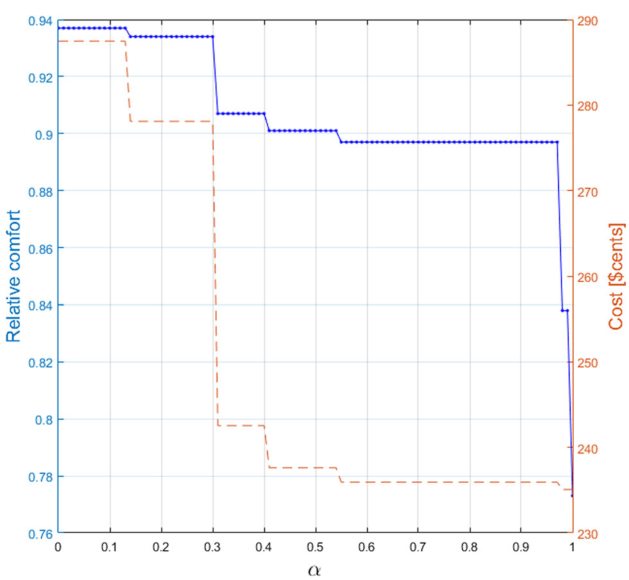

Fig. 14 Pareto fronts for cost and comfort on scenario 04

Table 5 SHC time allocation for scenario 4 and different α

ID	Expected	$\alpha = 1.00$		$\alpha = 0.98$	
		Actual	Δ	Actual	Δ
01	08:00	10:20	140	07:40	20
02	08:00	11:35	215	08:00	0
03	16:00	14:00	120	14:30	90
04	08:00	12:40	280	08:00	0
07	20:00	21:25	85	21:25	85
08	20:00	22:40	160	22:40	160
09	20:00	19:55	5	19:55	5
10	20:00	17:00	180	17:00	180
11	21:00	20:50	10	20:50	10

(multi-objective optimization) and 3 (multi-objective optimization with micro-generation) presented a reduction in electric energy cost with a relatively small percentage reduction in comfort. For scenario 3, even considering optimization of maximum economy ($\alpha = 1$) 83% of relative comfort was obtained. For the maximum comfort ($\alpha = 0$), a relative comfort of 92.65% was obtained, with a considerable saving of 10.55%.

Caution should be expressed for scenario 4 as results are even better: since it uses a different base-load, it simply states possible further gains could be attained in a distributed generation environment where loads could be entirely removed from the SHC control set. Further analysis is required with some form of negative pricing or demand suppression when considering a similar scenario to this.

5 Conclusions and Recommendations

This article answers two simultaneous goals in energy efficiency problems: cost and comfort. It is not a very simple task since there is a trade-off between user requests and diminishing energy costs. In this research we presented a novel smart home controller architecture for cost and comfort balancing using mathematical optimization software with

Table 6 Cost, economy and comfort for all scenarios

Scenario	UP cost	α	SHC cost	Economy (%)	UP comf	SHC comf	Relative comf (%)
01	4.50	–	–	–	–	–	–
02	4.50	–	3.06	32.00	–	–	–
03	4.50	1.00	3.06	32.00	699	580.2	83.00
03	4.50	0.55	3.06	32.00	699	630.6	90.21
03	4.50	0.00	4.03	10.44	699	647.6	96.65
04	3.79	1.00	2.35	38.05	569	440.1	77.35
04	3.79	0.98	2.35	38.05	569	476.6	83.76
04	3.79	0.00	2.87	24.24	569	533.1	93.69

Table 7 SHC expected cost—without scaled production

Device	Cost (US$)
Main board	35
Display	71
I/O converter	7
Box	20
Power source	3
Assembly costs	27
Total	163

real-load-based simulations for different user preferences setups. Technical limits to comfort maximization while minimizing energy costs within a load-limiting energy contract are also demonstrated. To the authors best knowledge there is no other architecture proposed with similar practical rules in the available literature.

This work has shown that the alpha values in a cost vs comfort relationship have very steep inclination (Fig. 9) in the Pareto front. This translates to opportunities in selecting not a single value but a set of specific intervals for alphas, simplifying the architecture (most precisely the interface) and decreasing computational costs as less scenarios (for diverging alphas) need to be calculated.

The solution implemented herein has some improvements over other approaches found in the literature, among which: (i) the Pareto front offers options to the users comfort x cost dilemma; (ii) the optimization method could be run for fixed loads and calendars once and kept in memory only for required profiles; (iii) the architecture doesn't require high processing power (as the optimization mechanism is done outside the SHC and loaded upon it); (iv) sensors and actuators are based on off-the-shelf elements, for SCADA and industrial automation processes, that are well known and relatively cheap (see Table 7), as a reference price, a local provider issues a home controller for approximately 349 US$ (2.2 times the proposed assembled hardware price for this project), although it's not a smart home controller, but merely a conventional controller as it lacks the optimization algorithms for cost vs. comfort management.

The solutions provided in the scenarios demonstrate the improved results obtained by a mathematical optimization problem in a SHC application. Although invariable with the architecture, it was shown that economical viability is possible with minimal comfort deterioration to the user.

Even though this architecture has proven, as this is an optimization problem with discrete variables that the Pareto front is non-convex, adopting an aggregated weights function does not result in good approximation. It's expected that further research work by the authors will develop an evolutionary algorithm for this approximation of the Pareto front for multi-objective

optimization as well as the possibility of using more than one activation cycle to some loads. With these improvements a full-fledged SHC could be tested for speed and economical analysis.

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