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Load Shifting Control and Management of Domestic Microgeneration Systems for Improved Energy Efficiency and Comfort

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***Abstract*—In this paper, an intelligent energy management system based on energy saving and user's comfort is introduced and applied to a residential smart home as a case study. The proposed multi-objective mixed-integer nonlinear programming (MINLP)-based architecture takes the advantages of several key modeling aspects such as load shifting capability and domestic energy micro-generation characteristics. To demonstrate the efficiency and robustness of the proposed model, several computer simulations are carried out under different operating scenarios with real data and different system constraints. Moreover, the superior performance of the proposed energy management system is shown in comparison with the conventional models. The numerical results also indicate that through wise management of demand and generation sides, there is a possibility to reduce domestic energy use and improve the user's satisfaction degree.**

***Keywords*—Energy efficiency, micro-generation systems, multi-objective optimization, demand side management.**

I. INTRODUCTION

The present and future smart grids play important roles in delivery of electricity from suppliers to industrial, commercial and residential zones in an efficient, reliable and secure manner. With the aid of such intelligent grids in micro/macro scales, not only the wasteful use of energy for householders and business owners would be decreased, but also further utilization of renewable energy sources (RESs) will be provided [1]. Since buildings contribute to a major portion of overall electricity consumption, many researchers around the world have elaborated on demand side energy management problem and have proposed a large number of power scheduling schemes both in domestic and residential sectors [2-8]. As an example, a domestic energy management methodology based on the optimal switching of thermal appliances has been presented in [2] to minimize energy consumption costs, while considering thermal constraints. In [3] an optimization algorithm has been proposed for minimization of users' electricity bills considering their comfort levels as the problem constraints. Although the authors introduced the waiting time ranges as measures of the user's comfort, they failed to model the behaviors of different home appliances. The authors of [4] proposed a game-based approach for optimal energy management of a residential building and justified the goodness of the global state by giving some reasons, but they failed to consider the user's satisfaction degree as an objective for efficient task scheduling. Optimal scheduling of in-home appliances with storage device buffering has been also presented in [5] considering the total cost minimization as the objective of the optimization problem. Likewise, an appliance commitment algorithm for household load scheduling has been introduced in [6] considering the minimum electricity consumption cost as the only objective. Beyond what has been stated in the field of demand side management in smart grids, there exist numerous techniques in recent works, which have been applied for domestic energy management and task scheduling aims [7-8]. Although these techniques have been mainly based on deterministic and/or meta-heuristic methods, they have failed to consider the users' convenience and comfort levels as competitive objectives in their optimization problems. In this paper, a multi-objective mixed integer nonlinear programming model is developed for optimal energy use in a home considering energy efficiency, user's convenience rate and thermal comfort level as three dependent objectives. Moreover, a composite architecture for home energy management system is presented, where each in-home device can be modeled as a collection of functions that represent its behavior. The overall energy management optimization framework is also improved from a thermal view point through introduction of different sources of heat generation and various heat flows

The rest of the paper is organized as follows: Section II deals with optimal home energy scheduling and its problem formulation. The case studies and simulation results are provided in Section III, whereas Section IV draws the paper's conclusions.

II. OPTIMAL HOME ENERGY SCHEDULING

A. System Description

In this paper, the case study includes a modern medium size house in a residential micro-grid with a home automation/energy management system (HAEMS) and a collection of schedulable devices that control the amount of

energy consumed (or produced) in the house over discrete time steps (Δh_{step}=1 hour) with regard to residents' comfort levels and energy consumption costs. The required thermal/electric energy is provided both by the utility and internal energy sources such as micro cogeneration systems and underfloor heating/cooling units. The surplus of electrical energy could be stored in batteries, while extra thermal energy could be saved inside the tank in the form of hot water. Through the use of smart meter, the HAEMS supports net metering, gets real-time electricity price and other input parameters (such as outdoor temperature and devices requests) and defines the optimal operation of in-home devices and demand response actions in every decision period considering the user's preferences, devices' constraints and total power limits in the house.

