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Optimal Energy Scheduling in Smart Buildings with Electric Vehicle and Demand Response

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Abstract: In a number of countries, smart microgrid (SMG) technology is being exploited in the energy system infrastructure along with other generators such as electric and storage systems. In the framework of SMGs, communication links between generation and demand sides have been established to optimise energy consumption by means of economic signals. The framework of energy management for Smart Home appliances is presented in the present paper, taking account of appliance and electric vehicle participation. The approach to the energy schduling at day-ahead is defined as three strategies, such as optimum use of existing appliances, optimal production of electricity resources and optimal discharge and charging for electrical vehicles. Reducing energy generation costs and minimizing emissions of air pollutants are key objectives. Two case studies with the aim of reducing costs and emissions while maximizing system flexibility are taken into account to demonstrate preference and viability of home energy scheduling.

Keywords: Smart microgrid (SMG), energy management, smart home appliances, electrical vehicles

1. Introduction

Countries with main challenges such as rising emissin problems, increasing fossil fuel consumption by energy generation units at power stations, and the deployment of distributed energy resources (DERs) are faced [1][2]. These main challenges have the potential to stimulate energy companies' interest in taking part in smart energy systems. By means of interoperability between the electrical generation and demand sides as well as bidirectional communication data, smart grids can control energy consumption at critical times [2][3]. The main applications for the smart grid that are likely to be regarded as Demand Management by means of energy market price signals are demand side management (DSM). Smart appliances and smart meters may be used to control energy consumption for the purpose of achieving information and real-time use in electricity distribution networks, thus smart grid at home management [4].

Nomenclature		
t,T	Time	Hour
n, N	RCs number	-
si	Irradiance of Solar	kW/m^2
S_{PV}	PV area	m^2
v, V_R, V_{Ci}, V_{Co}	Wind speed, Rated speed, cut-in speed, cut-off speed of WT	m/s

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$P_{N,WT}$	WT rated power	kW
P_d, P_{UG}	DG power and UG power	kW
η_{pv}	PV Efficiency	%
C_{DG},C_{UG}	DG cost and UG cost	$
D_{DLs}	Demand of the DL)	kW
A, B, C	DGs' Fuel factor	$/kW
D,E,F	DGs' Emission factor	g/kW
π_{UG},	UG price	$/kW
Ψ_{UG}	UG Emission factor	g/kW
P^{dch}_{PEV}, P^{ch}_{PEV}	Power discharge and power charge of PEV	kW
ψ	DLs' response level	%

Research on energy optimization is proposed in this section. For example, in [5], the energy planning of home appliances in smart home energy centers is presented to increase the profit of demand side. The reduction in power demand as well as energy prices and the uncertainty of demand in the energy systems are studied in [6]. In [7], multi-level modelling for energy scheduling is reported to optimize energy production in multiple energy markets. Economic modelling using an interval approach is proposed to cover load uncertainty in [8]. Dynamic tuning of residential energy planning to minimize losses is proposed in [9]. In [10], energy planning with interval modelling and demand uncertainty is proposed. A demand reduction reserve strategy is proposed in [11] to increase the renewable energy resources participation and the benefits of resource owners.

This paper introduces bi-objectives for smart building that involves consumer participation in energy scheduling. The optimization of the demand shifting (DS) strategy for electrical demand is undertaken, with the bi-objective functions of minimizing both emission and generation costs being taken into account. Furthermore, the utilization of plug-in electric vehicles (PEVs) to meet energy demands and improve the flexibility of the system is achieved through optimal charging and discharging techniques. The Pareto front is utilized to obtain solutions for bi-objectives via the augmented epsilon-constraint method.

In recent energy system, the electrical distribution networks have been transferring energy to demand side without any economic signals. However, the emergence of smart grids has presented modern opportunities for energy companies to supply load with minimum cost. Within this system, there are exists a real-time information base that facilitates mutual data exchange among units and demand. The sections of smart buildings in this study are as follows [12]:

1) DERs include wind turbines (WT), diesel generators (DGs), photovoltaic (PV) systems.

2) Customers who employ appliances like deferrable loads (DLs), can control their energy demand. DLs include PEVs, washing machines and dryers, which can be operated at various times.Also, customers in optimal energy operations can be known as responsive consumers (RCs).

