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Cost reduction and peak shaving through domestic load shifting and DERs

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ABSTRACT

With the development of home area network, residents have the opportunity to schedule their power usage at the home by themselves aiming at reducing electricity expenses. Moreover, as renewable energy sources are deployed in home, an 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 that considers both energy consumption and generation simultaneously. The proposed model arranges the household electrical and thermal appliances for operation such that the monetary expense of a customer is minimized based on the time-varying pricing model. In this model, the home gateway receives the electricity price information as well as the resident desired options in order to efficiently schedule the appliances and shave the peak as well. The scheduling approach is tested on a typical home including variety of home appliances, a small wind turbine, PV panel and a battery over a 24-h period.

1. Introduction

In the past few decades, typically a power system is just planned generation sources since the vast majority of loads are not controllable. Moreover, flat rate of electricity price offers little incentive to the customers to schedule their 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 [1,2]. It is actually impractical to ask consumers to schedule their usage optimally since they are neither a system operator nor an economist. Hence, an automatic 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 within the consumption side. The appliance commitment problem determines a best fit schedule for each device considering technical constraints and economic circumstances as well. An 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 in Ref. [3]. A HEMS model has been proposed in Ref. [4] to manage operations of a few devices within a building. The authors in Ref. [5] proposed a demand response algorithm presenting a "user-expected price" (UEP) which indicated the dynamic pricing scheme of electricity tariffs. A simple yet effective load management system, along with renewable and non-renewable sources, was proposed in Ref. [6], in order to reduce electricity bill together with carbon emissions. The authors in Ref. [7] presented a model which enables the participation of sub-aggregators in a residential complex consisting of a smart building in addition to parking lot. However, the customers were not capable of generating electricity as well as selling the excess electricity back to the grid, but they can set their loads in accordance with the price signal. A multi agent solution to energy management problem of a hybrid system has been proposed in Ref. [8]. In comparison to the appliance commitment strategy, this method has some restrictions such as agent intelligence upon an appliance and also appliances coordination. Boukettaya et al. [9] developed the supervisory control, where the objective was to meet the demand and then to check technical constraints toward blackout prevention and cost reduction.

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Nomenclature

Abbreviations, superscripts and subscripts

AC	Air Conditioning
CHP	Combined Heat and Power
CPP	Critical Peak Pricing
DER	Distributed Energy Resource
DI	Discomfort index
EB	Energy Box
ECA	Electrically Controllable Appliances
ESS	Electrical Storage 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
MC	Master Controller
MILP	Mixed Integer Linear Programming
NG	Natural Gas
OCA	Optically Controllable Appliances
PDF	Probability Density Function
PHEV	Plug-in Hybrid Electric Vehicle
RTP	Real Time Pricing, Real Time Price
SM	Smart Meter
TCA	Thermostatically Controllable Appliances
TDM	Thermal Dynamic Model
TOU	Time Of Use
TSS	Thermal Storage System
UB	Upper Bound
UEP	User-Expected Price
WTR	Water

Parameters

ρ^w	Air density
A^w	Wind turbine blade area
η^w	Wind turbine efficiency
V^{nom}	Wind turbine nominal wind speed
$V^{cut\text{-}in}$	Wind turbine cut-in wind speed
$V^{cut\text{-}out}$	Wind turbine cut-out wind speed
v_t	Wind speed at time t (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)
TP_t^{OUT}	The outside air temperature ($^\circ C$)
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
$P_{\min}^{chp,elec}$	The Minimum electrical output of CHP
$P_{\max}^{chp,elec}$	The Minimum electrical output of CHP
$\Delta P_{\max}^{chp,elec}$	The CHP electrical output maximum ramp rate
$P_{ini}^{chp,elec}$	The initial electrical power generated by CHP
U_{ini}^{chp}	The CHP initial status
P^{gas}	The energy per unit volume of natural gas
η^{Boi}	Conversion efficiency of boiler
$P_{\min}^{Boi}$	The Minimum output of boiler
$P_{\max}^{Boi}$	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	The computational time step (second or minute)
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
$T_{\min}^{IN}$	Minimum indoor temperature
$T_{\max}^{IN}$	Maximum indoor temperature
$T_{\min}^{WTR}$	Minimum water temperature
$T_{\max}^{WTR}$	Maximum water temperature
$T_{\min}^{fr}$	Minimum fridge temperature
$T_{\max}^{fr}$	Maximum fridge temperature
$T_{\min}^{frz}$	Minimum freezer temperature
$T_{\max}^{frz}$	Maximum freezer temperature
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
EP^{th}	Agreed imported electricity threshold
P_t^{Pdc}	The difference between peak and base electricity demand price
m^{CHP}	Maintenance cost of CHP
m^{WT}	Maintenance cost of WT
m^{PV}	Maintenance cost of PV
m^{ESS}	Maintenance cost of ESS
m^{Boi}	Maintenance cost of boiler
m^{TSS}	Maintenance cost of TSS
P_t^E	The real time electricity price
P^{NG}	The natural gas price

Variables

t	Time
$p_t^{chp,elec}$	The CHP Electrical output
$p_t^{chp,thrm}$	The CHP Thermal output
$p_t^{chp,gas}$	The CHP imported gas at time t
u_t^{chp}	The CHP status at time t
v_t^{chp}	CHP cold start
P_t^{Boi}	Boiler's output
$V_t^{Boi,gas}$	The volume of boiler imported gas at time t
v_t^{Boi}	Boiler Cold starts
u_t^{Boi}	The boiler status at time t
EE_t^{ESS}	ESS energy at time
EP_t^{CH}	ESS charge at time t
EP_t^{DCH}	ESS discharge at time t
S_t^{ess}	ESS status at time t
TE_t^{TSS}	Heat stored in the thermal storage at time t
TP_t^{CH}	TSS charge at time t
TP_t^{DCH}	TSS discharge at time t
S_t^{TSS}	TSS status at time t
P_{start}	Starting probability function
$N_{year,mean}(A)$	The mean yearly starting frequency of appliance A
$S_{i,t}^{start}$	Appliance i starting status
$S_{i,t}^{finish}$	Appliance i finishing status
$t_{i,ST}$	Appliance i starting time
$t_{i,FN}$	Appliance i finishing time
EP_t^{ECA}	Electrical power demand of ECAs at time t
EP_i	Electrical power consumption of appliance i
$S_{i,t}$	Appliance i status at time t
T_t^{IN}	The indoor temperature
T_t^{WTR}	The hot water temperature
T_t^{fr}	The fridge temperature
T_t^{frz}	The freezer temperature
OS_t^{fr}	The fridge On/Off status at time t
EP_t^{fr}	The electrical power consumption of fridge
OS_t^{frz}	The freezer On/Off status at time t
EP_t^{frz}	The electrical power consumption of freezer
OS_t^{ac}	The cooling system On/Off status at time t
EP_t^{ac}	The electrical power consumption of cooling system
OS_t^{ht}	The heating system On/Off status at time t
EP_t^{ht}	The electrical power consumption of heating system
TP_t^{WTR}	The thermal power needed for hot water at time t
L_t^z	illumination level index of zone z at time t
V_t^{gas}	Imported natural gas at time t
$V_t^{boi,gas}$	Boiler natural gas consumption at time t
$V_t^{chp,gas}$	CHP natural gas consumption at time t
ζ_t	Over threshold value
$EP_t^{BY,GRD}$	the electrical power bought from the grid
$EP_t^{SL,GRD}$	the electrical power sold to the grid

A scheduler which was employing particle swarm optimization co-evolutionary version in order to maximize the benefits toward the customer was presented in Ref. [10]. The objective of authors in Ref. [11] was according to cogeneration systems which facilitated the heat and power exchange among generation units without electric power export. The authors in Ref. [12] got proper target total power usage for all appliances; however, the individual appliance particular scheduling scheme was not mentioned. The EB (energy box) concept which was capable of operating under dynamic pricing scheme and taking part in markets as an integrated and stand-alone units was presented in Ref. [13].

