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Optimal joint scheduling of electrical and thermal appliances in a smart home environment

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ABSTRACT

With the development of home area network, residents have the opportunity to schedule their power usage in the home by themselves aiming at reducing electricity expenses. Moreover, as renewable energy sources are deployed in home, a home energy management system needs to consider both energy consumption and generation simultaneously to minimize the energy cost. In this paper, a smart home energy management model has been presented in which electrical and thermal appliances are jointly scheduled. The proposed method aims at minimizing the electricity cost of a residential customer by scheduling various type of appliances considering the residents consumption behavior, seasonal probability, social random factor, discomfort index and appliances starting probability functions. In this model, the home central controller receives the electricity price information, environmental factors data as well as the resident desired options in order to optimally schedule appliances including electrical and thermal. The scheduling approach is tested on a typical home including variety of home appliances, a small wind turbine, photovoltaic panel, combined heat and power unit, boiler and electrical and thermal storages over a 24-h period. The results show that the scheduling of different appliances can be reached simultaneously by using the proposed formulation. Moreover, simulation results evidenced that the proposed home energy management model exhibits a lower cost and, therefore, is more economical.

1. Introduction

In the past few decades, typically a power system is just dispatched generation sources since the vast majority of loads are not controllable. Moreover, flat rate of electricity price does not encourage the customers to schedule their energy usage. In a smart grid, the bidirectional data flow together with interoperability between houses and the grid have come up with possibility to optimize each customer's electricity usage and, simultaneously, improve entire system operation via peak reduction [1]. It is actually impractical to ask consumers to schedule their usage optimally since they are neither a system operator nor an economist. Hence, an autonomous load management technique is needed which requires little awareness of consumers for setting up and maintaining and then allow them to evaluate costs and benefits with various schedules.

A Home Energy Management System (HEMS) is definitely an integral part of the smart grid on the consumption side. The appliance commitment problem determines the best fit schedule for each device considering technical constraints and economic circumstances as well. In [2] a energy scheduling method aiming at minimizing the overall cost of electricity and natural gas for a building operation over a time horizon while satisfying the energy balance and operating constraints of individual energy supply equipment and devices has been presented. An Expert Energy Management System (EEMS) has been proposed in [3] in order to schedule a micro grid. It has been used artificial neural network (ANN) to predict wind turbine generation. A simple yet effective load management system, along with renewable and non-renewable sources, was proposed in [4], in order to reduce electricity bill together with carbon emissions. In [5], a model for predictive controller in buildings considering hierarchical building control concept has been proposed. The energy supply and consumption levels were joined only by the thermal load. In [6], Agent-based strategies have been employed in order to schedule smart appliances. In comparison to the appliance commitment strategy, this method has some restrictions such as agent intelligence upon an appliance and also appliance coordination. In [7], the Point Estimate Method (PEM) has been exploited for modeling the solar and wind power uncertainties. The operation problem was solved via Particle Swarm Optimization (PSO) algorithm considering technical constraints. An optimal energy management model of a hybrid power supply system including solar panel, diesel generators and battery for off-grid applications has been presented in [8]. The authors in

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Nomenclature

Abbreviations, superscripts and subscripts

AC	air conditioning
AMI	Advanced Metering Infrastructure
ANN	artificial neural network
CHP	Combined Heat and Power
CN	Control Nodes
CPP	Critical Peak Pricing
CTA	Controllable Thermal Appliance
DER	Distributed Energy Resource
DG	Dispersed Generation
DI	Discomfort Index
EB	Energy Box
ECA	Electrically Controllable Appliances
ESS	Electrical Storage System
EEMS	Expert Energy Management System
EST	Earliest Starting Time
HAN	Home Area Network
HEMS	Home Energy Management System
HG	Home Gateway
HT	Heating Systems
IHD	In-Home Display
LB	Lower Bound
LFT	Latest Finishing Time
LOT	Length of Operation Time
CC	Central Controller
MILP	Mixed Integer Linear Programming
NG	Natural Gas
OCA	Optically Controllable Appliances
PDF	Probability Density Function
PHEV	Plug-in Hybrid Electric Vehicle
PEM	Point Estimate Method
PSO	Particle Swarm Optimization
RTP	Real Time Price
SM	Smart Meter
TCA	Thermally Controllable Appliances
TDM	Thermal Dynamic Modes
TOU	Time Of Use
TSS	Thermal Storage System
UB	Upper Bound
WSN	Wireless Sensor Network
WTR	Water

Parameters

V	wind speed (m/s)
k	shape factor of Weibull distribution for wind speed
C	scale factor of Weibull distribution for wind speed
EP_t^{WT}	wind turbine power output
EP_t^{PV}	solar cell power output
η^{PV}	the conversion efficiency of solar cell array (%)
A^{PV}	solar cell array area (m^2)
I_t	the sun irradiation at time t (kW/m^2)
T_t^{OUT}	the outside air temperature (°C)
β_1	scale factor of Weibull distribution for sun irradiation
β_2	scale factor of Weibull distribution for sun irradiation
α_1	shape factor of Weibull distribution for sun irradiation
α_2	shape factor of Weibull distribution for sun irradiation
η^{chp}	the CHP efficiency
$\mu^{chp,htp}$	heat-to-power ratio of CHP
$EP_{\min}^{CHP}$	the minimum electrical output of CHP
$EP_{\max}^{CHP}$	the minimum electrical output of CHP
$\Delta EP_{\max}^{CHP}$	the CHP electrical output maximum ramp rate
U_{ini}^{chp}	the CHP initial status
η^{Boi}	conversion efficiency of boiler
$TP_{\min}^{Boi}$	the minimum output of boiler
$TP_{\max}^{Boi}$	the maximum output of boiler
$EP^{ESS,sdc}$	self-discharging rate of ESS
η^{ESS}	ESS efficiency
EE_{ini}^{ESS}	the initial value of ESS
EP_{UB}^{CH}	upper bound of ESS charge rate
EP_{UB}^{DCH}	upper bound of ESS discharge rate
EE_{UB}^{ESS}	upper bound of ESS energy
$TP^{TSS,sdc}$	self-discharging rate of TSS
TE_{ini}^{TSS}	the initial value of TSS
TP_{UB}^{CH}	upper bound of TSS charge rate
TP_{UB}^{DCH}	upper bound of TSS discharge rate
TE_{UB}^{ESS}	upper bound of TSS energy
A	an appliance which belongs to ECA
h	the hour of the day
d	the day of the week
w	the week of the year
δ_{step}	the computational time step (s or min)
σ_{flat}	the standard deviation for social random factor
P_{social}	the social random factor
P_{season}	the seasonal changes
P_{hour}	the hourly probability factor
P_{step}	the step size scaling factor
TW^{fr}	the fridge time window
β^{fr}	the activity probability effect on the fridge temperature
α^{fr}	the model the effect of the on and off states on the fridge temperature
γ^{fr}	the models the thermal leakage due to the difference between the fridge and room temperature
TW^{ac}	the AC time window over which the AC can operate
TW^{ht}	the HT time window over which the HT can operate
β^{ac}	the activity probability effect on the indoor temperature (cooling system)
β^{ht}	the activity probability effect on the indoor temperature (heating system)
ρ^{ac}	the effect of outdoor and indoor temperature differences on indoor temperature (cooling system)
ρ^{ht}	the effect of outdoor and indoor temperature differences on indoor temperature (heating system)
$V_t^{CLD,WTR}$	the volume of the cold water which replaces the hot water in water tank at time t
$T^{CLD,WTR}$	the temperature of cold water which replaces the hot water in water tank at time t
C^{WTR}	the specific heat of water
V_{ST}^{WTR}	the volume of water storage
K_t	the "price elasticity" of the lighting load
L_t^{OUT}	outdoor illumination at time t
$L_t^{z,\min}$	the minimum required illumination level of zone z at time t
T_{des}^{fr}	desired fridge temperature
T_{des}^{frz}	desired freezer temperature
T_{des}^{WTR}	desired water temperature
T_{des}^{IN}	desired indoor temperature
$T_{\min}^{fr}$	minimum fridge temperature
$T_{\min}^{frz}$	minimum freezer temperature
$T_{\min}^{WTR}$	minimum water temperature
$T_{\min}^{IN}$	minimum indoor temperature
$T_{\max}^{fr}$	maximum fridge temperature
$T_{\max}^{frz}$	maximum freezer temperature

