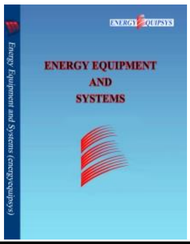
Energy Equip. Sys./ Vol. 12/No. 1/March 2024/ 63-77

Energy Equipment and Systems

http://energyequipsys.ut.ac.ir
www.energyequipsys.com



Home energy management system with Plug-in hybrid electric vehicles, energy storage system, and photovoltaic system commitment by considering different incentive and price-based demand response programs in smart grids

Authors

Sajjad Vakili[a]
Alireza Naminezhad[b]
Mahmood Mehregan[b*]
Sajjad Malboosi[b]

[a] Faculty of Mechanics, Electrical Power and Computer, Science and Research Branch, Islamic Azad University, Tehran, Iran

[b] Faculty of Mechanical Engineering, Shahrood University of Technology, Shahrood, Iran

Article history:
Received : 21 March 2023
Accepted : 9 November 2023

ABSTRACT

Intelligence and Smart power grids with the Demand Side Management (DSM) strategies enable Demand Response Strategies (DRS) that are especially used in residential districts. Plug-in hybrid electric vehicles (PHEVs), as another sort of load in the power system, have recently become increasingly popular as they provide an opportunity for customer benefits to reduce greenhouse gas emissions. Based on the level of introduction of PHEVs in the parking lot, charging behaviors in an area cause a change in the load profile of the power system. Therefore, it is necessary to examine the effect of the introduced level of PHEV on the load profile due to the expected charging behavior of residents. PHEVs also offer a variety of opportunities, including the ability to use EVs as storage units via vehicle-to-grid (V2G) options. In this paper, a joint evaluation of different DR techniques with a bilateral PHEV, energy storage system (ESS), and photovoltaic (PV) system is realized. Mixed integer Linear Programming (MILP) for a Home Energy Management (HEM) framework is proposed in this paper. A small-scale on-grid solar energy with a storage system and the V2G potential with different DR programs are all integrated into a single HEM system to select the most efficient and economical DR program.

Keywords: Smart Grid; Home Energy Management System; Electric Vehicle; Demand Response

Introduction and literature review

The need for sustainable advanced development that depends on more energy consumption on the one hand and achieving the goals of reducing energy intensity, on the other hand, requires methods of optimizing energy demand and consumption according to the needs of different energy sectors, such as buildings (C.W.Gellings, 2009). Energy, and in particular electricity, is one of the most important factors affecting the economic growth of any country. Traditionally, providing sufficient and safe energy to cope with the required demand requires expanding the production capacity and transmission of the

* Corresponding author: Mahmood Mehregan
Faculty of Mechanical Engineering, Shahrood University of Technology, Shahrood, Iran
E-mail address: mehregan@shahroodut.ac.ir

power system (T. Perumal et al., 2008). The smart grid provides insights to improve the efficiency and utilization of electricity from power plants to the end-user clients, alongside successfully adjusting generation, and storage capacity and empowering client's investment on the demand side market. With the developing significance of smart grid insights, smart homes that can check electricity usage in actual time and reduce the cost of electricity bills have also acquired special emphasis in research into possible demand-side measures. Smart grids are intended to help the high entrance of distributed demand-side resources along with an extensive demand-response system by stimulating economic signals and reliability. Furthermore, companies seek demand-side management and demand-side services for better network management (S.Borlease, 2013). Demand response programs oblige customers to diminish loads during periods of critical power system conditions (periods with high energy costs). With this significant energy consumption and increasing growth of industrial loads power plants lead to enhancing their electrical generation and hence, upgrading power transmission and distribution networks to deal with (P.Palensky and D. Dietrich, 2011). There are numerous advancements for DR exercises in residential areas. In particular, HEM and smart measurements play a vital role in the effective implementation of DR strategies. With various sorts of electrical loads, the household load curves have changed fundamentally. As another kind of end-user electric vehicle, EVs have become progressively important because the charge of the transportation area which is the biggest purchaser of petroleum derivatives, is a subject of current concern. EVs have a different construction with opportunities and challenges that should be investigated exhaustively. The energy required by EVs approaches the level expecting new power plant facilities. In addition, EVs can be utilized as an asset, particularly during peak times with V2H and V2G options. Today, one of the main purposes of implementing an intelligent network is to provide an energy management system by considering the optimal performance of each of the production sources in it and with the aim of better management of load demand under different conditions. DR is a mechanism in which consumers voluntarily participate to reduce peak consumption by modifying the consumption pattern of some of their equipment. Price tariffs have also been effective in residential electricity bills; showing a significant reduction in average monthly costs or using alternatives such as DG and RES to offset the electricity price in the day-ahead market (R.P.Odeh and D.Watts, 2019) and (H. Dorotic, 2020).

Introduction of HEMS

HEMS is significant due to concerns about global warming and energy shortages. This system assists in decreasing the electricity demand, especially at peak loads (H. Saele and O. S.Grande, 2011). HEMS is not only considered a way to diminish greenhouse gas emissions but also enables automatic power management in a home (K.J. Chua et al. 2013). Various efforts, including the control of diverse apparatus such as controllable and smart appliances (R.Missaou et al., 2014), heat water-smart thermostats (Duman AC et al., 2020), PHEV (G. Li and X.P.Zhang, 2012) with V2G and V2H charging and discharging scenarios (D.Steen et al., 2012), have been made to create a HEMS system. The system can also optimize the application of home instruments and simultaneously manage distributed small-scale own-generation and storage units (O.Erdinc, 2014). The theoretical literature of home energy control and management can be considered from 1979 when the operation of energy system management was based on microprocessors for the first time. Its performance improved especially with the development of the personal computer in the 1980s. In 1982, an improved algorithm and model for home energy management emerged to reduce costs by lowering demand and consumption time. The model includes solar energy, energy storage system (ESS) or batteries, plug-in electric vehicle (PEV), and domestic apparatuses (Xuan Hou et al., 2019).

Introducing DR (Demand Response)

Demand response techniques are presented by some power grid administrators as a source to lessen power demand throughout specific time spans to adjust supply and demand. Demand response is considered a category of demand-side management programs in which programs motivate end-clients to curtail their electricity consumption during peak periods (Z. Chen et al., 2012). Based on time-sensitive power rates such as time of use (TOU) (Sattarpour et al., 2018), incentive-based rates (IBR) (Sharifi et al., 2019), critical peak pricing (CPP) (Tom et al., 2020), and real-time pricing (RTP) (Javaid et al., 2017) in a way of penalty-reward (Paterakis, Erdinç, & Catalão, 2017), demand response (X. Li and S. Hong, 2014) is defined as an adjustment in the electrical consumption of end-users normal consumption pattern in response to a change in electricity prices (J.Zhao et al., 2013), therefore a reasonable option to facilitate the connection of technology in distribution networks and smart private local area (S. Nan et al., 2018). To accomplish these expected advantages of demand-side programs (M. H. Imani et al., 2018), a specific degree of automation is needed to both decrease consumer uncertainty in responding to price signals and show the intricacy of purchasers' response to daily electricity price fluctuations. This is called automatic demand response (ADR) (M. Pipattanasomporn et al., 2012) which is applied in South Africa (C. G. Monyei and A. O. Adequmi, 2011). limiting hourly demand or top-to-average ratios, for example, (S. Shao et al.,2011) may reduce peak demand, but this is probably not necessarily beneath the specific power threshold (X. Chen et al., 2013). Portable accessories can provide more flexibility to manage demands, like electric water heaters, which comprise 30% to 50% of household electricity consumption (Eskom and IDM, 2019) under the required power threshold. Although direct load control (DLC) models are numerous to performed during high electricity cost periods (M.Afzalan et al., 2019) and economic dispatch under renewable energy obligation to minimize generation cost and maximize renewable energy penetration, the main purpose of this article is to examine the home energy management system and use various demand response programs by considering the small-scale photovoltaic, ESS and PHEV economic home dispatch to minimize the household energy bills and increase network security by shifting loads to low-cost periods and also implementing limitation in household energy flow grid to home and vice versa.