In a spite of the fact that current HEMSs seem to be mainly designed to enhance residential energy efficiency, the vast majority of the related works did not account for users' behaviour in appliances usage and their preferences which is crucial in order to meet the customers need. Furthermore, a common assumption within these papers is that the HEMS is able to set the appliances power consumptions, which in turn might not be reasonable for some non-interruptible appliances. Moreover, limited studies have been conducted in scheduling algorithms which control thermal appliances, for instance heating and air conditioning systems, which use more energy in comparison to other appliances in home. On the other hand, some of the literature cited above did not account for the energy storage systems along with renewable generations as solar and wind. With growing needs for renewable portfolio standards, solar generation as well as wind generation turn into must-take sources in several countries around the world and about 30 U.S. States [14].

This paper presents a smart home that not only utilizes electrical and thermal energy but also is capable of generating and storing them by means of its own generation and storage units. Taking it one step further, it is capable of interacting with the upstream grid in order to take advantage of trading electricity. This study proposes an air conditioner and heater model which takes into account environment data such as outdoor temperature and sun irradiation [15] along with residential thermal losses [16], for thermal energy management that can be applied to the appliance scheduling problem. This study considers users' behaviour and preferences to schedule the loads. The impact of activity, weather and social factors on the energy consumption pattern have been considered by means of activity probability and social random factors. Home energy management scheduling problem with energy sources, electrically and Thermostatically 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

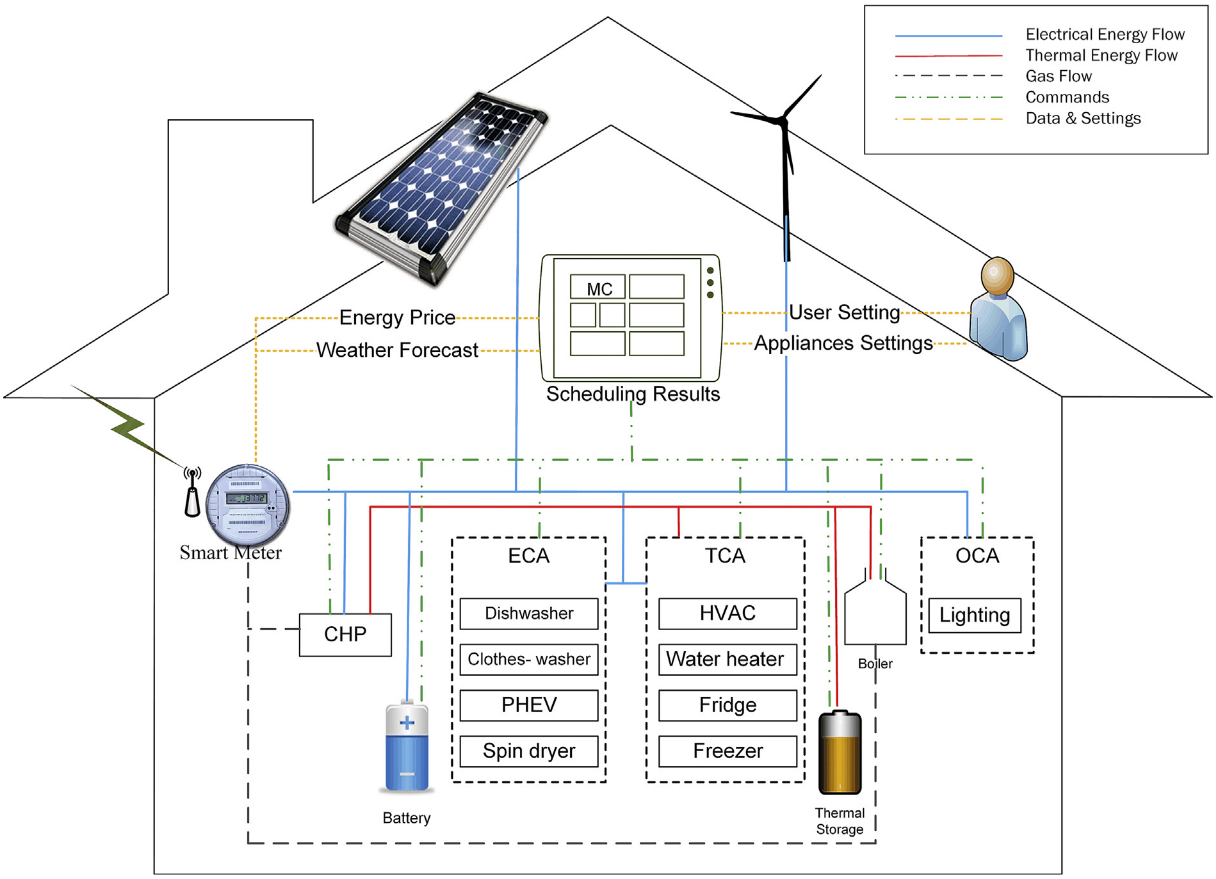

Fig. 1. Proposed system architecture.

over a finite horizon of time. The energy management 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. Considering renewable generation leads to complicate energy management module, by bringing more uncertainty, on the grounds that their function relies on environmental factors including sun irradiation, wind speed or even temperature. Afterward, the objective would be to balance various suppliers: Distributed Energy Resources (DER) and the main grid. Storage device whether electrical or thermal, are employed in order to enhance supply and demand of the residential microgrid through temporarily saving the surplus energy. For a system associated with renewable sources, which have intermittent nature this might be effective.

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 energy management system in this paper is to minimize energy cost under the dynamic price schemes by scheduling the home appliance usage so as to avoid peak hours. The overall architecture of the proposed system is demonstrated in Fig. 1. The Master controller (MC), the heart of energy management system controls and schedules both electrical and thermal appliance together with controllable DERs such as Combined Heat and Power (CHP). The MC cannot control renewable sources such as wind turbine and solar panels since they have intermittent behaviour and therefore they are uncontrollable. In the proposed model, domestic appliances are divided into three categories: Electrically Controllable Appliances (ECA) Thermostatically Controllable Appliances (TCA), Optically Controllable Appliances (OCA). ECAs, TCAs and OCAs only relate with MC and do not interact with each other. All the appliances operations along with controllable DERs and storages would have been scheduled by MC and the optimal schedule which is based on technical and economic constraints transferred to each equipment via Home Area Network (HAN). The ECAs can be scheduled by means of their starting time based on the starting probability function which will be discussed later. On the other hand, the TCAs have a great potential of scheduling due to their thermal storage capabilities while taking into account the thermal dynamic characteristic along with consumer comfort level. In order to obtain an optimal schedule over a time horizon, the MC needs to access thermal settings, the characteristics of appliance such as appliances time windows, energy price data and weather conditions as well as users preferences such as desired hot water temperature, room temperature and minimum required illumination level. As can be seen in Fig. 1 this data can be achieved thorough Smart Meter (SM) and user, which are shown by yellow dashed lines. The objective is to minimize energy costs over a day subject to technical constraints along with comfort zone constraints. The scheduling results will be sent to controllable devices and sources which is shown by green dotdash lines. The electrical and thermal energy flows are shown by blue and red lines respectively. The imported gas has been shown via dash grey lines.