$T^{WTR}_{\max}$	maximum water temperature	TP^{CH}_t	TSS charge at time t
$T^{IN}_{\max}$	maximum indoor temperature	TP^{DCH}_t	TSS discharge at time t
m^{CHP}	maintenance cost of CHP	S^{TSS}_t	TSS status at time t
m^{WT}	maintenance cost of WT	P_{start}	starting probability function
m^{PV}	maintenance cost of PV	$S^{start}_{i,t}$	appliance i starting status
m^{ESS}	maintenance cost of ESS	$S^{finish}_{i,t}$	appliance i finishing status
m^{Boi}	maintenance cost of boiler	$t_{i,ST}$	appliance i starting time
m^{TSS}	maintenance cost of TSS	$t_{i,FN}$	appliance i finishing time
P^{E}_t	the real time electricity price	EP^{ECA}_t	electrical power demand of ECAs at time t
P^{NG}	the natural gas price	EP_i	electrical power consumption of appliance i
		$S_{i,t}$	appliance i status at time t
Variables		T^{IN}_t	the indoor temperature
EP^{CHP}_t	the CHP Electrical output	T^{fr}_t	the fridge temperature
TP^{CHP}_t	the CHP Thermal output	T^{frz}_t	the freezer temperature
$p^{chp,gas}_t$	the CHP imported gas at time t	T^{WTR}_t	the hot water temperature
u^{chp}_t	the CHP status at time t	OS^{fr}_t	the fridge On/Off status at time t
v^{chp}_t	CHP cold start	TP^{WTR}_t	the thermal power needed for hot water at time t
TP^{Boi}_t	boiler's output	L^{z}_t	illumination level index of zone z at time t
$p^{Boi,gas}_t$	the boiler imported gas at time t	p^{gas}_t	imported natural gas at time t
v^{Boi}_t	boiler Cold starts	$p^{boi,gas}_t$	boiler natural gas consumption at time t
u^{Boi}_t	the boiler status at time t	$p^{chp,gas}_t$	CHP natural gas consumption at time t
EE^{ESS}_t	ESS energy at time	$EP^{BY,GRD}_t$	the electrical power bought from the grid
EP^{CH}_t	ESS charge at time t	$EP^{SL,GRD}_t$	the electrical power sold to the grid
EP^{DCH}_t	ESS discharge at time		
S^{ess}_t	ESS status at time t		
TE^{TSS}_t	heat stored in the thermal storage at time t		

[9] get proper target total power usage for all appliances; however, the individual appliance particular scheduling scheme is not taken into account. The [10] represented the EB (Energy Box) concept which is capable of operating under dynamic pricing scheme, taking part in markets as integrated and stand-alone units. To the best of our knowledge, as current HEMS seems to be mainly designed to enhance residential energy efficiency, the vast majority of the related works did not account for user behavior in appliance usage and their preferences which is crucial in order to meet the customers need. Moreover, limited studies have been conducted in scheduling algorithms which control thermal appliance, for instance heating and air conditioning systems, which use more energy in comparison to other appliances in home.

In this paper, a home energy management scheduling problem with energy sources, electrically and thermally controllable appliances such as washing machine, water heater and fridge models along with optically controllable appliance such as illumination is modeled as a Mixed Integer Linear Programming (MILP) problem over a finite horizon of time. The proposed method determines the best suited set point of all suppliers as well as storages in a manner that economically optimized power dispatch while scheduling different appliance categories. The innovative contributions of the proposed method can be summarized as follows:

- The Thermally Controllable Appliances (TCAs) are scheduled in according to both desired temperature and energy prices.
- A discomfort index has been introduced within the home energy scheduling model.

The rest of the paper is organized as follows. The proposed system architecture is described in Section 2. Section 3 formulates the energy management and scheduling problem into a MILP problem. The simulation result discussed in Section 4 and finally Section 5 concludes the paper.

2. Proposed system architecture

The main goal of the energy management system in this paper is to minimize energy cost under the dynamic price schemes by scheduling the home appliances usage. The overall architecture of the proposed system is demonstrated in Fig. 1. The Central Controller (CC) is the core of energy management system which controls and schedules both electrical and thermal appliances together with controllable DERs such as Combined Heat and Power (CHP). In the proposed method, domestic appliances are divided into three categories: Electrically Controllable Appliances (ECA), Thermally Controllable Appliances (TCA), and Optically Controllable Appliances (OCA). ECAs, TCAs and OCAs only relate with CC and do not interact with each other.

3. Problem formulation

In this paper, the energy management problem in a house is modeled as a MILP over a specific prediction horizon of period (T) along with discrete time steps $t(t \in T)$. In this study, the time resolution is considered30-min, therefore one day has 48 slots.

3.1. Wind turbine

The wind turbine output can be calculated by Eq. (1), which is based on wind speed, blade area, air density and constrained by both cut-in and cut-out speed [11].

$$EP^{WT}_t = \begin{cases} 0.5\rho A\eta^{w}\min(v_t, V^{nom})^3, \\ \forall t: V^{cut\text{-}in} \leqslant v_t \leqslant V^{cut\text{-}out} \\ 0, \forall t: V^{cut\text{-}out} \leqslant v_t, v_t \leqslant V^{cut\text{-}in} \end{cases} \tag{1}$$

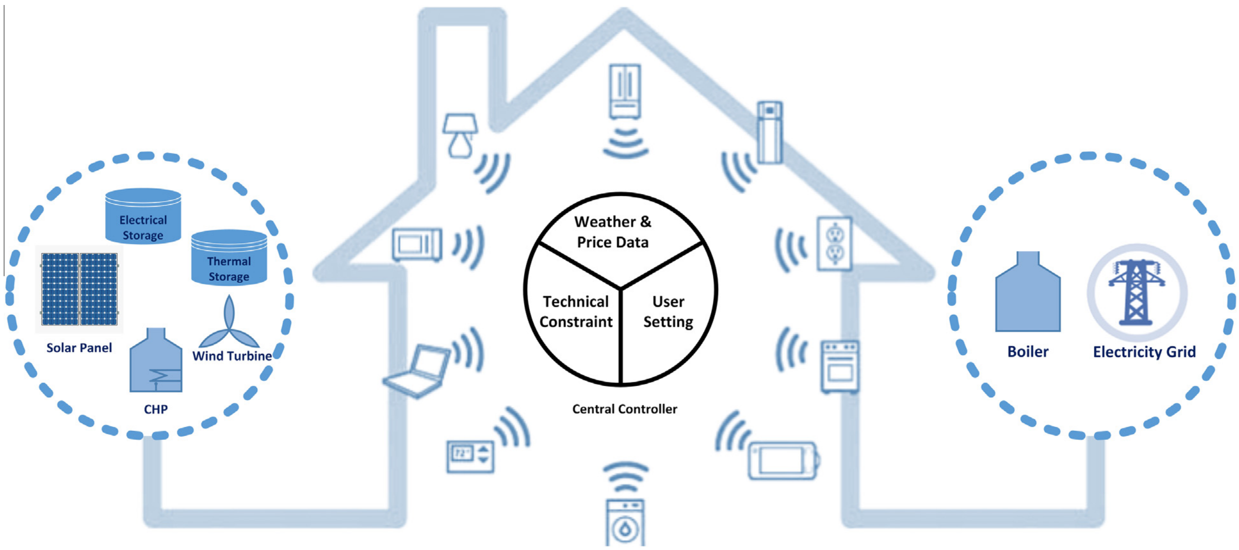

Fig. 1. Proposed system architecture.