Nomenclatures and acronyms

DR	Demand response
ESS	Energy storage system
EV	Electric vehicle
HEM	Home energy management
MILP	Mixed-integer linear programming
PV	Photovoltaic
V2G	Vehicle-to-grid
V2H	Vehicle-to-home

Parameters

CEEV	Charging efficiency of the EV.
CRESS	Charging rate of the ESS [kW per time interval].
CREV	Charging rate of the EV [kW per time interval].
DEESS	Discharging efficiency of the ESS.
DEEV	Discharging efficiency of the EV.
DRESS	Discharging rate of the ESS [kW per time interval].
DREV	Discharging rate of the EV [kW per time interval].
N1	Maximum power that can be drawn from the grid [kW].
N2	Maximum power that can be sold back to the grid [kW].
P	Household power demand [kW].
$PPV_{,pro}$	Power produced by the PV [kW].
$SOEESS_{,ini}$	Initial state-of-energy of the ESS [kWh].
$SOEESS_{,max}$	Maximum allowed state-of-energy of the ESS [kWh].
$SOEESS_{,min}$	Minimum allowed state-of-energy of the ESS [kWh].
$SOEEV_{,ini}$	Initial state-of-energy of the EV [kWh].
$SOEEV_{,max}$	Maximum allowed state-of-energy of the EV [kWh].
$SOEEV_{,min}$	Minimum allowed state-of-energy of the EV [kWh].
Λbuy	Price of energy bought from the grid [cents/kWh].
Λsell	Price of energy sold back to the grid [cents/kWh].

Variables

PESS,ch	ESS charging power [kW].
PESS,$_{dis}$	ESS discharging power [kW].
PESS,$_{sold}$	Power injected to grid from the ESS [kW].
PESS,$_{used}$	Power used to satisfy household load from the ESS [kW].
PPV, $_{sold}$	Power injected to grid from the PV [kW].
PPV, $_{used}$	Power used to satisfy household load from the PV [kW].
PEV, $_{sold}$	Power injected to grid from the EV [kW].
PEV, $_{used}$	Power used to satisfy household load from the EV [kW].
P_{grid}	Power supplied by the grid [kW].
Psold $_{Total}$	power injected to the grid [kW].
T	Period of the day index in time units [h or min].
SOEEV	State-of-energy of the EV [kWh].
SOEESS	State-of-energy of the ESS [kWh].
Ugrid Binary variable	1 if grid is supplying power
d_0 (i)	Initial load (consumption before running the program)
d_ (i)	moment load (consumption after program execution)
B_0 (i)	The amount of revenue from electricity consumption equal to d_0
B (d_ (i))	The amount of revenue from the use of electricity in the production of goods
ρ_0 (i)	Electricity price before load reduction
ρ_ ((i))	electricity price after load reduction
E (i)	The internal elasticity of the load
A (i)	The amount of the incentive bonus in period i

Highlights

The main novelties and research highlights have been presented in the following:

1. Dynamic pricing according to diverse DR strategies is considered.
2. The proposed method consists of modern control that would enable user-side load control.
3. A model to study coordinated control of building end-use loads with a small-scale solar power energy system, V2G capacity EV with two-way energy trading, ESS, and the use of MILP optimization is presented.
4. The effect of financial incentives or penalty factors on encouraging consumers to shift their demands to off-peak hours is evaluated.

Mathematical problem modeling:

Price elasticity and client reaction

At the beginning of the restructuring of traditional power systems, subscribers were usually not active in the market because consumers did not benefit from it. The main decision-makers are as follows: independent power generators, regional transmission companies, independent system operators, and power industry regulators. They had the necessary skills and data to take part in the electricity markets. In the market, the absence of subscribers and their insensitivity to the price of electricity at peak conditions has led to widespread blackouts. Therefore, demand response programs were designed to increase subscribers' sensitivity to electricity market price changes (D.S. Kirschen, 2003) which is defined in Eq.(1). Where d is the amount of energy and ρ is the cost of energy. The sensitivity of power consumption to the price signal is called elasticity or E and is defined as

$$E = \frac{\rho_0}{d_0}\frac{\partial d}{\partial \rho} \quad (1)$$

The mathematical expression of self and cross-elasticity is given by

$$E(i,j) = \frac{\rho_{0(j)}}{d_0(i)}\frac{\partial d(i)}{\partial \rho(j)} \quad (2)$$

Single period model

In the single period model, the customer profit function will be as Eq.(3) where $d_0(i)$ is Initial load (consumption before running the program),

$d\,(i)$: current load (consumption after program execution),

$B_0(i)$: The amount of revenue from electricity consumption equal to $d_0(i)$,

$B\big(d\,(i)\big)$: The amount of revenue from the use of electricity in the production of goods,

$\rho_{0(i)}$: Electricity price before load reduction, $\rho_{\,(i)}$: electricity price after load reduction,

$E(i)$: The internal elasticity of the load,

$d\ (i).\rho_{\ (i)}$: Customer cost,

$d_0(i) - d\ (i)$: Load changes before and after program execution,

$A(i)$:The amount of the incentive bonus in period i, and

$A(i).(d_0(i) - d\ (i))$ defined as program incentive prize:

$$S = B\left(d\ (i)\right) - d\ (i).\rho_{(i)} + p\left(\Delta d\ (i)\right) \tag{3}$$

In optimal conditions, the amount of consumption in order to achieve the maximum profit by equating the derivative of the amount of profit to consumption to zero is given by

$$\frac{\partial S}{\partial d\ (i)} = \frac{\partial B\left(d\ (i)\right)}{\partial d\ (i)} - \rho_{(i)} + \frac{\partial P}{\partial d\ (i)} = 0 \tag{4}$$

$$\frac{\partial B\left(d\ (i)\right)}{\partial d\ (i)} = \rho_{(i)} + A(i) \tag{5}$$

The customer profit function is usually presented with a quadratic function of power consumption, which is calculated using

$$B\left(d\ (i)\right) = B_0\ (i) + \rho_{0(i)}.\left[d_0\ (i) - d\ (i)\right]. \left[1 + \frac{d_0\ (i) - d\ (i)}{2E\ (i).\ d_0\ (i)}\right] \tag{6}$$

Derived from Eq. (6), one would have

$$\frac{\partial B\left(d\ (i)\right)}{\partial d\ (i)} = \rho_{0(i)}\ .\left[1 + \frac{d_0\ (i) - d\ (i)}{E\ (i).d_0\ (i)}\right] \tag{7}$$

Placing Eq. (5) into Eq. (7) results

$$\rho_{(i)} + A(i) = \rho_{0(i)}\ .\left[1 + \frac{d_0\ (i) - d\ (i)}{E\ (i).d_0\ (i)}\right] \tag{8}$$

$$\rho_{(i)} - \rho_{0(i)} + A(i) = \rho_{0(i)}\ .\left[\frac{d_0\ (i) - d\ (i)}{E\ (i).d_0\ (i)}\right] \tag{9}$$

Finally, according to the price of usage time and incentive bonus in the emergency load program, the consumer consumes to the extent that his profit is maximized. Using Eq. (9), the single-period load model is obtained as

$$d\ (i) = d_0\ (i).\left[1 + \frac{E\ (i).\left[\rho_{(i)} - \rho_{0(i)} + A(i)\right]}{\rho_{0(i)}}\right] \tag{10}$$

In Eq. (10), if A (i) = 0 means that there is no incentive or, the sensitivity of the demand to the load is equal to zero.