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 considered 30-min, therefore one day has 48 slots.

Historical electricity and gas price data are required for comparing between energy costs of self-generation and grid purchase. Gas price is fixed while electricity price follows dynamic pricing scheme for example Time of Use (TOU), Critical Peak Pricing (CPP) or Real Time Pricing (RTP). Electricity price in RTP updates at least once an hour therefore RTP has a much higher flexibility than TOU and CPP. All the variable and parameters in this section has been described in nomenclature.

3.1. Uncontrollable generations

As mentioned before uncontrollable generations have intermittent behaviour and therefore they cannot be controlled by MC. Renewable sources such as wind and solar generations are examples.

3.1.1. 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 speeds [17].

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

The Probability Density Function (PDF) of wind speed which is described by the Weibull distribution is given by

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

where, v_t, k and c stand for wind speed (m/s), shape factor and scale factor respectively.

3.1.2. 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 [18], power output EP_t^{PV} is represented by:

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

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 [19,20] that can be considered as a linear blend of two unimodal distribution functions [21]. 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.

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

3.2. Controllable generations

Controllable generations can be controlled by MC so as to manage the microgrid in a more efficient way, to avoid peak hours and reduce the overall costs. CHP and boiler are controllable sources.

3.2.1. 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 [22].

$$p_t^{chp,elec} + p_t^{chp,thrm} = V_t^{chp,gas} \eta^{chp}\left(p_t^{chp,elec}\right) \tag{5}$$

$$p_t^{chp,thrm} = p_t^{chp,elec} \mu^{chp,htp}\left(p_t^{chp,elec}\right) \tag{6}$$

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

$$\left|p_t^{chp,elec} - p_{t-1}^{chp,elec}\right| \le \Delta P_{\max}^{chp,elec} \tag{7}$$

Technical constraints of CHP output power are tracked in Eq. (8) and CHP cold starts are considered in Eq. (9). We approximate the non-linear terms by using four-piece linearization [23].

$$u_t^{chp} P_{\min}^{chp,elec} \le p_t^{chp,elec} \le u_t^{chp} P_{\max}^{chp,elec} \tag{8}$$

$$v_t^{chp} \ge u_t^{chp} - u_{t-1}^{chp} \tag{9}$$

$$p_{t-1}^{chp,elec} = P_{ini}^{chp,elec} \tag{10}$$

$$u_{t-1}^{chp} = U_{ini}^{chp}, \quad t = 1 \tag{11}$$

3.2.2. Boiler

Boiler provide a continual supply of heat which can be used for hot water and indoor heating. Fossil fuels such as natural gas are commonly used in boilers. In our study boiler is used for heating water and it uses natural gas as fuel. The boiler output is the result of multiplying conversion efficiency into the natural gas energy per unit volume (12). Technical constraints are tracked in (13). Cold starts of the boiler are modeled in (14).

$$p_t^{Boi} = V_t^{Boi,gas} \cdot P^{gas} \cdot \eta^{Boi} \tag{12}$$

$$u_t^{Boi} P_{\min}^{Boi} \le p_t^{Boi} \le u_t^{Boi} P_{\max}^{Boi} \tag{13}$$

$$v_t^{Boi} \ge u_t^{Boi} - u_{t-1}^{Boi} \tag{14}$$

3.3. Energy Storage System

The energy storage system including Electrical Storage System (ESS) and Thermal Storage System (TSS) are utilized to store electrical and thermal energy when there is a surplus generation. The ESS is mainly for exploiting the renewable sources output more efficiently. When ESS is full, selling back to the grid is the only choice even if the selling price is low. Electricity stored in the ESS at time t is presented by (15) and (16) 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.

$$EE_t^{ESS} = EE_{t-1}^{ESS} + \delta \cdot \eta^{ESS} \cdot EP_t^{CH} - \delta \cdot EP_t^{DCH} \Big/ \eta^{ESS} - \delta \cdot S_t^{ESS} EP^{ESS,sdc}, t > 1 \tag{15}$$

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

$$S_t^{ess} = \begin{cases} 1, & \text{if ESS is ON} \\ 0, & \text{if ESS is OFF} \end{cases} \tag{17}$$

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.

$$EE_t^{ESS} = EE_{ini}^{ESS}, t = 1, \quad t = 24 \tag{18}$$

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.

$$EP_t^{CH} \le EP_{UB}^{CH} \tag{19}$$

$$EP_t^{DCH} \le EP_{UB}^{DCH} \tag{20}$$

$$EE_t^{ESS} \le EE_{UB}^{ESS} \tag{21}$$

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. (22) and (23). 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.

$$TE_t^{TSS} = TE_{t-1}^{TSS} + \delta \cdot \eta^{TSS} \cdot TP_t^{CH} - \delta \cdot TP_t^{DCH} \Big/ \eta^{TSS} - \delta \cdot S_t^{TSS} TP^{TSS,sdc}, t > 1 \tag{22}$$

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

$$S_t^{TSS} = \begin{cases} 1, & \text{if TSS is ON} \\ 0, & \text{if TSS is OFF} \end{cases} \tag{24}$$

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:

$$TP_t^{CH} \le TP_{UB}^{CH} \tag{25}$$

$$TP_t^{DCH} \le TP_{UB}^{DCH} \tag{26}$$

$$TE_t^{ESS} \le TE_{UB}^{ESS} \tag{27}$$

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

$$TE_{t-1}^{TSS} = TE_{ini}^{TSS}, \quad t = 1 \tag{28}$$

$$TE_t^{TSS} = TE_{ini}^{TSS}, \quad t = 24 \tag{29}$$

3.4. Appliance

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

3.4.1. ECA scheduling

An optimal technique for scheduling all the ECA such as Plug-in Hybrid Electric Vehicle (PHEV) which are available for scheduling, is proposed based on the RTP pricing scheme. MC can schedule ECA as soon as HG receives RTP from the utility. ECA do not have to be carried out at distinct times but rather within a desired interval, besides residents usually prefer to run each appliance automatically at a time in order to avoid peak price. From this perspective, it is essential to set the parameters for individual appliance 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 In-Home Display (IHD) and sent toward the MC by means of Home Gate (HG). In this study these parameters are adopted from Ref. [24] 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).