B. Problem Formulation

The mathematical modelling of the aforementioned HAEMS system is presented as follows:

1) House Thermal Model

Considering different thermal nodes in a residential building, the heat can transfer through several paths: between the indoor air node and the outdoor environment (ϕ_{ao}) through thermal resistance R_{ao}, between the floor and the indoor air (ϕ_{fa}) through thermal resistance R_{fa} and finally between the floor and the ground (ϕ_{fg}) through thermal resistance R_{fg}:

$$\phi_{ao}(h) = \left(T_{indoor}(h) - T_{outdoor}(h)\right) / R_{ao} \tag{1}$$

$$\phi_{fa}(h) = \left(T_{floor}(h) - T_{indoor}(h)\right) / R_{fa} \tag{2}$$

$$\phi_{fg}(h) = \left(T_{floor}(h) - T_{ground}(h)\right) / R_{fg} \tag{3}$$

where, $T_{indoor}(h)$,$T_{\text{outdoor}}(h)$ and $T_{ground}(h)$ are the temperatures of indoor air, outdoor environment and the ground at hour h. Aiming at developing strategies to minimize the energy consumptions within a building, it is also crucial to understand the sources of energy generation and losses. In this paper, these sources mainly include the buildings' heating/cooling system, solar radiation, occupants' metabolisms and the effect of background electric appliances. Considering an underfloor heating/cooling system (UFH/CS) as the one shown in Fig. 1, the amount of thermal energy that is supplied to the floor of the house (ϕ_{HCS}) is determined as follows:

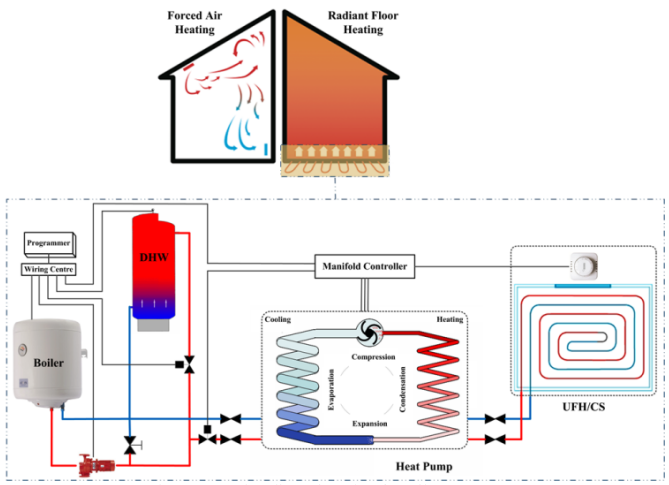


Fig. 1. Under floor heating/cooling system

$$\phi_{HCS}(h) = \begin{pmatrix} u_{HCS}(h)\cdot\eta_H(h) - \\ (1-u_{HCS}(h))\cdot\eta_C(h) \end{pmatrix} P_{HCS}(h) \tag{4}$$

$$P_{HCS}(h) \in \left[0, P_{HCS,\max}\right];\ \eta(h) \in \left[\eta_{\min}, \eta_{\max}\right] \tag{5}$$

where, u_{HCS} is a binary showing the system's Heating/Cooling operation status ("1":heating, "0":cooling), and P_{HCS} *(h)* is the power consumption of the heat pump at hour h limited by its upper bound $P_{HCS,max}$; $\eta_H(\eta_C)$ is the heating (cooling) coefficient of the performance.

As the second energy source, solar radiation plays a major role on the heating/cooling of a building. The hourly heat flow into an exterior surface of a building and then through that surface into the indoor environment can be expressed as:

$$\phi_{sa}(h) = UA_s\left(T_{eq\_out}(h) - T_{indoor}(h)\right) \tag{6}$$

$$T_{eq\_out}(h) = T_{outdoor}(h) + \frac{\alpha_s \varphi_{solar}(h)}{h_o} - \frac{\varepsilon\sigma\left(T^4_{outdoor}(h) - T^4_{surr}(h)\right)}{h_o} \tag{7}$$

where, h_o is the combined convection and radiation heat transfer coefficient, α_s and ε are the solar absorptivity and the emissivity of the surface, φ_{solar} is the solar radiation incident on the surface and σ is Stefan-Boltzmann constant. Likewise, U is the overall heat transfer coefficient of the exposed surface, and A_s is the surface area.