Multi-period model

The cross-elasticity defined by Eq. (2) states that the amount of load in period i depends on the price value in each of the other periods, so it must be calculated for a fixed period sensitive to all periods. Finally, the customer consumption function according to the price in different periods and incentive rewards are given by

$$d\ (i) = d_0\ (i) + \sum_{\substack{j=1 \\ j\neq i}}^{24} E\ (i.j)\frac{d_0\ (i)}{\rho_{0(j)}}\left[\rho_{(j)} - \rho_{0(j)} + A(j)\right] \tag{11}$$

Complete load response model

If Eq. (11), which is a function of customer consumption with respect to the elasticity of the load, is placed in Eq. (10), the amount of consumption in which the common profit is maximized is obtained using

$$d\ (i) = d_0\ (i)\left[\begin{array}{l} 1 + \dfrac{E(i,i)\left[\rho_{(i)} - \rho_{0(i)} + A(i)\right]}{\rho_{0(i)}} + \\ \displaystyle\sum_{\substack{j=1 \\ j\neq i}}^{24} E\ (i.j)\frac{1}{\rho_{0(j)}}\left[\rho_{(j)} - \rho_{0(j)} + A(j)\right] \end{array}\right] \tag{12}$$

$$d\ (i) = d_0\ (i)\left[\begin{array}{l} 1 + \dfrac{E(i,i)\left[\rho_{(i)} - \rho_{0(i)} + A(i) + pen(i)\right]}{\rho_{0(i)}} + \\ \displaystyle\sum_{\substack{j=1 \\ j\neq i}}^{24} E\ (i.j)\frac{1}{\rho_{0(j)}}\left[\rho_{(j)} - \rho_{0(j)} + A(j) + pen(j)\right] \end{array}\right] \tag{13}$$

According to Eq. (12), it is observed that the optimal consumption of the customer depends on the amount of encouragement and energy price in each period, and if the penalty for the subscribers is considered, it becomes Eq. (13).

Objective function

The minimization of the total cost of power utilization in Eq. (14) is the goal. The expense varies between the grid and energy offered to the grid by EV, ESS, and PV. Thus,

$$TC = \sum\nolimits_{t=1}^{24}\ (P_{grid}(t).\lambda_{buy}(t) - P_{sold}(t).\lambda_{sell}(t)) \tag{14}$$

A. Power balance

The load, consisting those of the house, required charge for EV and ESS supplied by the grid is expressed as

$$P_{grid}(t)+P_{pv,used}(t)+P_{EV,used}(t)+P_{ESS,used}(t)= d(t)+P_{EV,ch}(t)+P_{ESS,ch}(t) \quad (15)$$

B. ESS modeling

Equation (16) states that the power given by the ESS can be utilized to cover part of the building needs or re-injected into the grid. Conditions (17) and (18) impose a breaking point on the ESS charge and discharge capacity. This state of suspended ESS can be depicted by any of these conditions in time. The relevant power variable can have a value of zero. Equations (19) to (22) portray the state-energy of ESS. Condition (19) Mode-powers the energy in every stretch to have a worth in the past span in addition to the real measure of energy moved to the battery. At the start of time interval, the ESS energy mode overlaps with the ESS energy mode described by (20). Condition (21) restricts the battery power mode to not exactly the ESS limit. Similarly, (22) prevents deep battery discharge by applying a minimum state-energy limit.

$$\mathrm{P_{ESS,used}}(t)+\mathrm{P_{ESS,sold}}(t)=\mathrm{P_{ESS,dis}}(t).\mathrm{DE_{ESS}},\forall t \quad (16)$$

$$\mathrm{P_{ESS,\,ch}}(t)\le \mathrm{CR_{ESS}}.\mathrm{U_{ESS}}(t),\forall t \quad (17)$$

$$\mathrm{P_{ESS,\,dis}}(t)\le \mathrm{DR_{ESS}}.(1\text{-}\mathrm{U_{ESS}}(t)),\forall t \quad (18)$$

$$\mathrm{SOE_{ESS}}(t)=\mathrm{SOE_{ESS}}(t-1)+\left(\mathrm{CE_{ESS}}.\frac{\mathrm{P_{ESS,ch}}}{\Delta t}(t)\right)-\frac{\mathrm{P}_{\mathrm{ESS},dis}}{\Delta t}(t),\forall t\ge 1 \quad (19)$$

$$\mathrm{SOE_{ESS}}(t)=\mathrm{SOE_{ESS,ini}}, if t=1 \quad (20)$$

$$\mathrm{SOE_{ESS}}(t)\le \mathrm{SOE_{ESS,max}},\forall t \quad (21)$$

$$\mathrm{SOE_{ESS}}(t)\ge \mathrm{SOE_{ESS,min}},\forall t \quad (22)$$

C. EV modeling

Equation (23) applies the way that the genuine power given by the EV can be utilized to cover some portion of the family needs or re-infused into the grid.

$$\mathrm{P_{EV,used}}(t)+\mathrm{P_{EV,sold}}(t)=\mathrm{P_{EV,dis}}(t).\mathrm{DE_{EV}},\forall t\in\left[T^a,T^b\right] \quad (23)$$

$$\mathrm{P_{EV,\,ch}}(t)\le \mathrm{CR_{EV}}.\mathrm{U_{EV}}(t),\forall t\in\left[T^a,T^b\right] \quad (24)$$

$$\mathrm{P_{EV,\,dis}}(t)\le \mathrm{DR_{EV}}.(1\text{-}\mathrm{U_{EV}}(t)),\forall t\in\left[T^a,T^b\right] \quad (25)$$

$$\mathrm{SOE_{EV}}(t)=\mathrm{SOE_{EV}}(t-1)+\left(\mathrm{CE_{EV}}.\frac{\mathrm{P_{EV,ch}}}{\Delta t}(t)\right)-\frac{\mathrm{P}_{\mathrm{EV},dis}}{\Delta t}(t),\forall t\in\left[T^a,T^b\right] \quad (26)$$

$$\mathrm{SOE_{EV}}(t)=\mathrm{SOE_{EV,ini}}, if t=T^a \quad (27)$$

$$\mathrm{SOE_{EV}}(t)\le \mathrm{SOE_{EV,max}},\forall t\in\left[T^a,T^b\right] \quad (28)$$

$$\mathrm{SOE_{EV}}(t)\ge \mathrm{SOE_{EV,min}},\forall t\in\left[T^a,T^b\right] \quad (29)$$

$$\mathrm{SOE_{EV}}(t)=\mathrm{SOE_{EV,max}},\forall t\ge T^{f,c}\in\left[T^a,T^d\right] \quad (30)$$

$$\mathrm{SOE_{EV}}(t)=\mathrm{SOE_{EV,min}}, if\ t=T^{f,d}\in\left[T^a,T^d\right] \quad (31)$$

$$\mathrm{P_{EV,ch}}(t)=\mathrm{SOE_{EV}}(t)=\mathrm{P_{EV,dis}}(t)=\mathrm{P_{EV,used}}(t)=\mathrm{P_{EV,sold}}(t)=0,\forall t\in\left[T^a,T^d\right] \quad (32)$$

Conditions (24) and (25) apply the charge and discharge power limits to the EV. The suspended EV can be expressed in time by each conditions, and the corresponding power variable can be zero. Condition (26) Mode - forces each interval to have a value between the previous game plus the real value of energy sent to the EV battery. If the EV battery is discharged during that interval; In a negative period of time the energy is charged. When EV enters the household, the EV state-energy overlaps with the initial EV state-energy, which is expressed by Eq. (27). Condition (28) Mode - Limits the EV battery energy to lowest value of its capacity. Similarly, (29) prevents EV battery deep discharge of the by applying a minimum energy state limit. Equations (30) and (31) show a full charged or discharged EV battery in the lowest energy-state in the pre-selected period, and finally (32) ensures that the EV modeling variables are contacted separately. The period of the time EV enters the household and the time EV leaves the household is zero.