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

$$P_{start}\left(A, W, \delta, \sigma_{flat}, h, d\right) = P_{season}(A, W) P_{hour}(A, h, d) P_{step}(\delta) P_{social}\left(\sigma_{flat}\right) \tag{30}$$

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 is the computational time step (second or minute), σ_{flat} is the standard deviation for P_{social}, which is social random factor, patterns the weather and social factors affecting the common behaviour. The seasonal changes is modeled by P_{season}, the seasonal probability factor, the activity levels 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 it takes a value between

Table 1
ECA parameters.

Appliance	EST	LFT	LOT	POWER
Dishwasher	10:00	23:00	2:00	2
Clothes-washer	10:00	23:00	1:30	1.5
Spin dryer	10:00	23:00	1:00	1
PHEV	0:00	8:00	3:00	3

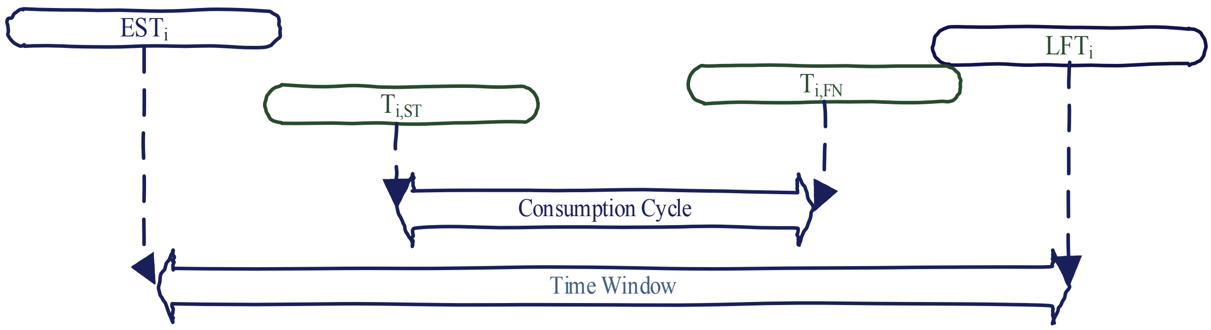

Fig. 2. ECAs' time window, consumption cycle, EST and LFT.

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 [25]. There are more Equations related to the probability factors, which are listed below:

$$\sum_{h=1}^{24} P_{hour}(A \in ECEA, h, d) = 1 \tag{31}$$

$$\frac{\sum_{W=1}^{52} P_{season}(A, W)}{52} = 1 \tag{32}$$

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

$$N_{year,mean}(A) = \sum_{W=1}^{52}\sum_{d=1}^{7}\sum_{h=1}^{24}\sum_{steps} < P_{start}\left(A, h, d, W, \delta, \sigma_{flat}\right) > = \sum_{W=1}^{52} P_{season}(A, W) \sum_{d=1}^{7}\sum_{h=1}^{24} P_{hour}(A, h, d) \sum_{steps} P_{step}(\delta) < P_{social}\left(\sigma_{flat}\right) > \tag{33}$$

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

$$\sum_{EST \le t \le LFT - LOT} S_{i,t}^{start} = 1, \quad \forall i \in ECA \tag{34}$$

$$\sum_{EST + LOT \le t \le LFT} S_{i,t}^{finish} = 1, \quad \forall i \in ECA \tag{35}$$

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.

$$S_{i,t}^{start} = \begin{cases} 1, & t = t_{i,ST} \\ 0, & otherwise \end{cases} \tag{36}$$

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

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

$$t_{i,FN} = t_{i,ST} + LOT_i \tag{39}$$

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.

$$EP_t^{ECA} = \sum_{i \in ECA} EP_i \cdot S_{i,t} \tag{40}$$

where EP_t^{ECA} is electrical power demand of ECAs at time t; EP_i is electrical power 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.

3.4.2. TCA scheduling

The thermostatically controllable appliances 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 master controller may be either high or low for which the customer feels uncomfortable. These conditions can be expressed as follows:

$$T_{\min}^{in} \le T_t^{in} \le T_{\max}^{in} \tag{41}$$

$$T_{\min}^{WTR} \le T_t^{WTR} \le T_{\max}^{WTR} \tag{42}$$

$$T_{\min}^{fr} < T_t^{fr} < T_{\max}^{fr} \tag{43}$$

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

where $T_{\min}^{in}$, $T_{\min}^{WTR}$, $T_{\min}^{fr}$ and $T_{\min}^{frz}$ are indoor, hot water, fridge and freezer temperature lower bound, respectively; $T_{\max}^{in}$, $T_{\max}^{WTR}$, $T_{\max}^{fr}$ and $T_{\max}^{frz}$ represent indoor, hot water, fridge and freezer 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.

3.4.2.1. Fridge. With the purpose of modeling the fridge operation, the operational constraints of the fridge are 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:

$$OS_t^{fr} = \begin{cases} 0 \text{ or } 1 & \text{if } t \in TW^{fr} \\ 0 & \text{if } t \notin TW^{fr} \end{cases} \quad (45)$$

$$OS_t^{fr} = \begin{cases} 1 & \text{if } T^{fr}(t=0) > T_{\max}^{fr} \\ 0 & \text{if } T^{fr}(t=0) < T_{\min}^{fr} \end{cases} \quad (46)$$

$$T_t^{fr} = T_{t-1}^{fr} + \delta\left(\beta^{fr} EP_t^{fr} - \alpha^{fr} OS_t^{fr} + \gamma^{fr}\right) \quad (47)$$

The fridge does not use power constantly and should only use power when the compressor is running. The fridge compressor operating status is defined by (45)–(47), where the customer specifies the TW^{fr} which is time window over which the fridge can operate. If the fridge temperature at t = 0 is more than the pre-defined upper limit, the compressor 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 compressor 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 effects 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.

The modeling of the freezer operation is just like fridge but the difference is in the activity probability as well as upper and lower bounds of temperature.

3.4.2.2. 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.

$$OS_t^{ac} = \begin{cases} 0 \text{ or } 1 & \text{if } t \in TW^{ac} \\ 0 & \text{if } t \notin TW^{ac} \end{cases} \quad (48)$$

$$OS_t^{ac} = \begin{cases} 1 & \text{if } T^{ac}(t=0) > T_{\max}^{in} \\ 0 & \text{if } T^{ac}(t=0) < T_{\min}^{in} \end{cases} \quad (49)$$

$$T_t^{in} = T_{t-1}^{in} + \delta\left(\beta^{ac} EP_t - \alpha^{ac} OS_t^{ac} + \rho^{ac}\left(T_t^{out} - T_t^{in}\right)\right) \quad (50)$$

$$OS_t^{ht} = \begin{cases} 0 \text{ or } 1 & \text{if } t \in TW^{ht} \\ 0 & \text{if } t \notin TW^{ht} \end{cases} \quad (51)$$

$$OS_t^{ht} = \begin{cases} 1 & \text{if } T^{ht}(t=0) < T_{\min}^{in} \\ 0 & \text{if } T^{ht}(t=0) > T_{\max}^{in} \end{cases} \quad (52)$$

$$T_t^{in} = T_{t-1}^{in} + \delta\left(\beta^{ht} EP_t + \alpha^{ht} OS_t^{ht} - \rho^{ht}\left(T_t^{in} - T_t^{out}\right)\right) \quad (53)$$

$$OS_t^{ht} + OS_t^{ac} \le 1 \quad (54)$$

In this model, The AC and HT can operate within time windows (TW^{ac} and TW^{ht} respectively) which have been specified by customer (48) and (51). If the indoor temperature at $t = 0$ is more (less) than the pre-defined upper (lower) limit, the AC (HT) will be turned on in the first time interval which is expressed by (49) and (52). Eq. (54) 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 Equations (50) and (53) 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^{ac} and ρ^{ht} represent the effect of outdoor and indoor temperature difference on indoor temperature which cause the residential thermal losses.