3) The operator serves as the intermediary among the DERs utility grid (UG), and RCs through data links. The operator has the ability to notify RCs regarding the use of appliances in relation to electricity prices during operation. Figure 1 depicts smart buildings with all sections included.

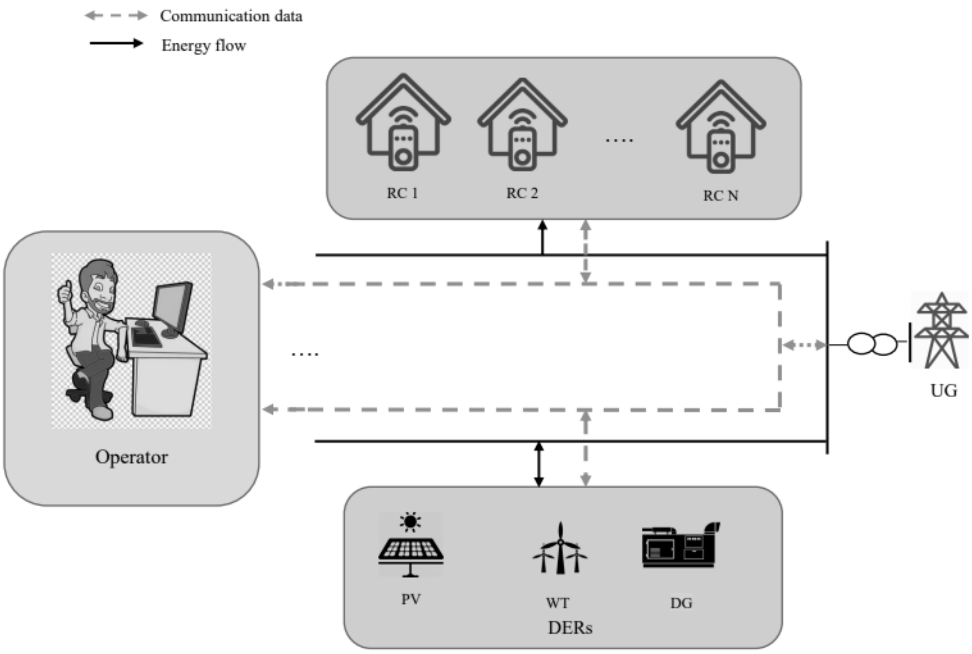

Fig. 1 - Proposed smart buildings with all sections

2. Mathematical Modeling of the System

Modeling system is formulated in this section.

2.1 DERs Formulation

Modeling DERs are as follow:

2.1.1 PV Modelling

The PV modeling is as follow [15]:

$$P_{PV}(si) = \eta_{PV} \times S_{PV} \times si \tag{1}$$

2.1.2 WT Modelling

Modeling WT is as follow [16]:

$$P_{WT}(v) = \begin{cases} 0 & if \quad v \le V_{Ci} \\ P_{N,WT} \times \left(\dfrac{v - V_{Ci}}{V_R - V_{Ci}} \right) & if \quad V_{Ci} \le v \le V_R \\ P_{N,WT} & if \quad V_R \le v \le V_{Co} \\ 0 & if \quad V_{Co} \le v \end{cases} \tag{2}$$

2.1.3 DGs Modelling

Modeling DG considering fuel costs is as follow [17]:

$$C_{DG}(t,d) = \left\{ AP_d^2(t,d) + BP_d(t,d) + C \right\} + \left\{ C_{SU} \times \mu^{on}(t,d) \right\} + \left\{ C_{SD} \times \mu^{off}(t,d) \right\} \tag{3}$$

2.1.4 DLs Modelling

Modeling DLs considering demand shifting strategy is as follow:

$$D_n(t,n) = D_{DL}(t,n) + D_{UC}(t,n) \tag{4}$$

$$D_{DL}(t,n)=\sum_{t'}\sum_{n=1}^{N}D_{DL}(t,t',n)-\sum_{t'}\sum_{n=1}^{N}D_{DL}(t',t,n) \tag{5}$$

$$0\le\sum_{t'}\sum_{n=1}^{N}D_{DL}(t,t',n)\le\psi\times\sum_{n=1}^{N}D_{DL}(t,n) \tag{6}$$

In equation (4), RCs encompass a variety of appliances, including uncontrollable appliances and DLs, which vary over time. Uncontrollable appliances are not amenable to energy management. By utilizing equation (5), the optimization of load demand can be achieved by shifting DLs. Additionally, equation (6) can be utilized to determine the participation rate of the DLs for RCs.