D. PV modeling

$$\mathrm{P}_{\mathrm{PV,used}}(t)+\mathrm{P}_{\mathrm{PV,sold}}(t)=\mathrm{P}_{\mathrm{PV,pro}}(t),\forall t \quad (33)$$

According to Eq. (33), the power output by PV is utilized to cover part of a household's requirements or re-injected into the grid.

E- General power injected into the network

$$\mathrm{P}_{\mathrm{sold}}(t)=\mathrm{P}_{\mathrm{PV,sold}}(t)+\mathrm{P}_{\mathrm{ESS,sold}}(t)+\mathrm{P}_{\mathrm{EV,sold}}(t),\forall t \quad (34)$$

The total output power into the grid includes the amount of power supplied by PV, EV and ESS previously stated. This value is applied by Eq. (34).

F- Power Transaction Limitations

$$\mathrm{P}_{\mathrm{grid}}(t)\leq N1.\mathrm{U}_{\mathrm{grid}}(t),\forall t \quad (35)$$

$$\mathrm{P}_{\mathrm{sold}}(t)\leq N2.\left(1\text{-}\mathrm{U}_{\mathrm{grid}}(t)\right),\forall t \quad (36)$$

Equations (35) and (36) implement the power exchange logic. If it is necessary to draw power from the network, it will no longer be possible to inject power into the network. The inverse is presented by these conditions. N1 is a positive integer that limits the power from the grid. This limit represents the constraint imposed by the collector or the content of the user-end electrification question to deal with a situation in which several households in the control area own the HEM system. Implementing variable peak power with time stretched over the network limit as a different DR strategy can be easily applied to this formula by replacing N1 with a time dependent variable. Similarly, N2 applies power that can be re-injected into the network and can be used by a time-dependent variable.

Methodology

In this article, the optimization method with software used for optimization is mentioned. It should be noted that in this simulation GAMS software will be used for optimization. Simulations have been performed on nine case studies in this paper to evaluate and demonstrate the efficiency and deficiency of different scenarios.

The calculated load response of a common house in Iran is utilized. The house has an approximate area of 140 square meters with four inhabitants with different electrical appliances including refrigerators, televisions, microwaves, washing machines and dishwashers, computers, ovens and so on. The house has a gas water heater system. Daily consumption is recorded and the average power consumption profile obtained for this time interval is shown in Fig. 1 and also Table 1 shows the load elasticity which illustrates the load response to the price signal. In this article, it is considered that the house has a small-scale PV system of one kilowatt. The PV system production data listed is a normalized version of a daily solar power plant production profile.

Table 1. The self and cross elasticity

	Peak	Off-peak	Valley
peak	-0.10	0.016	0.012
Off-peak	0.016	-0.10	0.01
Valley	0.012	0.01	-0.10

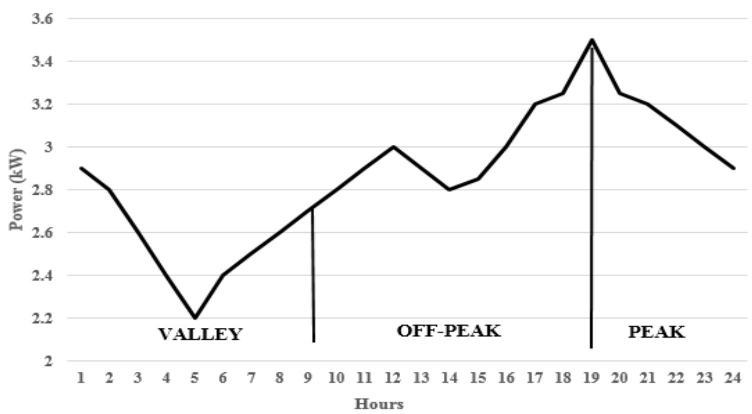


Fig.1. Iranian peak load curve on 28/08/2007 (Aalami and Yousefi, 2008).

Two-way EV operations include V2G (meaning energy is returned to the grid by EV) and V2H (i.e., part of the energy stored in the EV battery is utilized to support the part of the home load). The characteristics of the Chevy Volt car with a 16-kWh battery are considered. It is used with a limited charging station to charge 3.3 kW. It is assumed that the same power limit is valid for the discharge function of V2H and V2G modes. Discharging and charging efficiency is assumed to be 0.95 and the initial energy of the EV battery is equal to 8 kWh (50% energy state) when it reaches home and the lower limit of the EV energy state is 4.8 kWh (30% energy state) to avoid excessive discharge (Approximate value which states that no more than 70 to 80% of the battery capacity should be used). The above assumptions also apply to ESS, and ESS has a battery capacity of 1 kWh. It is assumed that the charge and discharge rate per hour is 0.2 kW. Its initial energy status is equal to 0.5 kWh, and its non-excessive discharge limit is equal to 0.25 kWh. It should be noted that in the intended sense, there is no cost based on storage devices such as EES and EV at HEM condition. For the pricing of energy purchased from the grid, a DR scheme based on different scenarios is considered and implemented according to Table 3 (Aalami, H.A. et al., 2010).

Results and analysis

As power markets are changed, consumers become presented with more unpredictable power costs. They might choose to change the demand profile of their demand to decrease the power prices. The customers in the DR programs can expect reserve funds in power bills assuming they lessen their power use in the peak periods. The DR programs have been executed with various objectives and priorities in the markets of power. This section has implemented different scenarios according to eight price and incentive-based demand response programs. In each scenario, there are four alternatives employed grid, Hybrid Electric vehicle, photovoltaic, and energy storage system. In each the amount of energy scheduled to supply the household energy and meet the consumer requirements by incorporating the two-way energy exchanges between the utility and end client and the utility, the method of net-metering is used. At the point when the accessible energy of the household sources can be sufficient to support the total needs, the abundance of energy can be sold to the grid. For valuing the purchased energy from the grid, a dynamic DR method can be used. The time-depend price signal is accessible to the consumer via intelligent metering. All householders play a vital role in providing energy by considering every single house as energy storage and decentralized them as a self-energy providing the power system to help the network in contingency conditions as in the EDRP and CAP market.

Table 2. Caption missing

Programs	Electricity price $/kwh	Incentive value $/kwh	Penalty value $/kwh
Base case	160	0	0
Time of use (TOU)	Valley = 40, Off-peak = 160, Peak = 400	0	0
Critical peak pricing (CPP)	800 @ 20, 21, 22 hours	0	0
Real time pricing (RTP)	40, 40, 40, 40, 20, 20, 20, 20, 160, 160, 160, 160,200, 200, 200, 200, 160, 160, 160, 500, 500,500, 160, 160 @ 1–24 hours	0	0
TOU&CPP	Valley = 40, Off-peak = 160, Peak = 400 and 800 at 20,21,22 hours	0	0
Direct load control	160 @ 1–24 hours	200	0
Emergency demand response program	160 @ 1–24 hours	400	0
Capacity	160 @ 1–24 hours	100	50
Interruptible &Curtailment	160 @ 1–24 hours	200	100