3.4.2.3. 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 Ref. [26]. The procedure to calculate the hourly hot water usage in residential sector is explained in detail in Ref. [27]. The modeling of hot water temperature requires a Thermal Dynamic Model (TDM) which describes its heat swap with cold water inflows [28].

$$\begin{aligned} TP_t^{WTR} = {} & C^{WTR} \cdot V_t^{CLD,WTR} \cdot \left(T^{CLD,WTR} - T_t^{WTR}\right) \\ & + C^{WTR} \cdot V_{ST}^{WTR} \cdot \left(T_{t+1}^{WTR} - T_t^{WTR}\right) \end{aligned} \quad (55)$$

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.

3.4.3. 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:

$$L_t^z + L_t^{OUT} \ge (1 + K_t) L_t^{z,\min} \quad (56)$$

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 this "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.

3.5. 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 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:

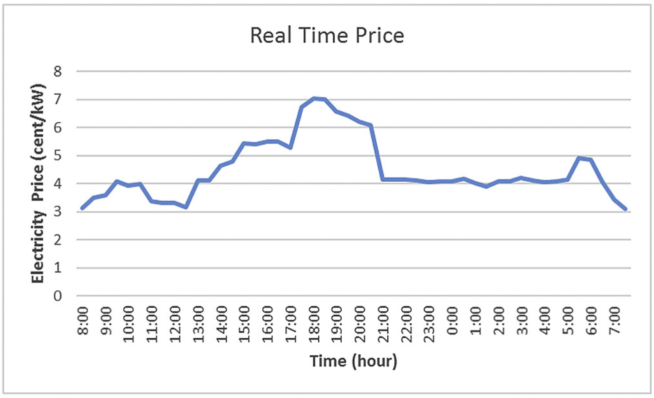

Fig. 3. Electricity real time price.

$$DI=\sum_{t\in T}\left(\left|T_t^{fr}-T_{des}^{fr}\right|+\left|T_t^{frz}-T_{des}^{frz}\right|+\left|T_t^{WTR}-T_{des}^{WTR}\right|+\left|T_t^{IN}-T_{des}^{IN}\right|\right)+\frac{\sum\limits_{i\in ECA}\sum\limits_{t\in T}\left|t_{i,ST}-EST_i\right|}{48} \tag{57}$$

$$T_{des}^{fr}=\frac{T_{\min}^{fr}+T_{\max}^{fr}}{2} \tag{58}$$

$$T_{des}^{frz}=\frac{T_{\min}^{frz}+T_{\max}^{frz}}{2} \tag{59}$$

$$T_{des}^{WTR}=\frac{T_{\min}^{WTR}+T_{\max}^{WTR}}{2} \tag{60}$$

$$T_{des}^{IN}=\frac{T_{\min}^{IN}+T_{\max}^{IN}}{2} \tag{61}$$

3.6. Peak demand charge

It is not economical for system operator to enhance the capacity of the base plants in order to meet the peak load, since the surplus energy during the off-peak hours cannot be stored as a result of large-scale energy storage technology scarcity. On the other hand, the peakers, which are plants brought online during peak hours, have high maintenance and operation costs. In order to reflect this, a further constraint, is presented in the model. During each time interval, when electricity demand from the grid is less than the agreed threshold EP^{th}, the normal electricity price is considered, but when electricity demand from the grid is more than the agreed threshold EP^{th}, the customer is charged with an extra cost proportional to the over threshold value ζ_t, therefore reducing electricity peak demand from the grid is desirable for both residents and utility.

Table 2
Preferred indoor, hot water, fridge, freezer and ground temperature of 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

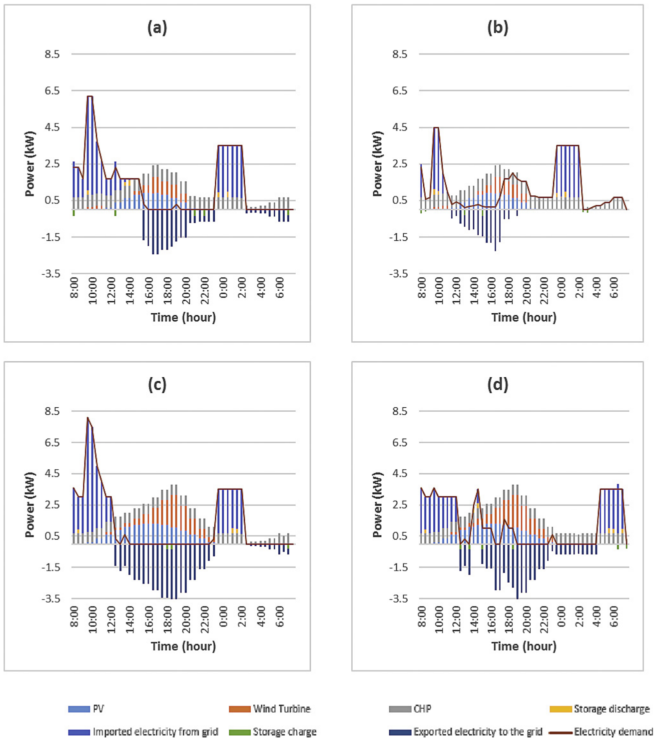

Fig. 4. "Micro" and "Normal" mode electrical balance, scenarios (1) to (4): (a) NWmE (b) NWmO (C) NSmE (d) NSmO.

$$\zeta_t=EP_t^{BY,GRD}-EP^{th},\ \ if\ \ EP_t^{BY,GRD}>EP^{th} \tag{62}$$

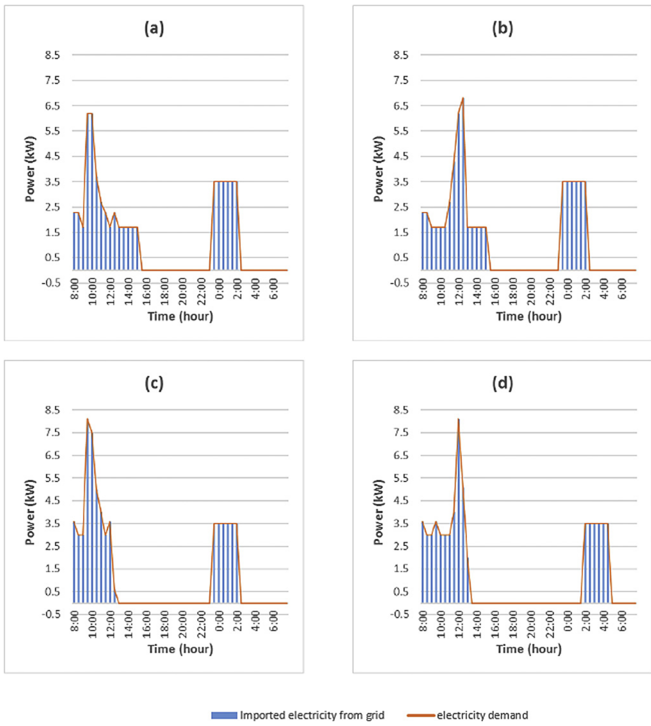

Fig. 5. "Macro" and "Normal" mode electrical balance, scenarios (5) to (8): (a) NWME (b) NWMO (C) NSME (d) NSMO.