Similar to other sources of thermal energy, the heat given off by the occupants' metabolisms, lights, appliances, and miscellaneous equipment such as computers, contribute to the internal heating of a building. Although such a heat gain differs during various users' activities, its average amount could be determined from the people's lifestyle. Putting all the mentioned thermal models into a nutshell, the temperature state functions of a given house could be determined as follows [9]:

$$\mathrm{T}_{floor}(h) = \mathrm{T}_{floor}(h-1) + \frac{\Delta h_{step}}{m_f\, c_{p,f}}\left(\phi_{HCS}(h) + \phi_{sf}(h) - \phi_{fg}(h) - \phi_{fa}(h)\right) \tag{8}$$

$$\mathrm{T}_{indoor}(h) = \mathrm{T}_{indoor}(h-1) + \frac{\Delta h_{step}}{m_a\, c_{p,a}}\left(\phi_{fa}(h) + \phi_{sa}(h) + \phi_{ihg}(h) - \phi_{ao}(h)\right) \tag{9}$$

Where, m_f, m_a, $c_{p,f}$ and $c_{p,a}$ are the mass and specific heat capacity coefficients of the floor and air, respectively and $\phi_{ihg}(h)$ is the internal heat gain of the building from the occupants' metabolisms and other home appliances at hour h. $\phi_{sf}(h)$ is the heat obtained directly from solar radiation when it enters the house through the windows and is absorbed by the floor area (A_f) with solar absorptivity of α_f :

$$\phi_{sf}(h) = \alpha_f \cdot \varphi_{solar}(h) \cdot A_f \tag{10}$$

2) Micro- Cogeneration System

To serve the home's hot water needs and provide unmet residential demand, a micro-combined heat and power system (micro-CHP) composed of a water tank, a backup boiler and a Fuel Cell (FC) unit is used in this study. The FC unit converts natural gas G_{FC} into electricity P^e_{CHP} and heat P^{th}_{CHP} as follows:

$$P^e_{CHP}(h) = \frac{G_{FC}(h)}{G_{ref}} \cdot \eta_e = P^{th}_{CHP}(h) \cdot \frac{\eta_e}{\eta_{th}} \tag{11}$$

$$P^e_{CHP}(h) \in \left[P^e_{CHP,\min}, P^e_{CHP,\max}\right];\ P^{th}_{CHP}(h) \in \left[P^{th}_{CHP,\min}, P^{th}_{CHP,\max}\right] \tag{12}$$

$$\left|P^{e}_{CHP}(h)-P^{e}_{CHP}(h-1)\right|\le P^{e}_{CHP,ramp} \tag{13}$$

where, G_{ref} is the natural gas consumption rate of a CHP system for producing 1 kWh energy and η_e and η_{th} are the electric and thermal efficiencies of the FC unit, respectively. The electrical and thermal power outputs of a micro-CHP unit are also constrained by certain minimum and maximum capacities as well as ramp rates modelled in (12)-(13). It should be noted that the same constraints must also be satisfied for the auxiliary boiler. The energy storage content $Q_{st}(h)$ and the water storage temperature ($T_{st}(h)$) can be also updated at each time step as:

$$Q_{st}(h+1)=Q_{st}(h)+\begin{pmatrix}P^{th}_{CHP}(h)+P^{th}_{aux}(h)-\\P^{th}_{D}(h)-P^{th}_{loss}(h)\end{pmatrix}\cdot\Delta h_{step} \tag{14}$$

$$T_{st}(h+1)=\frac{V^{th}_{D}(h)\cdot\left(T_{cw}-T_{st}(h)\right)+V_{tot}\cdot T_{st}(h)}{V_{tot}}+\frac{P^{th}_{CHP}(h)+P^{th}_{aux}(h)}{V_{tot}\cdot C_w}$$
$$-\left(\frac{1}{V_{tot}\cdot C_w}\right)\left(\frac{A_{st}}{R_{st}}\right)\left(T_{st}(h)-T_b(h)\right);\qquad T_{st}(h)\in\left[T_{st,\min},T_{st,\max}\right] \tag{15}$$

where, $P^{th}_{D}(h)$ and $P^{th}_{loss}(h)$ are the heat demand and heat loss of the hot water storage at hour h, respectively, V_{tot} and $V^{th}_{D}(h)$ are the total storage volume and hourly occupants' hot water demand in liter, T_{cw} and $T_b(h)$ are the entering cold water and the basement temperatures, respectively. A_{st} is the surface area of the tank and R_{st} is the R-value of the insulation material.Cw is the specific heat capacity of water,