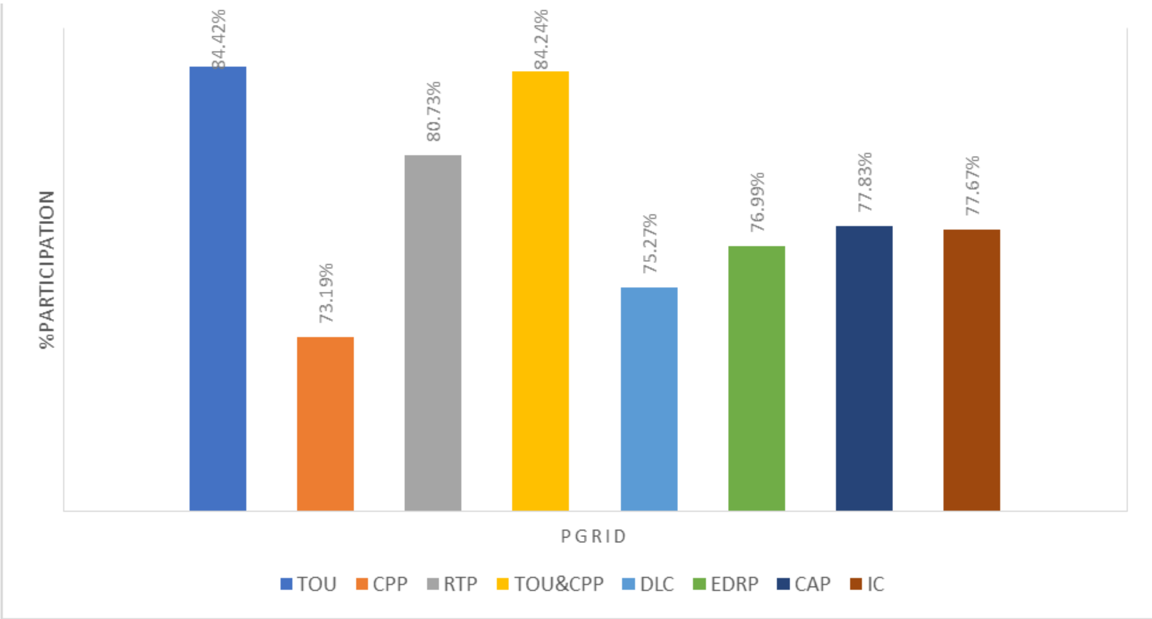


Fig.2. Grid energy usage (*TOU: Time of use, CPP: Critical peak pricing, RTP: Real time pricing, DLC: Direct load control, EDRP: Emergency demand response program, CAP: Capacity market, I/C: Interrupt /Curtailment)

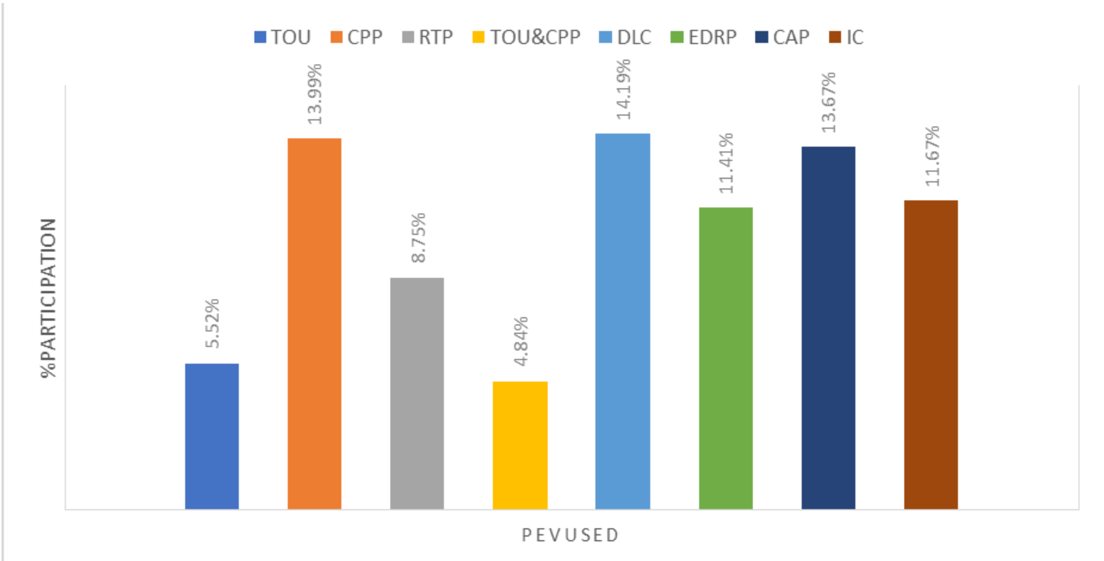


Fig.3. Hybrid Electric vehicle energy participation in difference DR programs (TOU: Time of use, CPP: Critical peak pricing, RTP: Real time pricing, DLC: Direct load control, EDRP: Emergency demand response program, CAP: Capacity market, I/C: Interrupt /Curtailment)

In Fig.2 the house power consumption provided through the power grid is shown. As can be seen in this figure, the eight incentive/price programs of demand response client reaction are compared. The highest share of purchases from the grid took place in the TOU program on the other side, the lowest share of purchases from the network was the CPP program. This shows the impact of the price signal on lessening the amount of energy utilization from the network during critical times of the system or peak periods. This is due to imposing 20 times the price during peak periods of 20, 21, and 22 hours.

Although the share of buying energy from the grid is high in the joint DR program of TOU and CPP as can be seen in Fig.8, the cost in this program is at its lowest for the consumer, which is due to the other sources of energy supplying the house. A quick look at Fig.3, Fig.4, and

Fig.5, depicts the hybrid car, photovoltaic system, and storage, which have undertaken the commitment of providing energy, respectively. Electric car plays the most important role in the DLC program and has a minimum commitment of 4.84 in TOU&CPP. This is due to the difference in the price.

The photovoltaic system due to its sensitivity to sunlight and its dependence of it on the amount of radiation can only be produced and used during sunny hours. According to the solar power plant provision trend during the daytime considered as the optimization input source, it can be seen that in three programs RTP, DLC and IC programs have the lowest amount of home energy supply, which is the reason for the reasonable price. The amount of energy is beneficial enough for selling to the grid, this means that for the maximum benefit of the consumer, the consumer in the optimization program according to the price of energy and through the photovoltaic system production prefers to provide approximately 8 percent, and other alternatives are used to supply the house. On the contrary, it shows its largest share in CPP, EDRP, and TOU&CPP programs due to the higher prices in these plans. 10 percent of the lack of purchasing energy from the network is provided in this way.