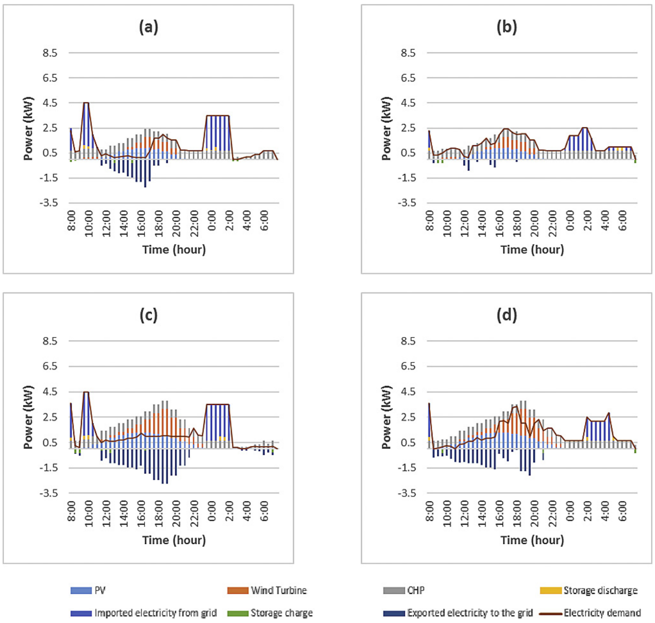

Fig. 6. “Micro” and “Peak demand charge” mode electrical balance, scenarios (6) to (12): (a) PWmE (b) PWmO (C) PSmE (d) PSmO.

3.7. Energy balances

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

$$V_t^{gas} - V_t^{boi,gas} - V_t^{chp,gas} = 0 \tag{63}$$

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.

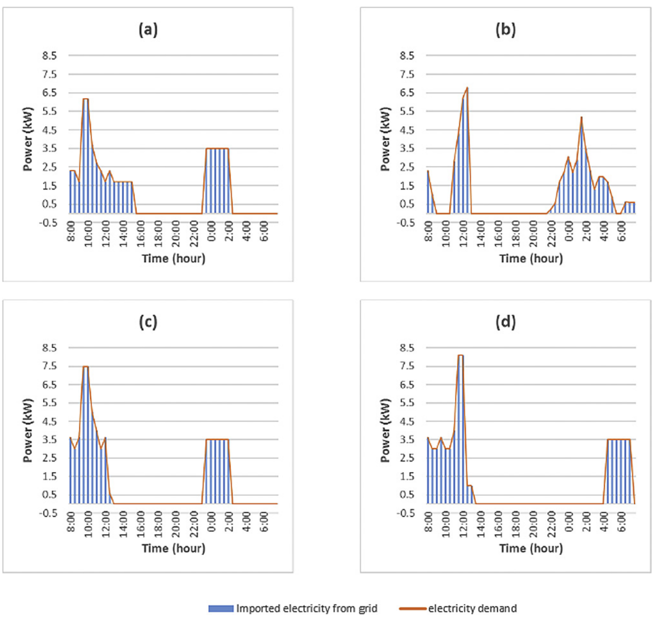

Fig. 7. “Macro” and “Peak demand charge” mode electrical balance, scenarios (13) to (16): (a) PWME (b) PWMO (C) PSME (d) PSMO.

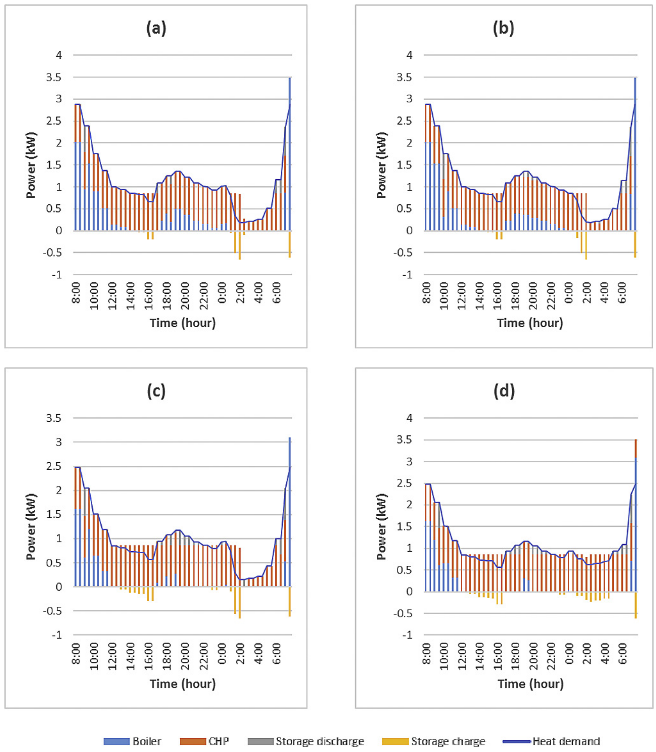

Fig. 8. “Micro” and “Normal” mode thermal balance, scenarios (1) to (4): (a) NWmE (b) NWmO (C) NSmE (d) NSmO.

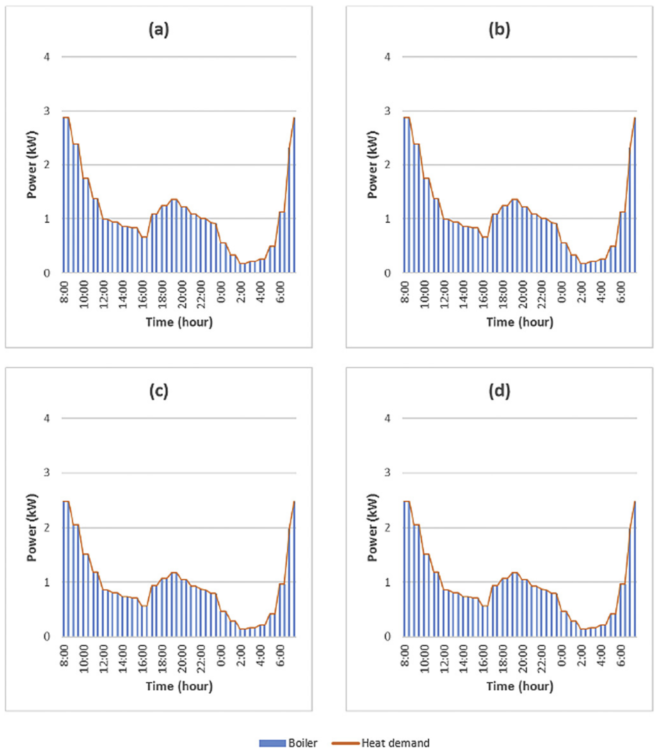

Fig. 9. “Macro” and “Normal” mode thermal balance, scenarios (5) to (8): (a) NWME (b) NWMO (C) NSME (d) NSMO.