3) Energy Storage Device

Considering an energy storage/production unit, the update function for the state of charge (SOC) is given by [10]:

$$SOC(h+1)=SOC(h)+\frac{\left(P_{Batt,ch}(h)-P_{Batt,dch}(h)\right)\cdot\Delta h_{setp}}{E_{Batt}} \tag{16}$$

$$P_{Batt,ch}(h)\le P_{ch,\max}\cdot\eta_{ch}\cdot u_{Batt}(h)$$

$$P_{Batt,dch}(h)\le\left(\frac{P_{dch,\max}}{\eta_{dch}}\right)\cdot\left(1-u_{Batt}(h)\right) \tag{17}$$

$$SOC_{\min}\le SOC(h)\le SOC_{\max}$$

where, E_{Batt} is the battery capacity, $P_{ch,max}$ and $P_{dch,max}$ are the battery maximum charging and discharging powers and η_{ch} and η_{dch} are the battery's charging and discharging efficiencies. Similarly, $u_{Batt}(h)$ is a binary variable that shows the battery's status at hour h ("1"=charging and "0"=discharging).

4) Schedulable Tasks and Residential Load Model

Residential loads generally fall into two categories: schedulable loads (shiftable and curtailable tasks) and fixed loads. While loads such as refrigerator are regarded as fixed ones, vacuum cleaner, washer and dryer are examples of schedulable tasks that use most of the electricity in a house and have their own list of operating parameters (OP) that need to be set by residents for efficient scheduling as [11]:

$$OP_i=\begin{Bmatrix}Start\,Time(h_{s,i}),End\,Time(h_{f,i}),Runtime(LOT_i),\\Power(EEC_i),Preferred\,Time\,Range(PTR_i),\\Priority(\omega_i)\end{Bmatrix} \tag{18}$$

For each task $i\in N$, there are also several constraints that must be met suitably:

$$\sum_{h=h_{s,i}}^{h_{f,i}}s_i(h)=LOT_i \tag{19}$$

$$P_{Dschd,i}(h)=\frac{EEC_i}{LOT_i}\cdot s_i(h)\ ;\quad\forall\left(h\in\left[h_{s,i},h_{f,i}\right],\ i\in N\right) \tag{20}$$

$$\sum_{h=h_{s,i}}^{h_{f,i}}\left|s_i(h)-s_i(h-1)\right|\le 2 \tag{21}$$

$$\sum_{h=h_{s,j}}^{h_{f,j}}s_j(h)\cdot H\left(\lambda-LOT_i+\sum_{t=h_s}^{h}s_i(t)\right)=LOT_j \tag{22}$$

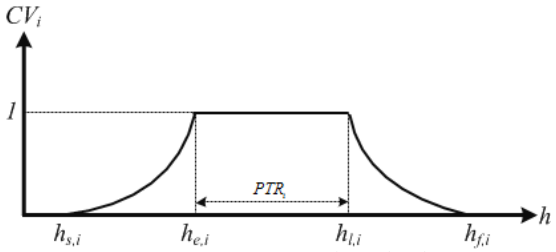
where, $s_i(h)$ is a binary value with "1" for task i scheduling and "0" for task i dropping, $h_s=min(h_{s,i},h_{s,j})$, λ is a positive number smaller than 1 and $H(\cdot)$ denotes a Heaviside step function.

5) Objective Function

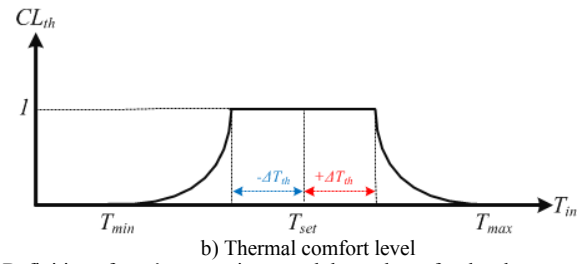
In this work, the following mixed objective function is considered as the model of optimization:

$$Min:\ J=\frac{\sum_{h=1}^{T}\begin{pmatrix}\rho_{grid}(h)\cdot P_{grid}(h)\\+\rho_{gas}\cdot\left(u_{CHP}(h)\cdot G_{FC}(h)+u_{aux}(h)\cdot G_{aux}(h)\right)\end{pmatrix}}{\xi_1\cdot\sum_{i=1}^{N}\omega_i\cdot CV_i(h)+\xi_2\cdot\sum_{h=1}^{T}CL_{th}(h)} \tag{23}$$

in which, the numerator shows the total cost of operation in short-term for a typical house and the denominator denotes the user's comfort levels. In the above equation, $\rho_{grid}(h)$ and ρ_{gas} are the real time electricity and natural gas prices, $P_{grid}(h)$ is the amount of power exchanged with the utility at hour h, and $G_{FC}(h)$ and $G_{aux}(h)$ are the hourly amount of gas consumed by the FC unit and the auxiliary boiler, respectively.