2.1.5 PEV Modelling

The RCs have the ability to utilize PEV as a localized power resource. These PEVs possess the capacity to function with two opposing characteristics, namely, 1) load demand operation during charging and 2) unit generation during discharging. The conduct of the PEV can be represented through the following model [18]:

$$0\le P_{PEV}^{dch}(t)\le u_{PEV}\times P_{PEV}^{r} \tag{7}$$

$$0\le P_{PEV}^{ch}(t)\le\left[1-u_{PEV}(t)\right]\times P_{PEV}^{r} \tag{8}$$

The PEV power in both discharging and charging states are constrained by the maximum power, as modeled by equations (7) and (8), respectively. Within these equations, the binary variable u_{PEV} denotes the infeasibility of simultaneous charging and discharging modes by the PEV during a given hour.

2.2 Objective Functions Modelling

Modeling objective functions as follow:

2.2.1 Energy Generation Costs

The primary objective function pertains to the minimization of energy generation costs associated with the production of energy by both DGs and UG.

$$\min f_1=\sum_{t=1}^{T}\left\{\sum_{d=1}^{D}C_{DG}(t,d)+C_{UG}(t)\right\} \tag{9}$$

The energy cost of DGs, denoted as C_{DG}, is given in section 3.1.3. Subsequently, the energy cost in UG is considered as follows:

$$C_{UG}(t)=P_{UG}(t)\times\pi_{UG}(t) \tag{10}$$

2.2.2 Emission Polluting

The secondary objective function pertains to the reduction of pollutant emissions caused by UG and DG:

$$\min f_2=\sum_{t=1}^{T}\left\{\sum_{d=1}^{D}E_d(d,t)+E_{UG}(t)\right\} \tag{11}$$

Where:

$$E_d(t,d)=\left\{DP_d^2(t,d)+EP_d(t,d)+F\right\} \tag{12}$$

$$E_{UG}(t)=P_{UG}(t)\times\Psi_{UG} \tag{13}$$

Equations (12) and (13) represent emission models of DGs and UG, respectively.

2.2.3 Constraints

The system has constraints are as follow:

$$P_{UG}(t)+P_{PV}(t)+P_{PEV}^{dch}(t)+\sum_{d=1}^{D}P_d(t,d)+P_{WT}(t)=D_n(t)+P_{PEV}^{ch}(t) \tag{14}$$

$$P_d^{\min}\le P_d(t,d)\le P_d^{\max} \tag{15}$$

The constraints identified as (14) and (15) relate to the power balance and energy limitations for DGs, respectively. The power balance denotes that the power generated in the generation side is used by the load at any given time.

3. Solving Method

The augmented epsilon-constraint method is introduced to optimization of the objective functions, simultaneously. This method is modelled as follow [18] [19] [20]:

$$\min\left[f_1(x)-\delta\sum_{n=1}^{N}\frac{s_n}{r_n}\right] \qquad 10^{-6}\le\delta\le 10^{-3} \tag{16}$$

$$f_n(x)+s_n-\varepsilon_n^z \qquad n=2,3,...,N\,;s_n\in R^+ \tag{17}$$

Where:

$$\varepsilon_n^z=f_n^{\max}-\left[\frac{f_n^{\max}-f_n^{\min}}{q_n-1}\right]\times z \qquad z=0,1,...,q_n \tag{18}$$

3.1 Decision Making Modelling

Given that multi-objectives are optimized concurrently; solutions are obtained for objectives with contrasting natures. As a result, the operator assumes the role of the primary decision maker, with the ability to maximize interaction between objectives. To this end, a hybrid decision making procedure utilizing fuzzy and weight sum methods is employed. The modelling of this hybrid decision making procedure is outlined below [17] [21]:

$$\vartheta_i^k=\begin{cases}1 & f_i^k\le f_i^{\min}\\ \dfrac{f_i^{\max}-f_i^k}{f_i^{\max}-f_i^{\min}} & f_i^{\min}\le f_i^k\le f_i^{\max}\\ 0 & f_i^k\ge f_i^{\max}\end{cases} \tag{19}$$

$$\vartheta^k=\frac{\sum_{i=1}^{I}\omega_i.\vartheta_i^k}{\sum_{k=1}^{K}\sum_{i=1}^{I}\omega_i.\vartheta_i^k} \tag{20}$$

Where:

$$\sum_{i=1}^{I}\omega_i=1 \qquad \omega_i\ge 0 \tag{21}$$

In this procedure, all objectives undergo normalization through the utilization of the fuzzy method as presented in equation (19). Subsequently, the weight sum method is employed to identify the optimal solution, wherein a maximum amount of the membership function ϑ_k is selected as the optimal solution by (20).