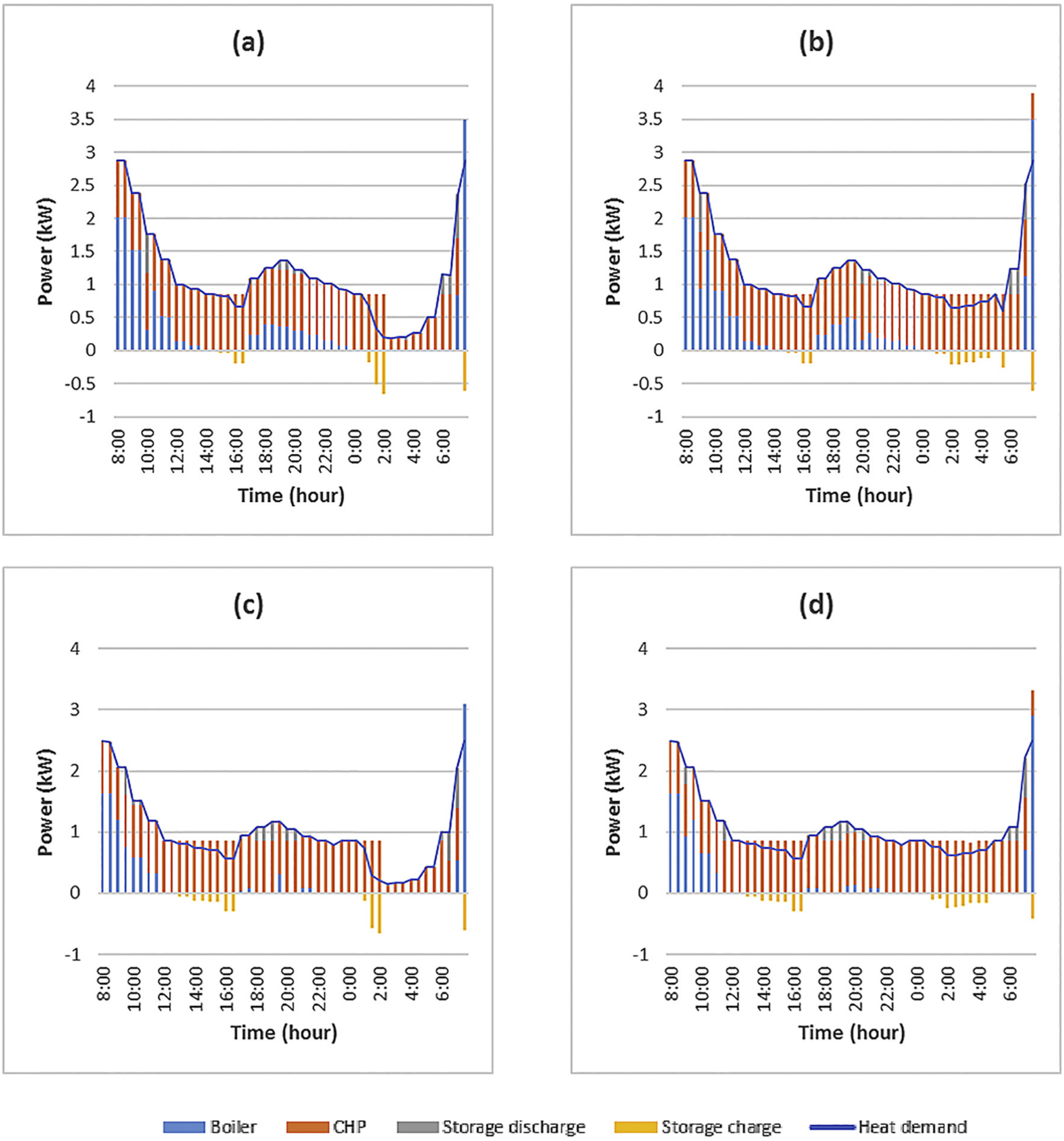

Fig. 10. "Micro" and "Peak demand charge" mode thermal balance, scenarios (6) to (12): (a) PWmE (b) PWmO (C) PSmE (d) PSmO.

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

$$TP_t^{TCA} = TP_t^{CHP} + TP_t^{BOI} + TP_t^{DCH,TSS} - TP_t^{CH,TSS} \tag{65}$$

3.8. 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 do 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 as well as peak demand from main grid subject to aforementioned constraints. The objective function can be expressed as:

$$\Phi = \sum_{t \in T} \Big[\Big(P_t^E \big(EP_t^{BY,GRD} - EP_t^{SL,GRD} \big) + P^{NG} \cdot V_t^{NG,CHP} + m^{CHP} EP_t^{CHP} + m^{WT} EP_t^{WT} + m^{PV} EP_t^{PV} + m^{ESS} EP_t^{DCH} + m^{B} TP_t^{B} + m^{TSS} TP_t^{DCH} + \psi \cdot P_t^{Pdc} \cdot \zeta_t \Big] \delta \tag{66}$$

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

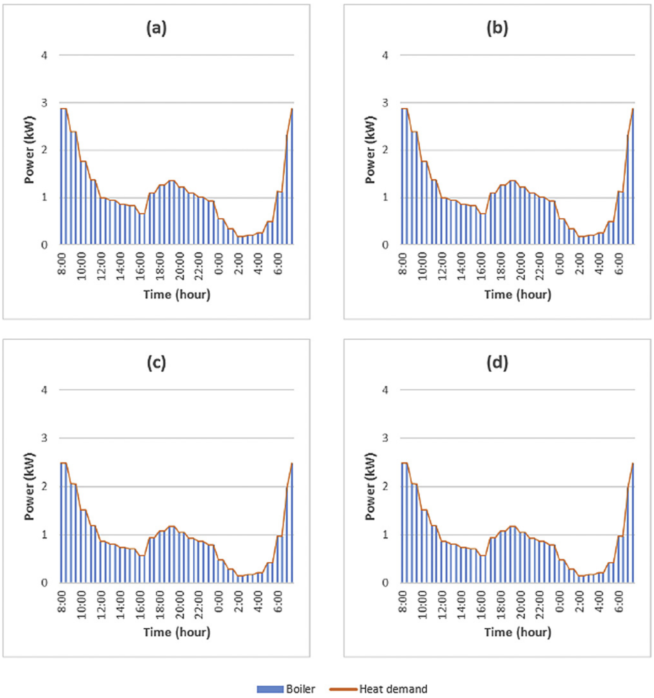

Fig. 11. "Macro" and "Peak demand charge" mode thermal balance, scenarios (13) to (16): (a) PWME (b) PWMO (C) PSME (d) PSMO.