a) User's convenience level



b) Thermal comfort level

Fig. 2. Definition of user's convenience and thermal comfort level

It is notable that $CV_i(h)$ is the user's convenience level when task i is executed at hour h and $CL_{th}(h)$ is the level of thermal comfort experienced by the inhabitants at each time step. Likewise, $\zeta_{1,2}$ are the weighting coefficients reflecting the significance of the proposed terms. To evaluate the user's convenience degree and his thermal comfort level at each time

step, two utility functions are defined as depicted in Fig. 2. These functions reflect the user's living habits and include his preferences for indoor temperature and task scheduling. Likewise, T_{set} is the user-specified set point for indoor temperature and ΔT_{th} is the threshold temperature difference. The mentioned mixed objective function must be optimized subject to the following demand-supply balance equation and all the previously mentioned constraints for the considered problem:

$$P_{grid}(h)+P^{e}_{CHP}(h)-\left(P_{Batt,ch}(h)-P_{Batt,dch}(h)\right)=P_{D}(h) \quad (24)$$

III. Simulation Results

For the simulation studies, one of the variations of a real single-zone, low-energy house in Sydney, Australia is considered as the case study [12]. All the controllable devices and schedulable loads mentioned in the previous section are implemented and included in the experimental house using the parameters shown in Tables I and II, respectively.

TABLE I
Parameters used in computer simulations

Param.	Value	Unit	Param.	Value	Unit
House Thermo-Electrical Specifications and Parameters					
$P^{max}_{,House}$	5.5	kW	h_o	17	W/m2·°C
$P_{grid,max}$	±5.5	kW	m_f, m_a	2300,1.198	Kg/m^3
ε, α_s	27,73	%	$c_{p,f}, c_{p,a}$	0.88,1.02	kJ/kg·°C
α_f	53.7	%	A_f	*1.2*	m^2
Micro-Cogeneration unit parameters					
$P^{e}_{CHP,min}$	0.3	kW	$P^{th}_{aux,min}$	4	kW
$P^{e}_{CHP,max}$	1.5		$P^{th}_{aux,max}$	19	
$P^{e}_{CHP,ramp}$	0.9	kW/h	G_{ref}	92.4×10^{-3}	m^3/h
$\eta_e, \eta_{th}, \eta_{aux}$	30, 70, 86	%	S_{CHP}	8	¢/start
A_{st}	1.99	m^2	V_{tot}	200	Liter
R_{st}	2.818	m^2·°C /W	$T_{st,min}$	60	°C
			$T_{st,max}$	80	
C_w	0.00117	kWh/Lit.°C	T_{cw}	10	°C
Under Floor Heating and Cooling System Specifications					
$P_{HCS,max}$	2	kW	$\eta_{H,min}$	100	%
			$\eta_{H,max}$	400	
T_{set}	25	°C	$\eta_{C,min}$	100	%
			$\eta_{C,max}$	300	
ΔT_{th}	hot weather condition			±3	°C
	cold weather condition			±2	
Energy Storage Device specifications					
E_{Batt}	24	KWh	SOC	20 - 80	%
$P_{ch/dch,max}$	3.3	KWh	η_{ch}, η_{dch}	87, 90	%

TABLE II
Schedulable Tasks Parameters

Appliance	UTR	PTR	LOT	EEC	ω
Washing Machine	7:00-21:00	8:00-14:00	2	1	1
Dishwasher	6:00-18:00	14:00-18:00	2	1.4	2
Clothes Dryer	9:00-21:00	11:00-17:00	1	1.8	1
Iron	1:00-13:00	5:00-7:00	1	1.1	2
Vacuum Cleaner	8:00-20:00	9:00-12:00	1	0.65	2
Microwave	8:00-19:00	11:00-14:00	1	0.9	3
Rice Cooker	10:00-18:00	14:00-17:00	2	0.6	3
Electric Kettle	4:00-12:00	06:00-07:00	1	1	3
Toaster	1:00-10:00	6:00-8:00	1	0.8	3

Similarly, the hourly electrical power consumption of the house along with the hot water demand is shown in Fig. 3. To include both the heating and cooling cases, two different simulations regarding cold and hot weather conditions are also executed with the same scenario but with different external parameters such as outdoor/basement temperatures, solar radiations and real time utility electricity prices, as shown in Figs. 4-5, respectively. It is noteworthy that the natural gas price is assumed to be 33 ¢/m3 all year round. It should be mentioned that all of the algorithms and simulations were carried out on a PC with an Intel i5-2430M chip running Windows 7(64 bit) with GAMS solvers.