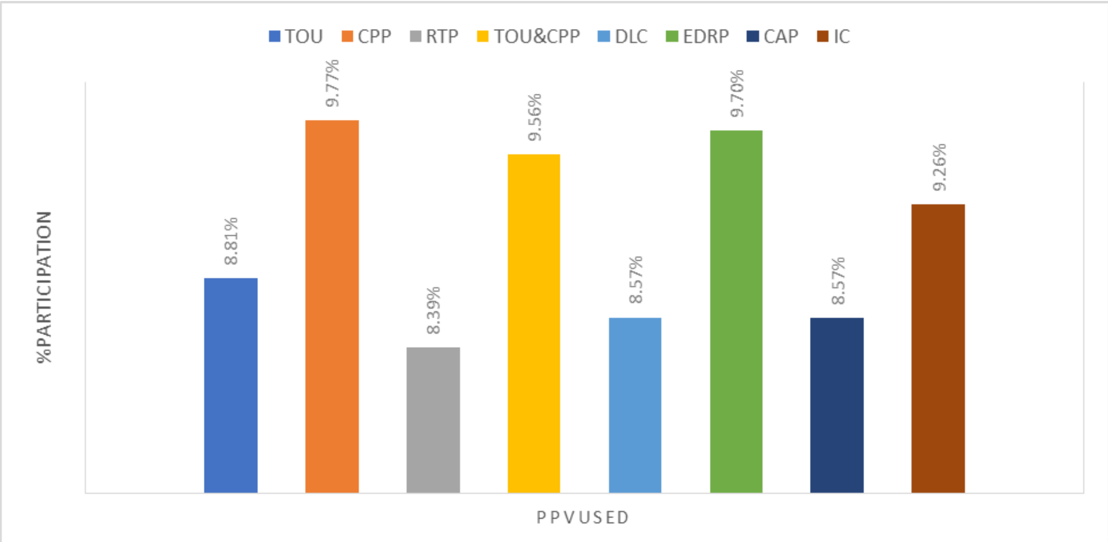


Fig.4. photovoltaic energy participation in difference DR programs

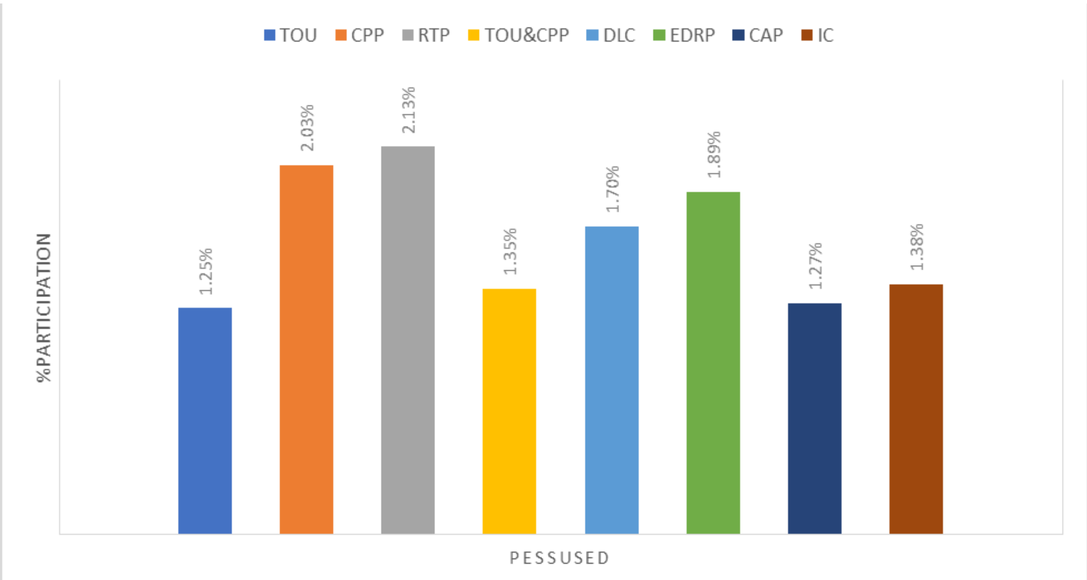


Fig.5. ESS (energy storage system) energy participation in difference DR programs

Finally, the storage system, whose share in each program is shown in Fig. 5, plays an important role in supplying the house. When the photovoltaic system shows the lowest level of participation in the programs, the storage device makes the most of it by using its stored energy during the day. Charging when the grid energy price is at its lowest state, and at times when the price of energy is at its highest, it discharges its energy and sells its surplus to the grid to increase the consumer's profit and reduce the energy consumption from the grid simultaneously.

Figures 6 and 7 will be examined in the following, which compare load response programs that are divided into two subcategories based on price and incentive plans-price-based programs are applied to the consumer with regard to price signals through the electricity market. An attempt is made to control the amount of electric energy consumption in the hours when the network has the highest load by increasing the price. In Fig. 6, the comparison of different types of price-based load feedback programs were compared according to the amount of base load. Figure one shows the Iranian peak load curve on 28/08/2007 and Fig. 6 and Fig.7 are the same load curve named BASE LOAD which starts from 7 am. It shows that the maximum network load occurs between 8 and noon. These programs are activated and according to the price offered in different programs, they reduce the amount of consumption. The amount of profit for the customer is maximized during the hours of 1 to 10 in the morning, low load mode. It is the system that is preferred in this program that the consumption will be transferred to these hours and the storage system and electric car charging will be done during these hours.

In incentive-based load response programs, a fee for encouraging the consumer to participate in these programs is considered, which, if the consumer helps the grid at the required times, is equal to the amount injected kilowatt-hours. Incentives will be given to the network if the consumer participates in programs such as cap, according to the nature of this program and the responsibility of supplying the network load, according to the announcement of the amount of assistance or reduction of consumption at the times announced by the network operator. Consumption should be reduced to the same amount as announced so that the consumer is not subject to a fine. One of the features of this program is the consideration of fines during peak hours. It is considered in Fig. 7, that in the conditions of the emergency of the network, due to the high incentive rate in the EDRP program, the amount of consumption has decreased drastically and is even close to zero until the stability of the network. be maintained in these programs due to the same price rates It can be seen in different hours with the mode without applying for load response programs that in other hours there are drastic changes in the amount of text consumption, only in the peak hours, the changes in consumption are observed.