The Probability Density Function (PDF) of wind speed which is described by the Weibull distribution is given by (2) where, v, k and c stand for wind speed (m/s), shape factor and scale factor respectively [12].

$$f(v) = (k/c)(v/c)^{(k-1)}e^{-(v/c)^k}, \quad 0 < v < \infty \tag{2}$$

3.2. Solar panel

The house is equipped by a rooftop solar panel. The proposed energy management system tries to maximize the benefit from solar energy in order to minimize the overall cost of the residential customer. In the PV system [13], power output EP_t^{PV} is represented by:

$$EP_t^{PV} = \eta^{PV}.A^{PV}.I_t.(1 - 0.005(T_t^{OUT} - 25)) \tag{3}$$

where, η^{PV} is the conversion efficiency of solar cell array (%), A^{PV} he array area (m^2), I_t is the sun irradiation at time t (kW/m^2) and T_t^{OUT} is the outside air temperature (°C). The distribution of hourly sun irradiation usually complies with a bimodal distribution [14,15] that can be considered as a linear blend of two unimodal distribution functions [16]. The unimodal distribution functions could be modeled by Weibull PDF as follow where ω is a weighted factor, α_1 and α_2 are shape factors, together with β_1 and β_2 which are scale factors.

$$\begin{aligned} f(I) = {} & \omega(\alpha_1/\beta_1)(I/\beta_1)^{(\alpha_1-1)}e^{-(I/\beta_1)^{\alpha_1}} \\ & + (1-\omega)(\alpha_2/\beta_2)(I/\beta_2)^{(\alpha_2-1)}e^{-(I/\beta_2)^{\alpha_2}}, \quad 0 < I < \infty \end{aligned} \tag{4}$$

3.3. CHP

The CHP generator uses up gas and produce heat in addition to electricity. The overall conversion process efficiency and also the heat-to-power ratio can be approximated using functions of the CHP output [17].

$$EP_t^{CHP} + TP_t^{CHP} = p_t^{chp,gas}\eta^{chp}\left(EP_t^{CHP}\right) \tag{5}$$

$$TP_t^{CHP} = EP_t^{CHP}\mu^{chp,htp}\left(EP_t^{CHP}\right) \tag{6}$$

Eq. (7) and also (8) model the CHP electrical output maximum ramp rate.

$$\Delta P_{\max}^{chp,elec} \geqslant EP_t^{CHP} - EP_{t-1}^{CHP} \tag{7}$$

$$\Delta EP_{\max}^{CHP} \geqslant EP_t^{CHP} - EP_{t-1}^{CHP} \tag{8}$$

Technical constraints of CHP output power are tracked in Eq. (9) and CHP cold starts are considered in Eq. (10). The non-linear terms has been approximated by using four-piece linearization [18].

$$u_t^{chp}EP_{\min}^{CHP} \leqslant EP_t^{CHP} \leqslant u_t^{chp}EP_{\max}^{CHP} \tag{9}$$

$$v_t^{chp} \geqslant u_t^{chp} - u_{t-1}^{chp} \tag{10}$$

$$EP_t^{CHP} = EP_{ini}^{CHP} \tag{11}$$

$$u_{t-1}^{chp} = U_{ini}^{chp}, \quad t = 1 \tag{12}$$

3.4. Boiler

The boiler's output is the result of multiplying conversion efficiency into the natural gas (13) [19]. Technical constraints are tracked in (14). Cold starts of the boiler are modeled in (15).

$$TP_t^{Boi} = p_t^{Boi,gas} \cdot \eta^{Boi} \tag{13}$$

$$u_t^{Boi}TP_{\min}^{Boi} \leqslant TP_t^{Boi} \leqslant u_t^{Boi}TP_{\max}^{Boi} \tag{14}$$

$$v_t^{Boi} \geqslant u_t^{Boi} - u_{t-1}^{Boi} \tag{15}$$

3.5. Energy storage system

Electricity stored in the Electrical Storage System (ESS) at time t is presented by (16) and (17) taking into account the electricity charged, the electricity discharged and also self-discharging rate. During charging or discharging process electrical energy would be lost, so turn-around efficiency of ESS is considered.

$$EE_t^{ESS} = EE_{t-1}^{ESS} + \delta \cdot \eta^{ESS} \cdot EP_t^{CH} - \delta \cdot EP_t^{DCH}/\eta^{ESS} - \delta \cdot S_t^{ESS}EP^{ESS,sdc}, \quad t > 1 \tag{16}$$

$$EE_t^{ESS} = EE_{ini}^{ESS} + \delta \cdot \eta^{ESS} \cdot EP_t^{CH} - \delta \cdot EP_t^{DCH}/\eta^{ESS} - \delta \cdot S_t^{ess} EP^{ess,sdc}, \quad t = 1 \tag{17}$$

$$S_t^{ess} = \begin{cases} 1, & \text{if ESS is ON} \\ 0, & \text{if ESS is OFF} \end{cases} \tag{18}$$

where EE_t^{ESS} is ESS energy at time t, δ is time interval duration, η^{ESS} is ESS efficiency, EP_t^{DCH} is ESS discharge at time t, EP_t^{CH} is ESS charge at time t, S_t^{ess} is ESS status at time t and $EP^{ess,sdc}$ is ESS self-discharging rate. The ESS has an initial value at the beginning of each day which is modeled by EE_{ini}^{ESS}. In order to prevent net accumulation, the ESS must return to its initial value at the end of each day.

$$EE_t^{ESS} = EE_{ini}^{ESS}, \quad t = 1, \ t = 24 \tag{19}$$

In order to maintain the storage and avoid damaging it or reduce its capacity, discharge or charge rate of electricity along with energy stored in storage should not exceed the limits which are defined by the manufacturer.

$$EP_t^{CH} \leqslant EP_{UB}^{CH} \tag{20}$$

$$EP_t^{DCH} \leqslant EP_{UB}^{DCH} \tag{21}$$

$$EE_t^{ESS} \leqslant EE_{UB}^{ESS} \tag{22}$$

where EP_{UB}^{CH} is upper bound of ESS charge rate; EP_{UB}^{DCH} is upper bound of ESS discharge rate and EE_{UB}^{ESS} is upper bound of ESS energy.

The thermal energy storage is a firmly simplified model of a water tank with thermal stratification. Heat stored in the thermal storage at time t is based on Eqs. (23) and (24). The heat loss during the storage process is showed in the same manner as represented for the electrical storage by self-discharging. The Equations are same as electrical storage.

$$TE_t^{TSS} = TE_{t-1}^{TSS} + \delta \cdot \eta^{TSS} \cdot TP_t^{CH} - \delta \cdot TP_t^{DCH}/\eta^{TSS} - \delta \cdot S_t^{TSS} TP^{TSS,sdc}, \quad t > 1 \tag{23}$$

$$TE_t^{TSS} = TE_{ini}^{TSS} + \delta \cdot \eta^{TSS} \cdot TP_t^{CH} - \delta \cdot TP_t^{DCH}/\eta^{TSS} - \delta \cdot S_t^{TSS} TP^{TSS,sdc}, \quad t = 1 \tag{24}$$

$$S_t^{TSS} = \begin{cases} 1, & \text{if TSS is ON} \\ 0, & \text{if TSS is OFF} \end{cases} \tag{25}$$

The rates of discharge and charge of heat cannot exceed the thermal storage discharge and charge limits based on the type of storage medium, mass and latent heat of the material:

$$TP_t^{CH} \leqslant TP_{UB}^{CH} \tag{26}$$

$$TP_t^{DCH} \leqslant TP_{UB}^{DCH} \tag{27}$$

$$TE_t^{ESS} \leqslant TE_{UB}^{ESS} \tag{28}$$

As mentioned before, at the end of each day, the thermal storage must return to its initial value, in order to avoid net accumulation.

$$TE_{t-1}^{TSS} = TE_{ini}^{TSS}, \quad t = 1 \tag{29}$$

$$TE_t^{TSS} = TE_{ini}^{TSS}, \quad t = 24 \tag{30}$$

3.6. Appliance

As mentioned before, there are three categories of domestic appliances: Electrically Controllable Appliances (ECA), Thermally Controllable Appliances (TCA) and Optically Controllable Appliances (OCA). In this section scheduling of each category will be stated.

3.6.1. ECA scheduling

An optimal technique for scheduling all the ECAs which are available for scheduling, is proposed based on the RTP pricing scheme. CC can schedule ECAs as soon as HG receives RTP from the utility. ECAs do not have to be carried out at distinct times but rather within a desired interval, besides residents usually prefer to run each ECA automatically at a time in order to avoid peak price. From this perspective, it is essential to set the parameters for individual ECA including operation time interval from Earliest Starting Time (EST) to Latest Finishing Time (LFT) during which the appliance can be activated, together with its power consumption and Length of Operation Time (LOT). All of these parameters can be set on the IHD and sent toward the CC by means of HG. In this study the parameters are adopted from [20] and shown in Table 1. The operation time of each ECA has to be within the provided time window, from EST to LFT (see Fig. 2).