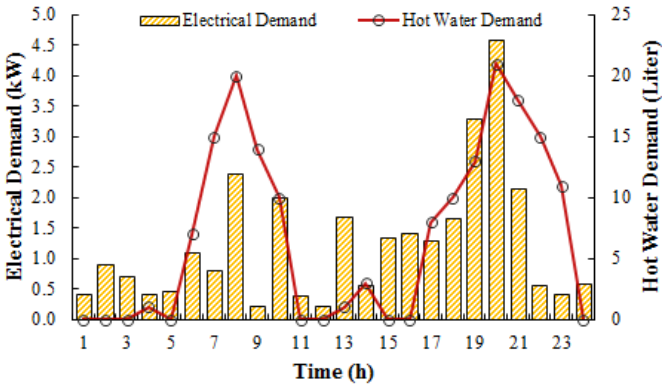


Fig. 3. Total electrical and hot water demands

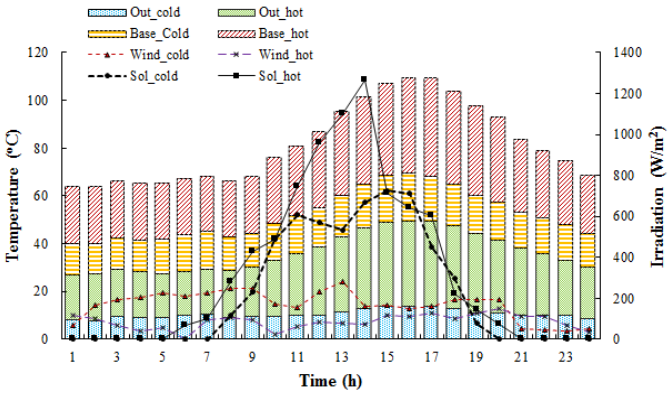


Fig. 4. Weather observations for the Sydney area

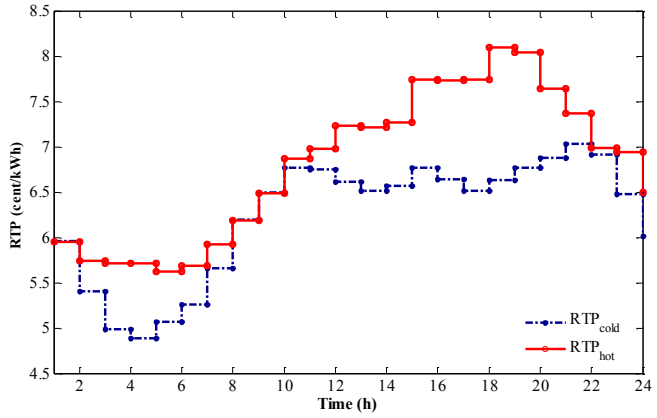


Fig. 5. Real-time utility electricity price

Fig. 6 shows the simulations results for each of the examined cooling/heating scenarios considering different controllers. As observed in the figure, the smart controller which benefits from a HAEMS improves the mixed objective function value (Mobj) up to 55% and 25% with respect to the naïve controller (which describes a situation in which the household does not possess or run a HAEMS) and normal controller (which determines energy management in a cost effective way under RTP changes) in a hot weather condition and up to 63% and 38% in a cold weather condition. From the same figure it can be observed that the controllers' performances are not the

same in heating and cooling scenarios mainly due to the sun effects on the peak cooling load of a building. As can be seen from Fig. 7, in a hot weather condition, not only the solar heat enters the house directly through the glazing, but also the heat transfers from the exposed side of the building into the indoor environment, which in turn increases the indoor temperature and decreases the cooling capacity of the system.