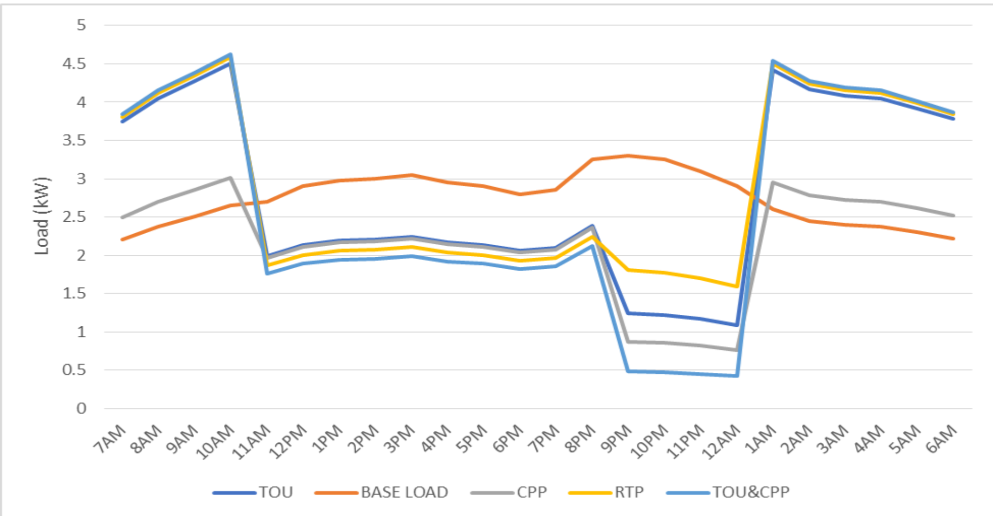


Fig.6. Load curve at price-based DR programs

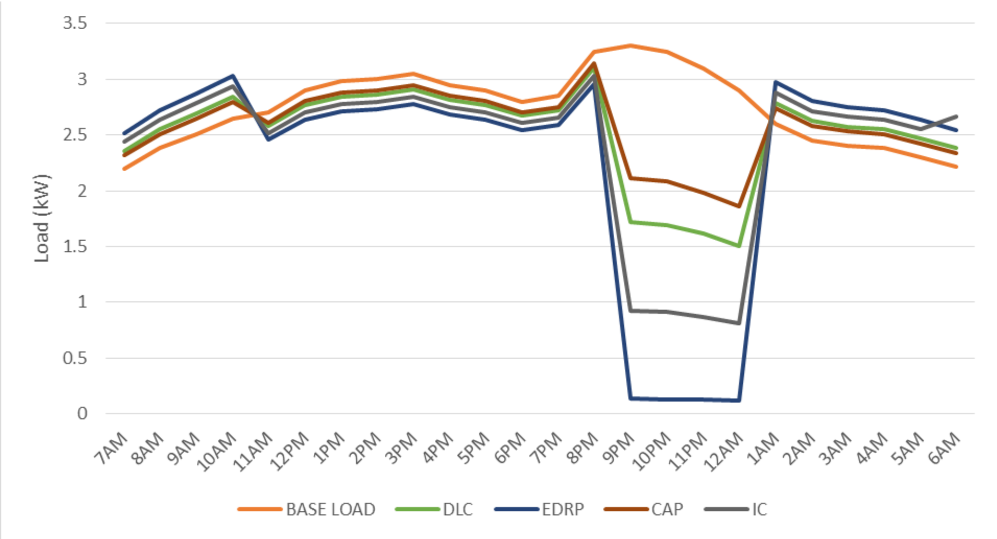


Fig.7. Load curve at incentive-based DR programs

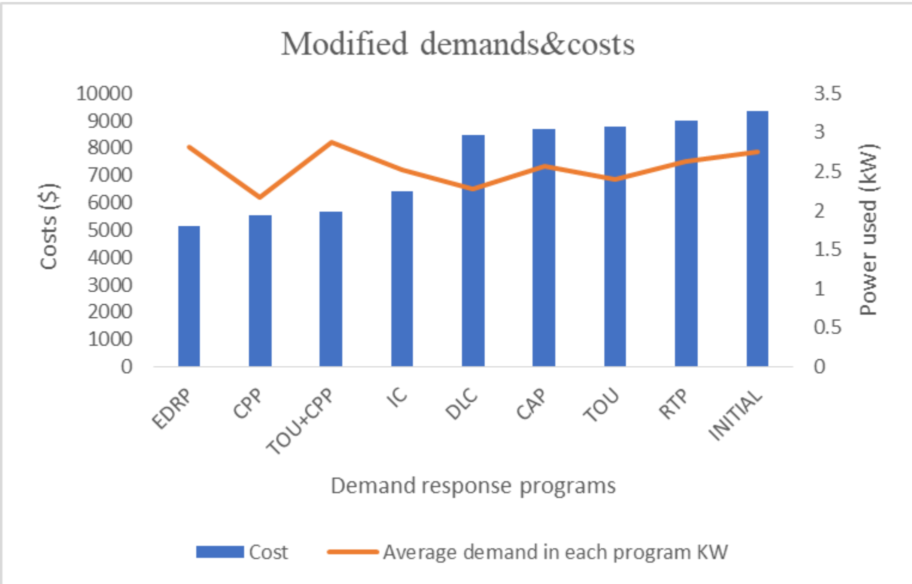


Fig. 8. Household energy consumption cost in different scenarios

The comparison of different demand response programs in a similar consumption condition according to Fig. 8 illustrates the largest consumer benefit due to reducing the energy in the EDRP program. Basically, programs based on encouragement have the greatest effect on consumer willingness. However, in price-based programs, almost 60% has been added to consumer costs in all programs. This is due to price policies at different times. Overall, among these programs, in price-based, the TOU&CPP, and in incentive-based programs, the EDRP in emergencies can be mentioned. In these two programs according to the lowest amount of cost, the largest energy has been received from the grid in a total of 24 hours, which not only shows customer satisfaction and well-being but also assists the stability of the power network.

Conclusion

The principal role of this paper centers on intelligent management performance. The utilizing dynamic pricing, diverse DR strategies, power restriction, a small-scale solar power energy system, V2G capacity, and the ability of an EV with two-way energy trading, ESS, and using MILP optimization method, make the HEM structure. Bi-directional energy exchange from the grid to the home and vice versa is possible through measuring smart tools. The energy extracted from the grid has a different price in a day interval, while it is assumed that the energy offered to the grid is paid at a flat rate. The actual data is from an original family of four using a PV site. Case studies ranging from diverse demand response methods to considering various self-supplies have been tried. The effect of DR method based on peak power shading has also been examined. In this study, the premise is that customers are willing to charge their EVs as soon as they arrive. Compared to the base model, this method offers a more efficient performance by reducing electricity costs, which is approximately 44% a significant figure. With the expansion of smarter technologies, performance has been integrated with a HEM system that provides more economical use of electricity. In fact, the smart technologies manifestation will prepare more economical and flexible possibilities for the final client to play a role in the daily power market, thus maintaining the regular operation of the electricity market with economic benefits. The present method can be well adapted to wider formulations such as shift devices (washing machines, dishwashers, and other HVAC systems). The desirable performance of a district including several intelligent households is also easily applicable to the present method, by varying the objective function to minimize or maximize the problem. Therefore, the model can give a decent premise for creating blockchain methodologies for bigger-scale utilization.

References

[1] A. Khodaei, M. Shahidehpour, and S. Bahramirad, "SCUC with hourly demand response considering intertemporal load characteristics," IEEETrans. Smart Grid, vol. 2, no. 3, pp. 564–571, Sep. 2011, DOI: 10.1109/TSG.2011.2157181.

[2] C. W. Gellings, The Smart Grid: Enabling Energy Efficiency and Demand Response. Boca Raton, FL, USA: CRC Press, 2009.

[3] C. G. Monyei, A. O. Adequmi, Demand side management potentials for mitigating energy poverty in South Africa, Energy Policy 111 (2011) 298-311, https://doi.org/10.1016/j.enpol.2017.09.039.

[4] Duman AC, Erden HS, Gonul O, Guler O, A home energy management system with an integrated smart thermostat for demand response in smart grids, Sustainable Cities and Society (2020), https://doi.org/10.1016/j.scs.2020.102639.

[5] D. Steen, L. A. Tuan, O. Carlson, and L. Bertling, "Assessment of electric vehicle charging scenarios based on demographical data," IEEETrans. Smart Grid, vol. 3, no. 3, pp. 1457–1468, Sep. 2012. DOI: 10.1109/TSG.2012.2195687.

[6] D. S. Kirschen, "Demand - side view of electricity markets," IEEE Trans. on Power Systems, vol. 18, no. 2, pp. 520-527, May 2003, DOI: 10.1109/TPWRS.2003.810692.

[7] D. S. Kirschen, G. Strbac, P. Cumperayot, and D. Mendes,"Factoring the elasticity of demand in electricity prices," IEEE Trans. on Power Systems, vol. 15, no. 2, pp. 612-617, May 2000, DOI: 10.1109/59.867149.

[8] Eskom, IDM, Integrated Demand Management (2019).https://www.eskomidm.co.za

[9] F. de Angelis, M. Boaro, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints,"IEEE Trans. Ind. Informat., vol. 9, no. 3, pp. 1518–1527, Aug. 2013, DOI: 10.1109/TII.2012.2230637.

[10] G. Li and X. P. Zhang, "Modeling of plug-in hybrid electric vehicle charging demand in probabilistic power flow calculations," IEEE Trans.Smart Grid, vol. 3, no. 1, pp. 492–499, Mar. 2012, DOI: 10.1109/TSG.2011.2172643.

[11] H. Saele and O. S. Grande, "Demand response from household customers: Experiences from a pilot study in Norway," IEEE Trans. Smart Grid, vol. 2, no. 1, pp. 102–109, Mar. 2011, DOI: 10.1109/TSG.2010.2104165.