3.6.1.1. ECA starting probability function. The appliance consumption cycle is initiated based on its starting probability which is defined by the starting probability function P_{start}

$$P_{start}(A, W, \delta, \sigma_{flat}, h, d) = P_{season}(A, W) P_{hour}(A, h, d) P_{step}(\delta_{step}) P_{social}(\sigma_{flat}) \tag{31}$$

Table 1
ECAs' parameters.

	Appliance	POWER (kW)	EST (h)	LFT (h)	TW (h)	DU (h)
1	Dishwasher	1	2	14	12	2
2	Clothes-washer	1	2	14	12	1.5
3	Spin dryer	2.5	2	14	12	1
4	Stove	3	1	13	12	0.5
5	Oven	5	1	13	12	0.5
6	microwave	1.7	1	13	12	0.5
7	Laptop	0.1	4	15	11	2
8	PC	0.3	4	15	11	3
9	Vacuum cleaner	1.2	2	16	14	0.5
10	PHEV	3.5	16	24	8	3
11	Sensors	0.01	0	24	24	24
12	Coffee maker	0.8	1	13	12	0.5
13	TV	0.6	4	15	11	1.5
14	Radio/player	0.2	4	15	11	1
15	other occasional loads	1	7	15	8	1

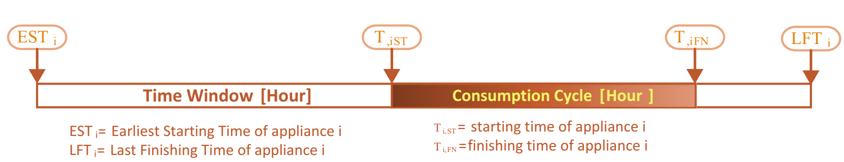

Fig. 2. ECAs' time window, consumption cycle, EST and LFT.

where A is an appliance which belongs to ECA, h is the hour of the day, d stands for the day of the week while W represents the week of the year, δ_{step} is the computational time step (s or min), σ_{flat} is the standard deviation for P_{social}, which is social random factor, patterns the weather and social factors affecting the common behavior. The seasonal changes is modeled by P_{season}, the seasonal probability factor, the activity probability during the day is modeled through P_{hour} the hourly probability factor, P_{step} stands for the step size scaling factor, which scales the probabilities in accordance with δ. P_{start} is specified for each time interval δ which it takes a value between 0 and 1. The turning on is checked by using the probability P_{start}, when the appliance is off. Starting occurs when P_{start} is larger than threshold value. When the length of operation (LOT) is reached the appliance is turned off. There are more Equations related to the probability factors, which are listed below:

$$\sum_{h=1}^{24} P_{hour}(A \in ECA, h, d) = 1 \tag{32}$$

$$\frac{\sum_{W=1}^{52} P_{season}(A, W)}{52} = 1 \tag{33}$$

The mean yearly starting value can be calculated by summing the daily starting frequencies.

$$\begin{aligned} N_{year,mean}(A) &= \sum_{W=1}^{52}\sum_{d=1}^{7}\sum_{h=1}^{24}\sum_{steps}\langle P_{appl}(A,h,d,W,\delta,\sigma_{flat})\rangle \\ &= \sum_{W=1}^{52} P_{season}(A,W)\sum_{d=1}^{7}\sum_{h=1}^{24} P_{hour}(A,h,d)\sum_{steps} P_{step}(\delta)\langle P_{social}(\sigma_{flat})\rangle \end{aligned} \tag{34}$$

3.6.1.2. ECA scheduling. Each ECA has to be started once and subsequently finished once which are expressed as follows:

$$\sum_{EST \leqslant t \leqslant LFT-LOT} S_{i,t}^{start} = 1, \quad \forall i \in ECA \tag{35}$$

$$\sum_{EST+LOT \leqslant t \leqslant LFT} S_{i,t}^{finish} = 1, \quad \forall i \in ECA \tag{36}$$

where $S_{i,t}^{start}$ is appliance i starting status and is one if the appliance turns on in period t and is zero in all other times. $S_{i,t}^{finish}$ is appliance i finishing status and is one if the appliance turns off and is zero in all other times respectively.

$$S_{i,t}^{start} = \begin{cases} 1, & t = t_{i,ST} \\ 0, & otherwise \end{cases} \tag{37}$$

$$S_{i,t}^{finish} = \begin{cases} 1, & t = t_{i,FN} \\ 0, & otherwise \end{cases} \tag{38}$$

$$S_{i,t} = \begin{cases} 1, & t_{i,ST} \leqslant t \leqslant t_{i,FN} \\ 0, & otherwise \end{cases} \tag{39}$$

$$t_{i,FN} = t_{i,ST} + LOT_i \tag{40}$$

where $t_{i,ST}$ and $t_{i,FN}$ are appliance i starting and finishing time, respectively.

Within each time slot, the total electricity consumption of ECAs is the sum of the power consumption from all running ECAs.

$$EP_t^{ECA} = \sum_{i \in ECA} EP_i . S_{i,t} \tag{41}$$

where EP_t^{ECA} is electrical power demand of ECAs at time t; EP_i is electrical power consumption of appliance i and $S_{i,t}$ is a binary variable and shows appliance i status at time t which is 1 if the appliance is on and is 0 if the appliance is off.

3.6.2. TCA scheduling

The thermostatically controllable appliance can be either electrical or thermal, such as air conditioner or water heater. They are scheduled in according to both desired temperature and energy prices. The indoor, fridge and hot water temperature (T_t^{fr}, T_t^{IN} and T_t^{WTR}) should be limited to the desired temperature decided by the customer, for the temperature adopted by the central controller may be either high or low for which the customer feels uncomfortable. These conditions can be expressed as follows:

$$T_{\min}^{in} \leqslant T_t^{in} \leqslant T_{\max}^{in} \tag{42}$$

$$T_{\min}^{WTR} \leqslant T_t^{WTR} \leqslant T_{\max}^{WTR} \tag{43}$$

$$T_{\min}^{fr} < T_t^{fr} < T_{\max}^{fr} \tag{44}$$

$$T_{\min}^{frz} < T_t^{frz} < T_{\max}^{frz} \tag{45}$$

where $T_{\min}^{in}$, $T_{\min}^{WTR}$ and $T_{\min}^{fr}$ are indoor, hot water and fridge temperature lower bound, respectively; $T_{\max}^{in}$, $T_{\max}^{WTR}$ and $T_{\max}^{fr}$ represent indoor, hot water and fridge temperature upper bound, respectively. The preferred temperature may vary from one house to another. In this study, the conventional bounds on the temperature, which are defined by the user to reflect customer convenience, are used as the technical constraint in the scheduling procedure. The above constraints guarantee that the TCA temperature is within the customer's preferred range.

3.6.2.1. Fridge. With the purpose of modeling the fridge operation, the operational constraints of the fridge is considered. Therefore, the model maintains the fridge inside temperature within a specified range, while considering technical facets of the fridge operation in addition to the customer preferences. The fridge operational constraints are given as follows:

$$OS_t^{fr} = \begin{cases} 0 \text{ or } 1 & \text{if } t \in TW^{fr} \\ 0 & \text{if } t \notin TW^{fr} \end{cases} \tag{46}$$

$$OS_t^{fr} = \begin{cases} 1 & \text{if } T^{fr}(t=0) > T_{\max}^{fr} \\ 0 & \text{if } T^{fr}(t=0) < T_{\min}^{fr} \end{cases} \tag{47}$$

$$T_t^{fr} = T_{t-1}^{fr} + \delta(\beta^{fr} EP_t^{fr} - \alpha^{fr} OS_t^{fr} + \gamma^{fr}) \tag{48}$$

The fridge time window over which the fridge can operate is defined by (46), where the customer specifies the TW^{fr}. If the fridge temperature at $t = 0$ is more than the pre-defined upper limit, it will be turned on.