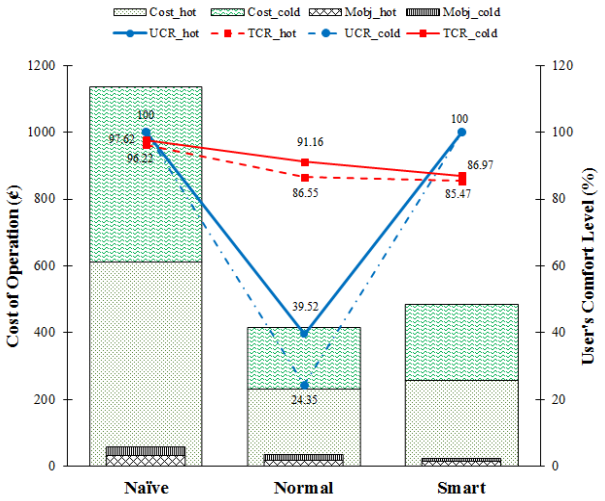


Fig. 6. Controllers' performances for the examined cooling/heating scenarios

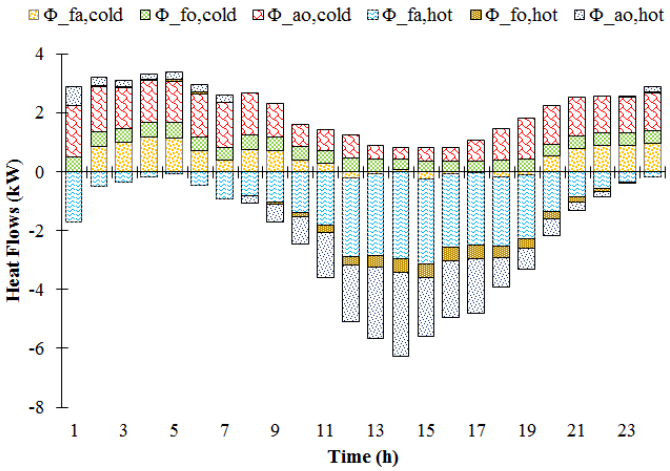


Fig. 7. Heat flows through different paths for the examined cooling/heating scenarios

To get better insights about the smart controller performances, the optimal operation of the household devices, FC-based micro-CHP unit and battery along with the amount of power exchange between the house and the utility are also shown in Fig. 8 for the given demand profiles in a typical hot weather condition. As it can be observed from Fig.8, during some periods of time when the real-time electricity prices are relatively low, most of the residential load is supplied by the utility; and the charging process of the battery is done with lower costs. With the growth of demand and bids of the utility during the other hours of the day, in-home units including the CHP and the battery, not only generate electricity in a cost effective way to meet the load, but also sell the surplus of energy to the utility and make profits. Besides, optimal scheduling of household devices is done effectively regarding to associate operational constraints and user's preferences.

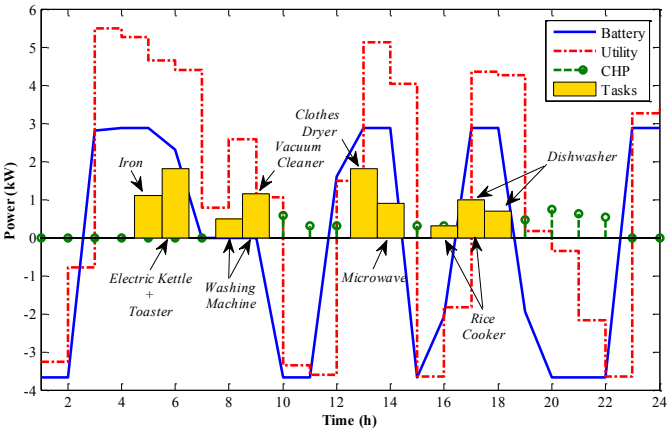


Fig. 8. Optimal operation management of devices and units

IV. CONCLUSION

In this paper, a smart energy management system for residential scenarios has been described and valuated through different operating conditions. The proposed model could schedule household devices and micro-sources optimally taking into account a meaningful balance between the energy saving and a comfortable lifestyle. It was demonstrated through simulation case studies that under different system constraints the proposed algorithm could not only reduce the domestic energy use, but also ensured an optimal task scheduling and a thermal comfort zone for the inhabitants. To verify the efficiency and robustness of the proposed model, a number of simulations were also performed under different heating/cooling scenarios with real data and the obtained results were compared with those from conventional models.

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