[12] Hlalele TG, Zhang J, Naidoo RM, Bansal RC, Multi-Objective Economic Dispatch with Residential Demand Response Program

Under Renewable Obligation, Energy, https://doi.org/10.1016/j.energy.2020.119473
[13] H. Dorotic, M. Ban, T. Puksec, N. Duic, Impact of wind penetration in electricity markets on optimal power-to-heat capacities in a local district heating system, Renewable and Sustainable Energy Reviews 132 (2020)110095. https://doi.org/10.1016/j.rser.2020.110095
[14] H. Aalami and G. Reza Yousefi, “Demand Response model considering EDRP and TOU programs”, Transmission and Distribution Conference and Exposition, 2008. T&D. IEEE/PES. DOI:10.1109/TDC.2008.4517059.
[15] H.A Aalami, M. Parsa moghaddam,G.R Yousefi “Modeling and prioritizing demand response programs in power markets” Electric Power Systems Research , Volume 80, Issue 4, April 2010, Pages 426-435, https://doi.org/10.1016/j.epsr.2009.10.007.
[16] Javaid, N., Naseem, M., Babar, M., Mahmood, D., Ahmed, S., Alrajeh, N., & Iqbal, Z. (2017). A new heuristically optimized Home Energy Management controller for smart grid. Sustainable Cities and Society, Vol. 34, 211-227, https://doi.org/10.1016/j.scs.2017.06.009.
[17] J. Zhao, S. Kucuksari, E. Mazhari, and Y. J. Son, “Integrated analysis of high-penetration PV and PHEV with energy storage and demand response,” Appl. Energy, vol. 112, pp. 35–51, Dec. 2013, https://doi.org/10.1016/j.apenergy.2013.05.070.
[18] K. M. Tsui and S. C. Chan, “Demand response optimization for smart home scheduling under real-time pricing,” IEEE Trans. Smart Grid, Vol. 3, no. 4, pp. 1812–1821, Dec. 2012, DOI: 10.1109/TSG.2012.2218835.
[19] K. J. Chua, S. K. Chou, W. M. Yang, and J. Yan, “Achieving better energy efficient air conditioning—A review of technologies and strategies,” Appl. Energy, vol. 104, pp. 87–104, Apr. 2013, https://doi.org/10.1016/j.apenergy.2012.10.037.
[20] M. Restegar, M. F. Firuzabad, and F. Aminifar, “Load commitment in a smart home,” Appl. Energy, vol. 96, pp. 45–54, Aug. 2012, https://doi.org/10.1016/j.apenergy.2012.01.056.
[21] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, “An algorithm for intelligent home energy management and demand response analysis,” IEEE Trans. Smart Grid, vol. 3, no. 4, pp. 2166–2173, Dec. 2012, DOI: 10.1109/TSG.2012.2201182.
[22] M. Kuzlu, M. Pipattanasomporn, and S. Rahman, “Hardware demonstration of a home energy management system for demand response applications,” IEEE Trans. Smart Grid, vol. 3, no. 4, pp. 1704–1711, Dec. 2012, DOI: 10.1109/TSG.2012.2216295.
[23] M. H. Imani, M. J. Ghadi, S. Ghavidel, L. Li, Demand response modelling in micro-grid operation: a review and application for incentive-based and time-based programs, Renewable and Sustainable Energy Reviews 94 (2018) 486-499, https://doi.org/10.1016/j.rser.2018.06.017.
[24] M. Afzalan, F. Jazizadeh, Residential loads fexibility potential for demand response using energy consumption patterns and user segments, Applied Energy 254 (2019) 113693, https://doi.org/10.1016/j.apenergy.2019.113693.
[25] O. Erdinc, “Economic impacts of small-scale own generating and storage units, and electric vehicles under different demand response strategies for smart households,” Appl. Energy, vol. 126, pp. 142–150, Aug. 2014, https://doi.org/10.1016/j.apenergy.2014.04.010.
[26] P. Palensky and D. Dietrich, “Demand side management: Demand response, intelligent energy systems, and smart loads,” IEEE Trans. Ind.Informat., vol. 7, no. 3, pp. 381–388, Aug. 2011.
[27] Paterakis, N. G., Erdinç, O., & Catalão, J. P. S. (2017). An overview of Demand Response: Key-elements and international experience. Renewable and Sustainable Energy Reviews, 69(July 2016), 871–891. https://doi.org/10.1016/j.rser.2016.11.167
[28] Q. Hu and F. Li, “Hardware design of smart home energy management system with dynamic price response,” IEEE Trans. Smart Grid, vol. 4, no. 4, pp. 1878–1887,

Dec. 2013, DOI: 10.1109/TII.2011.2158841.

[29] R. Missaoui, H. Joumaa, S. Ploix, and S. Bacha, “Managing energy smart homes according to energy prices: Analysis of a building energy management system,” Energy Build., vol. 71, pp. 155–167, Mar. 2014, https://doi.org/10.1016/j.enbuild.2013.12.018.

[30] R. P. Odeh, D. Watts, Impacts of wind and solar spatial diversification on its market value: A case study of the Chilean electricity market, Renewable and Sustainable Energy Reviews 111 (2019) 442-461 https://doi.org/10.1016/j.rser.2019.01.015.

[31] S. Borlease, Smart Grids: Infrastructure, Technology and Solutions.Boca Raton, FL, USA: CRC Press, 2013.

[32] S. Shao, M. Pipattanasomporn, and S. Rahman, “Demand response as a load shaping tool in an intelligent grid with electric vehicles,” IEEE Trans. Smart Grid, vol. 2, no. 4, pp. 624–631, Dec. 2011, DOI: 10.1109/TSG.2011.2164583.

[33] Sattarpour, T., Nazarpour, D., & Golshannavaz, S. (2018). A multi-objective HEM strategy for smart home energy scheduling : A collaborative approach to support microgrid operation. Sustainable Cities and Society, 37(September 2017), 26–33. https://doi.org/10.1016/j.scs.2017.09.037

[34] Sharifi, A. H., & Maghouli, P. (2019). Energy management of smart homes equipped with energy storage systems considering the PAR index based on real-time pricing. Sustainable Cities and Society, 45(October 2017), 579–587. https://doi.org/10.1016/j.scs.2018.12.019

[35] S. Nan, M. Zhou, G. Li, Optimal residential community demand response scheduling in smart grid, Applied Energy 201 (2018) 1280-1289, https://doi.org/10.1016/j.apenergy.2017.06.066.

[36] T. Perumal, A. R. Ramli, and C. Y. Leong, “Design and implementation of SOAP-based residential management for smart home systems,” IEEE Trans. Consum. Electron., vol. 54, no. 2, pp. 453–459, May 2008, DOI: 10.1109/TCE.2008.4560114.

[37] Tom, J., Mastani, M., Panchabikesan, K., Sun, Y., Haghighat, F., Moreau, A., & Robichaud, M. (2020). Performance of a self-learning predictive controller for peak shifting in a building integrated with energy storage. Sustainable Cities and Society, 60(April2019),102285. https://doi.org/10.1016/j.scs.2020.102285

[38] W. Su, H. R. Eichi, W. Zeng, and M. Y Chow, “A survey on the electrification of transportation in a smart grid environment,” IEEE Trans.Ind. Informat., vol. 8, no. 1, pp. 1–10, Feb. 2012, DOI: 10.1109/TII.2011.2172454.

[39] Xuan Hou, Jun Wang, Peng Wang, Tao Wang : Smart Home Energy Management Optimization Method Considering ESS and PEV. 14th IEEE Conference on Industrial Electronics and Applications (ICIEA)(September 2019), https://doi.org/10.1109/ICIEA.2019.8833667.

[40] X. Li and S. Hong, “User-expected price-based demand response algorithm for a home-to-grid system,” Energy, vol. 64, pp. 437–449, Jan. 2014, https://doi.org/10.1016/j.energy.2013.11.049.

[41] X. Chen, T. Wei, and S. Hu, “Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home,” IEEETrans. Smart Grid, vol. 4, no. 2, pp. 932–941, Jun. 2013, DOI: 10.1109/TSG.2012.2226065.

[42] Z. Chen, L. Wu, and Y. Fu, “Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization,” IEEE Trans. Smart Grid, vol. 3, no. 4, pp. 1822–1831, Dec. 2012, DOI: 10.1109/TSG.2012.2212729.