The fridge temperature at time t, depends on the fridge temperature at time $t-1$, the activity probability of the fridge at time t, fridge On/Off status at time t, and its heat losses. The activity probability effect on the fridge temperature is modeled by means of β^{fr}, therefore more activity probability means more cooling demand on the fridge, that is defined as the number of the fridge door opening and closing during a time interval, which affects the fridge temperature. The α^{fr} and γ^{fr}model the effect of the on and off states on the fridge temperature. The γ^{fr} models the thermal leakage due to the difference between the fridge and room temperature.

3.6.2.2. Air conditioning and heating. The air conditioning (AC) and heating (HT) systems principals are similar to each other, so there are common set of Equations for both AC and HT system.

$$OS_t^{ac} = \begin{cases} 0 \text{ or } 1 & \text{if } t \in TW^{ac} \\ 0 & \text{if } t \notin TW^{ac} \end{cases} \quad (49)$$

$$OS_t^{ac} = \begin{cases} 1 & \text{if } T^{ac}(t=0) > T_{\max}^{in} \\ 0 & \text{if } T^{ac}(t=0) < T_{\min}^{in} \end{cases} \quad (50)$$

$$T_t^{in} = T_{t-1}^{in} + \delta(\beta^{ac} EP_t - \alpha^{ac} OS_t^{ac} + \rho^{ac}(T_t^{out} - T_t^{in})) \quad (51)$$

$$OS_t^{ht} = \begin{cases} 0 \text{ or } 1 & \text{if } t \in TW^{ht} \\ 0 & \text{if } t \notin TW^{ht} \end{cases} \quad (52)$$

$$OS_t^{ht} = \begin{cases} 1 & \text{if } T^{ht}(t=0) < T_{\min}^{in} \\ 0 & \text{if } T^{ht}(t=0) > T_{\max}^{in} \end{cases} \quad (53)$$

$$T_t^{in} = T_{t-1}^{in} + \delta(\beta^{ht} EP_t + \alpha^{ht} OS_t^{ht} - \rho^{ht}(T_t^{in} - T_t^{out})) \quad (54)$$

$$OS_t^{ht} + OS_t^{ac} \leqslant 1 \quad (55)$$

In this model, The AC/HT time window over which the AC/HT can operate is defined by (49) and (52) where the customer specifies TW^{ac} and TW^{ht} settings. If the indoor temperature at $t = 0$ is less (more) than the pre-defined lower (upper) limit, the AC/HT will be turned on in the first time interval which is expressed by (50) and (53). The Eq. (55) guarantees that the HT and AC do not run at the same time. The dynamics of indoor temperature for the AC and HT systems are expressed by Eqs. (51) and (54), respectively. The indoor temperature at time t, depends on the indoor temperature at time $t-1$, the activity probability of the indoor at time t, AC/HT on or off status at time t, and the difference between the outdoor and indoor temperature. The activity probability effect on the indoor temperature is modeled by means of β^{ac}/β^{ht}, therefore more activity probability means more cooling/heating demand on the indoor; ρ^{ht} and ρ^{ac} represents the effect of outdoor and indoor temperature differences on indoor temperature which cause the residential thermal losses.

3.6.2.3. Water heater. Hot water usage differs from one house to another, based on the number of occupants, their usage pattern and the in-home facilities (bath, shower, etc.). A regular hourly domestic hot water usage in summer as well as the one in winter is adopted from [21]. The procedure to calculate the hourly hot water usage in residential sector is explained in detail in [22]. The modeling of hot water temperature requires a thermal dynamic model (TDM) which describes its heat swap with cold water inflows [23].

$$TP_t^{WTR} = V_t^{CLD,WTR} \cdot \left(T^{CLD,WTR} - T_t^{WTR}\right) + C^{WTR} \cdot V_{ST}^{WTR} \cdot \left(T_{t+1}^{WTR} - T_t^{WTR}\right) \quad (56)$$

where TP_t^{WTR} is the thermal power needed for hot water at time t; $V_t^{CLD,WTR}$ is the volume of the cold water which replaces the hot water in water tank at time t; $T^{CLD,WTR}$ is the temperature of cold water which replaces the hot water in water tank at time t; C^{WTR} is the specific heat of water and V_{ST}^{WTR} is the volume of water storage.

3.6.3. OCA scheduling

The OCAs such as lighting loads are scheduled based on illumination. The lighting load is modeled by means of the illumination level index and depends on the activity probability which represents the house occupancy in lighting load calculation. The minimum required illumination can be supplied through the lighting system together with outdoor illumination (sunshine). The lighting load of a zone z in the house is expressed as follows:

$$L_t^z + L_t^{OUT} \geqslant (1 + K_t) L_t^{z,\min} \quad (57)$$

The aforementioned constraint guarantees that the total indoor illumination is more than a minimum requisite level. It is supposed that residents tend to decrease illumination during peak-price hours. The K_t declares the "price elasticity" of the lighting load, $0 < K_t < 1$. It means that during peak price hours K_t is equal to 0, which represents using the minimum required illumination level; and during off-peak price hours K_t is equal to 1, which corresponds to the household utilizes more lighting than the minimum required illumination level. The lighting load is affected by the house occupancy through the minimum required illumination level.

3.7. Discomfort index

In this paper, a new index named Discomfort Index (DI) is proposed. The DI is defined as the deviation from the most desired temperature and in addition to load shifting from the preferred running period. The desired temperature is the average of upper and lower bounds of temperature while the preferred running period starts at EST and lasts for LOT. The DI can be calculated as follows:

$$\mathrm{DI} = \sum_{t \in T} \left(\left| T_t^{fr} - T_{des}^{fr} \right| + \left| T_t^{frz} - T_{des}^{frz} \right| + \left| T_t^{WTR} - T_{des}^{WTR} \right| + \left| T_t^{IN} - T_{des}^{IN} \right| \right) + \frac{\sum_{i \in ECA} \sum_{t \in T} \left| t_{i,ST} - EST_i \right|}{48} \quad (58)$$

$$T_{des}^{fr} = \frac{T_{\min}^{fr} + T_{\max}^{fr}}{2} \quad (59)$$

$$T_{des}^{frz} = \frac{T_{\min}^{frz} + T_{\max}^{frz}}{2} \quad (60)$$

$$T_{des}^{WTR} = \frac{T_{\min}^{WTR} + T_{\max}^{WTR}}{2} \quad (61)$$

$$T_{des}^{IN} = \frac{T_{\min}^{IN} + T_{\max}^{IN}}{2} \quad (62)$$

3.8. Energy balances

During each time period, the provision of natural gas need to satisfy the below condition:

$$p_t^{gas} - p_t^{boi,gas} - p_t^{chp,gas} = 0 \quad (63)$$

The electricity demand through each interval is supplied by DERs along with the grid. Also, the bidirectional energy flows with the grid and the storage should be considered which are modeled through $EP_t^{BY,GRD}$ and $EP_t^{SL,GRD}$, the electrical power bought/sold from/to the grid. The consumed heat through each interval is equivalent to the generated heat by CHP, boiler and the charge/discharge of thermal storage system.

$$EP_t^{ECA} + EP_t^{TCA} + EP_t^{OCA} = EP_t^{PV} + EP_t^{WT} + EP_t^{CHP} + EP_t^{DCH,ESS} + EP_t^{BY,GRD} - EP_t^{CH,ESS} - EP_t^{SL,GRD} \quad (64)$$

$$TP_t^{TCA} = TP_t^{CHP} + TP_t^{Boi} + EP_t^{DCH,TSS} - EP_t^{CH,TSS} \quad (65)$$

3.9. Objective function

There are two issues in customers' goal. First nearly all customers care about their energy bills and tend to reduce them, second, some of customers may also care about their appliance carry out assigned task as soon as possible and also desired temperature for indoor, hot water and other thermal loads. Obviously, these goals are conflicting, for instance the user may postpone the operation of an appliance to another hour so as to reduce the cost. Yet, they may choose to pay more and get the work done sooner or make hot water warmer. Indeed there is a trade-off between these two goals. The objective is to minimize the overall energy cost subject to aforementioned constraints. Total cost encompasses operation and maintenance cost of the DERs and energy storage systems; along with purchased natural gas and electricity in addition to the revenue from selling electricity back to the grid.

$$OBJ = \sum_{t \in T} \Big[P_t^E \left(EP_t^{BY,GRD} - EP_t^{SL,GRD} \right) + P^{NG} \cdot p_t^{gas} + m^{CHP} EP_t^{CHP} + m^{WT} EP_t^{WT} + m^{PV} EP_t^{PV} + m^{ESS} EP_t^{DCH} + m^{Boi} TP_t^{Boi} + m^{TSS} TP_t^{DCH} \Big] \delta \tag{66}$$

where m^{CHP}, m^{PV} and m^{ESS} are maintenance cost of CHP, wind turbine, PV, ESS, boiler and TSS per kW, respectively; P_t^E is the real time electricity price and P^{NG} shows natural gas price.