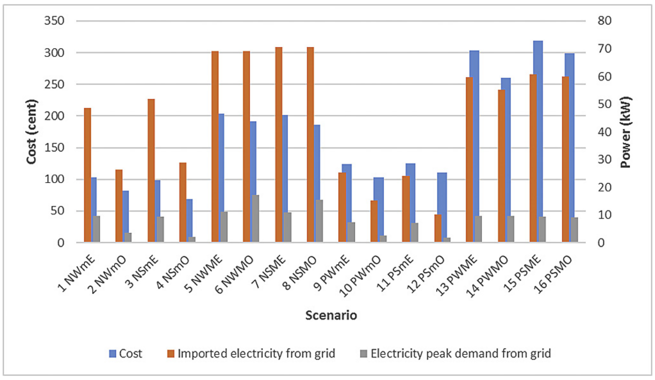

Fig. 12. Cost, Imported electricity from grid, peak demand from grid comparison of 16 scenarios.

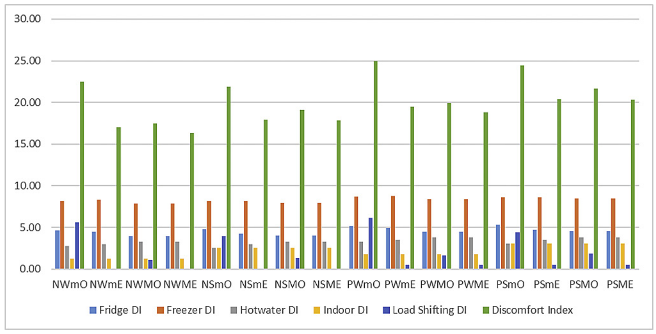

Fig. 13. Discomfort index comparison of different scenarios.

with purchased natural gas and electricity in addition to the revenue from selling electricity back to the grid.

Where m^{CHP}, m^{PV} and m^{ESS} are maintenance cost of CHP, PV and ESS per kW, respectively; P_t^E is the real time electricity price and P^{NG} shows natural gas price. the P_t^{Pdc} is the difference between peak and base electricity demand price from grid and ζ_t is the over threshold value.

There are two schemes "N" and "P", indicating "Normal price" and "Peak demand charge". The "Normal Price" scheme aims to minimize total cost while "Peak demand charge" scheme tries to minimize both total cost and peak demand from the grid. In "N" schemes $\psi = 0$ while in "P" schemes $\psi = 1$.

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 several profiles such as sun irradiation, wind speed, outdoor temperature and illumination in summer and winter used in this work are taken from Ref. [29]. The real time electricity prices are taken from Ref. [30] and have been shown in Fig. 3. It is assumed that the TCAs' state are On in the first time interval.

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 in each scheme, which are *WmO, WME, SmO,* and *SME*. "$\underline{W}$" represents

Table 3
Cost, imported electricity and peak demand comparison of all scenarios for a day.

Scenario	Cost (cent)	Imported electricity from grid (kW)	Electricity peak demand from grid (kW)
1 NWmE	102.61	48.58	9.61
2 NWmO	82.05	26.35	3.47
3 NSmE	98.26	51.96	9.35
4 NSmO	69.18	28.87	2.16
5 NWME	204.12	69.18	11.10
6 NWMO	191.06	69.18	17.20
7 NSME	201.75	70.68	11.00
8 NSMO	185.58	70.68	15.50
9 PWmE	123.79	25.22	7.46
10 PWmO	102.61	15.17	2.64
11 PSmE	125.71	24.12	7.05
12 PSmO	110.44	10.10	1.67
13 PWME	303.87	59.78	9.70
14 PWMO	259.96	55.29	9.64
15 PSME	318.76	60.68	9.40
16 PSMO	298.64	59.91	9.11

"*winter*" while "*S*" shows "*summer*"; "*m*" is "*microgrid*" indicating that the house is equipped with microgrid including DERs and storage systems in addition to upstream grid and boiler, whereas "*M*" for "*macrogrid*" showing that the electrical and thermal demand of the house is provided solely by the upstream 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. As mentioned before "*N*" and "*P*", indicating "*Normal price*" and "*Peak demand charge*" schemes, therefore there are 16 scenarios which are (1) *NWmE,* Normal price, Winter, microgrid, Earliest starting time (2) *NWmO,* Normal price, Winter, microgrid, Optimized scheduling (3) *NSmE,* Normal price, Summer, microgrid, Earliest starting time (4) *NSmO,* Normal price, Summer, microgrid, Optimized scheduling (5) *NWME,* Normal price, Winter, macrogrid, Earliest starting time (6) *NWMO,* Normal price, Winter, macrogrid, Optimized scheduling (7) *NSME,* Normal price, Summer, macrogrid, Earliest starting time (8) *NSMO,* Normal price, Summer, macrogrid, Optimized scheduling (9) *PWmE,* Peak demand charge, Winter, microgrid, Earliest starting time (10) *PWmO,* Peak demand charge, Winter, microgrid, Optimized scheduling (11) *PSmE,* Peak demand charge, Summer, microgrid, Earliest starting time (12) *PSmO,* Peak demand charge, Summer, microgrid, Optimized scheduling (13) *PWME,* Peak demand charge, Winter, macrogrid, Earliest starting time (14) *PWMO,* Peak demand charge, Winter, macrogrid, Optimized scheduling (15) *PSME,* Peak demand charge, Summer, macrogrid, Earliest starting time (16)*PSMO,* Peak demand charge, Summer, macrogrid, Optimized scheduling.

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. All of these temperatures are shown in 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 are shown in Figs. 4–7. According to ECAs' time window from EST to LFT and their starting probability function, the MC tries to minimize the cost by scheduling the ECAs within their time windows considering their starting probability functions together with the RTP so as to avoid peak hours and reduce the cost. During price peak hours, instead of buying energy from the grid, the house uses all other energy supplying resources and it sells electricity back to the grid which is illustrated in Figs. 4–7. 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.

Figs. 8–11 illustrate the thermal balance of the proposed system in different scenarios. In Figs. 8 and 10 there are a boiler, a CHP and a storage to provide the heat demand, but in Figs. 9 and 11 the boiler provides the heat demand solely.

As shown in Figs. 8(a) and (c) and 10(a) and (c) in "E" scenarios the heat demand profiles are similar. In Figs. 9 and 11 the demand profiles are just like each other for there is no CHP; so there is no correlation between heat and electricity. Hence, the TCA are scheduled individually regardless of ECA and OCA. In Figs. 8 and 10, due to CHP there is a correlation between heat and electricity, therefore the ECA scheduling can affect the TCA scheduling. Subsequently the heat demand profiles in Fig. 6 are different from each other.

The comparison of cost, imported electricity and peak demand from the grid are demonstrated in Fig. 12 as well as Table 3. 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 which stands for DERs presence, 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 ECA scheduling. As a result, the 'ME' scenarios are the most expensive schedules, since they have neither ECA scheduling nor DERs. The overall cost in "P" schemes are more than "N" schemes due to peak demand charge, on the other hand the imported electricity from the grid has been reduced.

As shown in Fig. 13, the "O" scenarios have higher discomfort index (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 difference. The fridge DI in "mO" scenarios are more than "mE" and then "MO" and "ME", in other words in "mO" scenarios fridge temperature is more than "mE" and then "MO" and "ME". Therefore, the more DI will result in fewer costs.

5. Conclusion

In this paper, an energy management model for a home including micro generations and energy storage system has been presented. 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 ECA, TCA 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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