4. Simulation result

To demonstrate the effectiveness of the proposed method, the energy management model has been applied to a home including a verity of appliances and micro generation resources. The domestic energy resources include the PV, wind turbine, CHP, boiler, electrical and thermal storages and the upstream grid along with different type of appliances. The profiles of sun irradiation, wind speed, outdoor temperature and illumination in summer and winter are taken from [24–26]. The real time electricity prices are taken from [27] which have been shown in Fig. 3. It is assumed that the TCAs' state are ON in the first time interval.

The proposed model is solved using mixed-integer Linear programming (MILP) solver Cplex [28] under GAMS on a Pentium IV, 2.6 GHz processor with 4 GB of RAM. Cplex optimizers are designed to solve large, difficult problems quickly and with minimal user intervention. For problems with integer variables, Cplex uses a branch and cut algorithm which solves a series of linear programming, sub-problems. Because a single mixed integer problem generates many sub-problems, even small mixed integer problems can be very compute intensive and require significant amounts of physical memory. Regarding the condition of the problem in this paper, the advantage of the branch and cut algorithm is that it provides rigorous lower and upper bounds on the solution, which in turn provide information regarding the optimality of the solution. More details on Cplex solver and its features are available in [28].

In order to apply different environment conditions such as sun irradiation and outdoor temperature, both summer and winter seasons are considered. Four scenarios are deployed, which are WmO, WME, SmO, and SME. "W" represents "winter" while "S" shows "summer"; "m" is "microgrid" indicating that the house is considered as a microgrid including DERs and storage systems, whereas "M" for "macrogrid" showing that the electrical and thermal demand of the house is provided solely by the main grid and the boiler, respectively. The "O" represents "optimized scheduling" while "E" shows "Earliest starting time". In state "O", the ECAs are scheduled based on different parameters and constraints that mentioned above, and in state "E", the ECAs start at the beginning of their time window. The preferred indoor temperature is between 17 and 23 (°C) while the preferred hot water range is between 48 and 58 (°C), the fridge and freezer desired temperature ranges are between 2 and 8 (°C) and between −20 and −10 (°C), respectively. The ground temperature in winter and summer are 11.2 (°C) and 16.5 (°C) which will affect the cold water temperature (see Table 2). Based on various parameters and profiles, the energy management system provides a smart home with an optimal schedule for heating and air conditioning along with controllable electrical and thermal appliances together with each energy resource. The electrical balance integrating the various supply and demands of each scenario is shown in Figs. 4 and 5. According to ECAs' time window from EST to LFT and their starting probability function, the CC tries to minimize the cost by scheduling the ECAs within their time windows considering their starting probability functions together with the RTP in order to avoid peak hours and reduce the cost. During price peak hours, instead of buying energy from the grid, the house uses all own energy supplying resources and it sells electricity back to the grid which is illustrated in Figs. 4 and 5. As shown in "O" scenarios, the load profiles are smoother due to appliance scheduling, while in "E" scenarios the load profiles have one or more spikes, because some of ECAs have same EST, so they start simultaneously and there will be a sudden increase in the electricity demand.

Table 2
Preferred indoor, hot water, fridge, freezer and ground temperature in all scenarios (°C).

Scenario	Indoor	Hot water	Fridge	Freezer	Ground
Winter	17 to 23	48 to 58	2 to 8	−10 to −20	11.2
Summer	17 to 23	48 to 58	2 to 8	−10 to −20	16.5

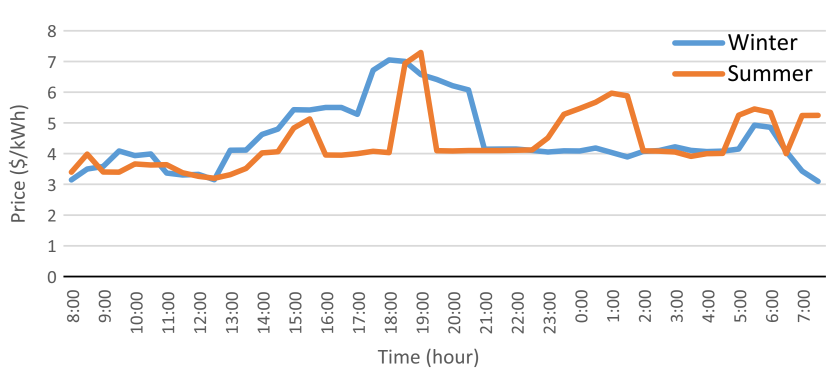

Fig. 3. Electricity real time price in winter and summer.

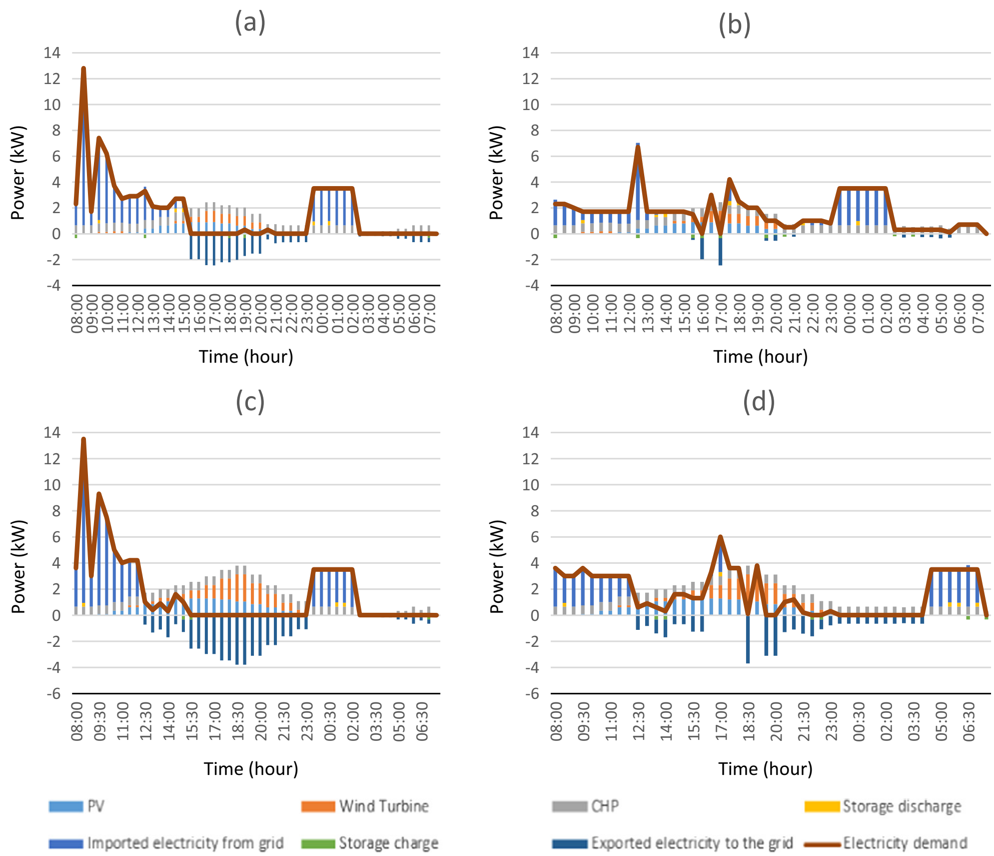

Fig. 4. "Micro" mode electrical balance, scenarios: (a) WmE (b) WmO (C) SmE (d) SmO.

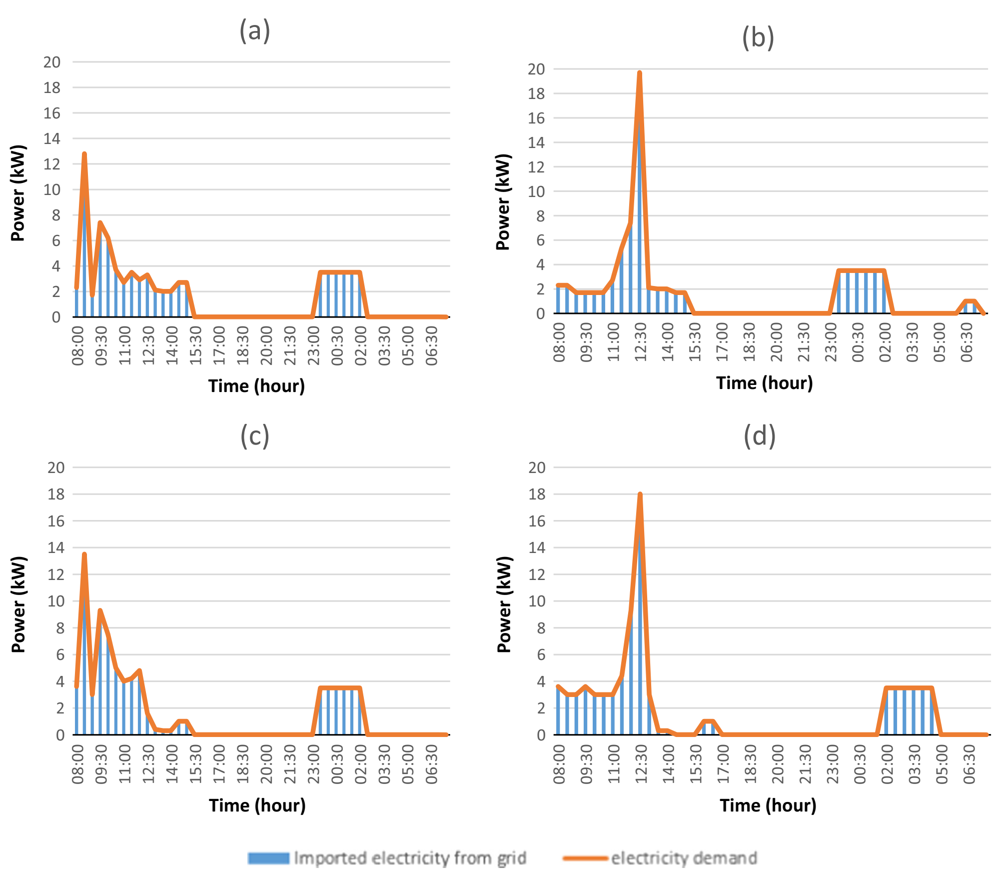

Fig. 5. "Macro" mode electrical balance, scenarios: (a) WME (b) WMO (C) SME (d) SMO.

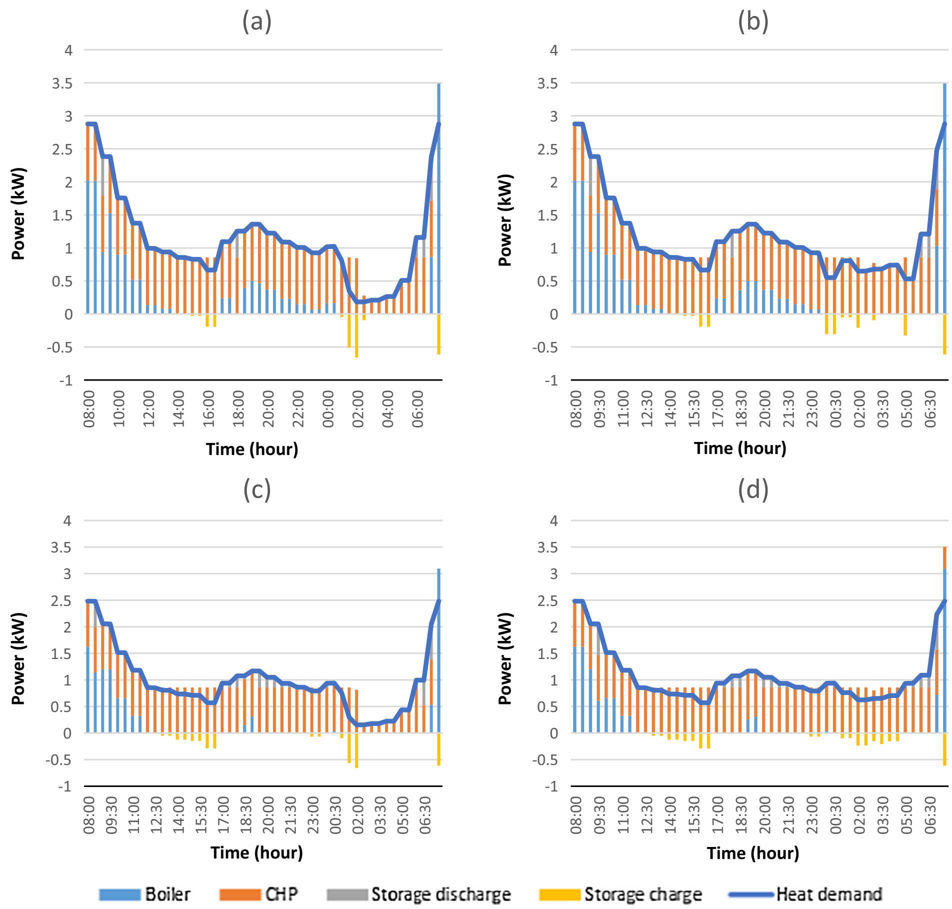

Fig. 6. “Micro” mode thermal balance, scenarios: (a) WmE (b) WmO (C) SmE (d) SmO.

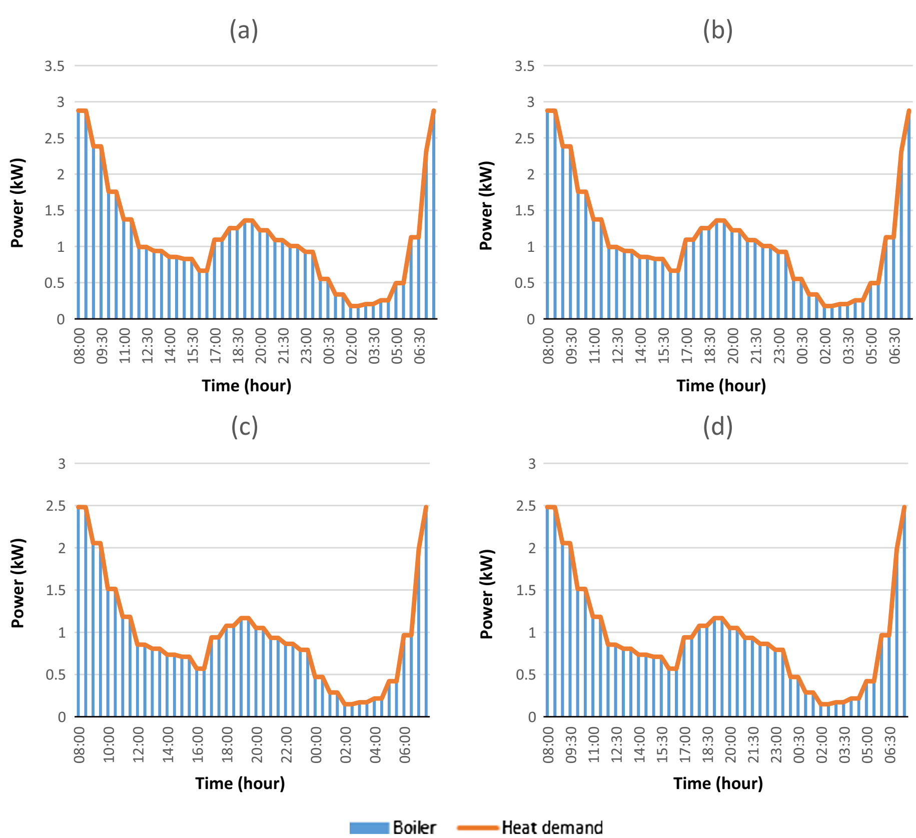

Fig. 7. “Macro” mode thermal balance, scenarios: (a) WME (b) WMO (C) SME (d) SMO.

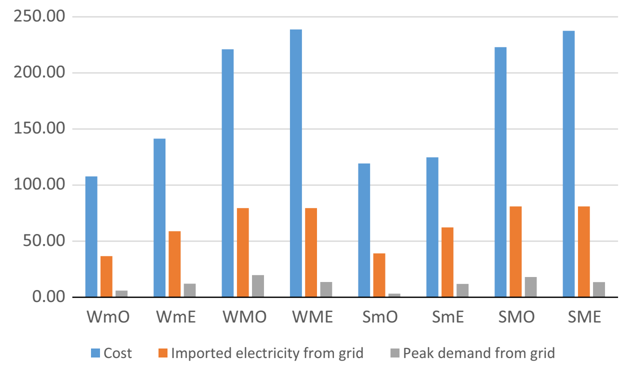

Fig. 8. Cost, imported electricity from grid, peak demand from grid comparison among different scenarios.

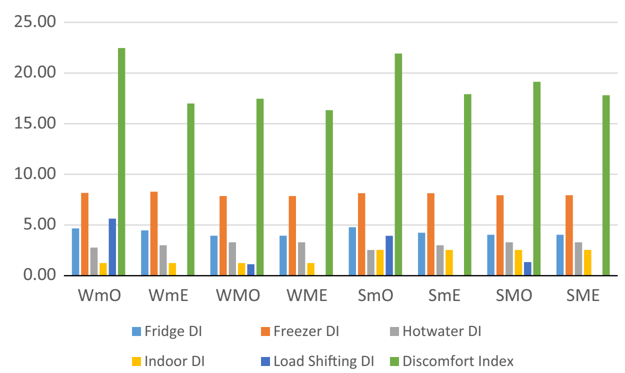

Fig. 9. Discomfort index comparison of different scenarios.

Figs. 6 and 7 illustrate the thermal balance of the home in different scenarios. In Fig. 6, there are a boiler, a CHP and storages to provide the heat demand, but in Fig. 7 the boiler provides the heat demand solely.

In Fig. 6, due to CHP there is a correlation between heat and electricity, therefore the ECAs scheduling can affect the TCAs scheduling. Subsequently the heat demand profiles in Fig. 6 are different from each other. On the other hand in Fig. 7, the demand profiles are just like each other for there is no CHP; so there is no correlation between heat and electricity. Hence, the TCAs are scheduled individually regardless of ECAs and OCA.

The comparison of cost, imported electricity and peak demand from the grid are demonstrated in Fig. 8. The total energy cost considering purchased gas and electricity together with maintenance costs and imported electricity can be reduced by scheduling the appliance and exploiting the DERs. As shown, the total energy cost and imported electricity from the grid in 'm' scenarios have been reduced significantly in comparison to 'M' scenarios which had no DERs. Also, in 'O' scenarios there are more cost saving than 'E' scenarios and less demand from the grid due to the ECAs scheduling. As a result, the 'ME' scenarios are the most expensive scheduling plan, since they have nor ECAs scheduling neither DERs.

As shown in Fig. 9, the "O" scenarios have higher DI and "E" scenarios have lower DI because they have no load shifting. In "mO" scenarios, the load shifting DI is more than other scenarios because of DERs presence in addition to load shifting capability. In summer scenarios, the indoor DI are more than winters. Fridge and freezer DI are almost like each other and there is a little differences. The fridge DI in "mO" scenarios are more than "mE" and then "MO" and "ME" (see Table 3). In other words, in "mO" scenarios fridge temperature is more than "mE' and then "MO" and "ME" which can be observed in Figs. 10 and 11. Also in comparison to Fig. 9, it can be observed that more DI will result in fewer costs. The total cost, imported electricity and computational time of each scenario

Table 3
Discomfort index comparison of different scenarios.

Discomfort index	WmO	WmE	WMO	WME	SmO	SmE	SMO	SME
Fridge DI	4.66	4.46	3.95	3.95	4.78	4.23	4.03	4.03
Freezer DI	8.17	8.28	7.85	7.85	8.14	8.14	7.94	7.94
Water heater DI	2.77	3.00	3.30	3.30	2.53	3.00	3.30	3.30
Indoor DI	1.24	1.24	1.24	1.24	2.54	2.54	2.54	2.54
Load shifting DI	5.63	0.00	1.13	0.00	3.94	0.00	0.00	1.33
Total DI	22.47	16.99	17.46	16.34	21.92	17.92	17.81	19.14

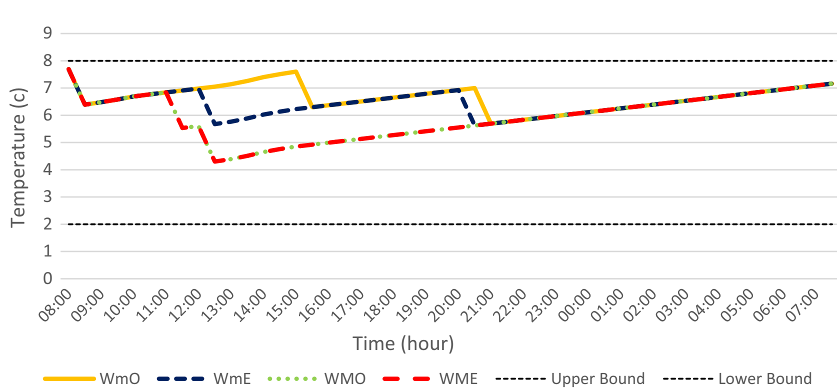

Fig. 10. Fridge temperature in winter scenarios.

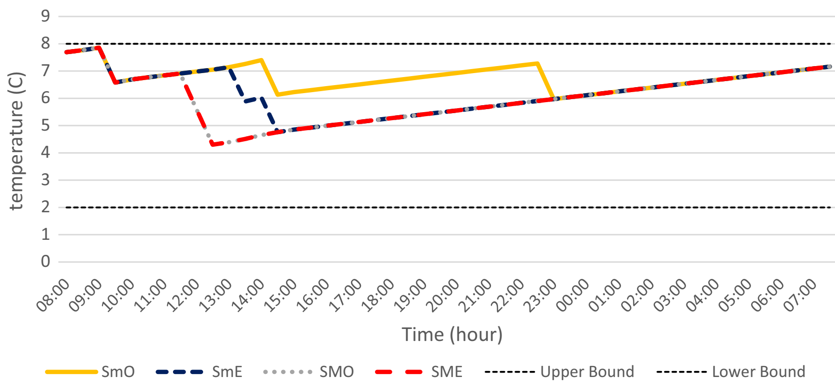

Fig. 11. Fridge temperature in summer scenarios.

Table 4
Comparison of cost, imported electricity from grid, peak demand and run time of scenarios.

Scenario	Cost (cent)	IMGRID (kW)	Peak demand(kW)	Run time (s)
WMO	221.07	79.47	19.71	0.464
WME	238.82	79.47	13.61	0.338
WmO	107.79	36.64	5.98	0.900
WmE	141.42	58.87	12.12	0.296
SMO	223.01	80.97	18.01	0.706
SME	237.57	80.97	13.51	0.431
SmO	119.26	39.16	3.18	0.640
SmE	124.76	62.25	11.86	0.336

have been shown in Table 3. As can be seen in "O" scenarios it takes more time to optimize due to appliance scheduling (see Table 4).

5. Conclusion

In this paper, an energy management model for a home including micro generations and energy storage system has been presented. In this study various types of appliances have been scheduled simultaneously. The electrically controllable, thermally controllable and optically controllable appliances which have been scheduled based on their starting probability, desired temperature and illumination level index considering technical constraint and energy prices. The discomfort index, the deviation from the most desired temperature in addition to load shifting from the preferred running period has been proposed too. In order to show the capability of the proposed model, the scheduling has been performed in different scenarios and the results of applying the scenarios have been analyzed and compared. This scheme worked efficiently by representing how a house should buy, sell, store or use electricity in order to minimize energy costs. The results show that the scheduling of ECAs, TCAs and OCA can be reached simultaneously by using the proposed formulation. Moreover, simulation results evidenced that the proposed home energy management model exhibits a lower cost and, therefore, is more economical. It also offers a feasible solution to optimal energy management among residential energy users.

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