4. Case Studies

The case studies are presented for validation of the proposed energy scheduling in buildings. To demonstrate the impacts of the RCs preformance in energy optimization, a simulation of the mathematical modeling has been done. The numerical simulation has been carried out using GAMS software, with the DICOPT solver. Two cases are included in Table 1 to authenticate the proposed approach.

Table 1 - Proposed case studies

Cases \ Strategies	DLs	PEV
1	-	-
2	✓	✓

Figure 2 displays the wind speed and solar irradiance, whereas the information regarding WT and PV is obtained from Reference [22] [23]. Table 2 presents the data pertaining to DGs. The load and prices of UG are depicted in Figure 3. The responsive level of DLs and emission factor of UG are taken into accounted by values of 20% and 980g/kW, respectively [23] [24]. Furthermore, the power of PEV is 50kW. Additionally, Figure 4 illustrates the flowchart of the proposed research.

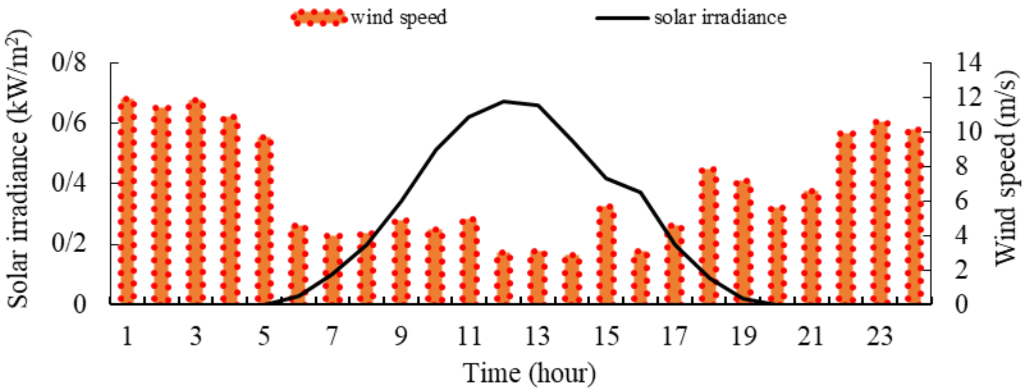

Fig. 2 - Wind speed and solar irradiance

Table 2 - DGs information

DGs \ Information	A	B	C	D	E	F	P^{min}	P^{max}
1	94.2	110.2	124	95.3	90.3	130	0	200
2	98.2	115.6	132	90.3	95.3	135	0	220

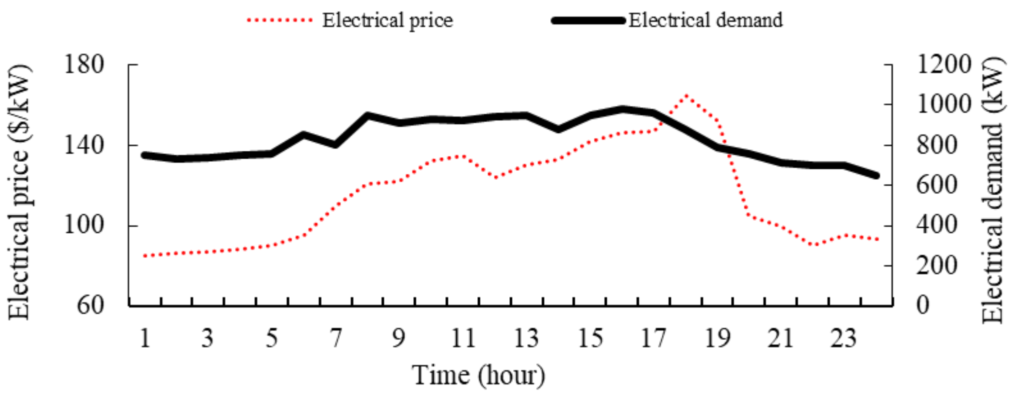

Fig. 3 - Electricity price of UG and demand

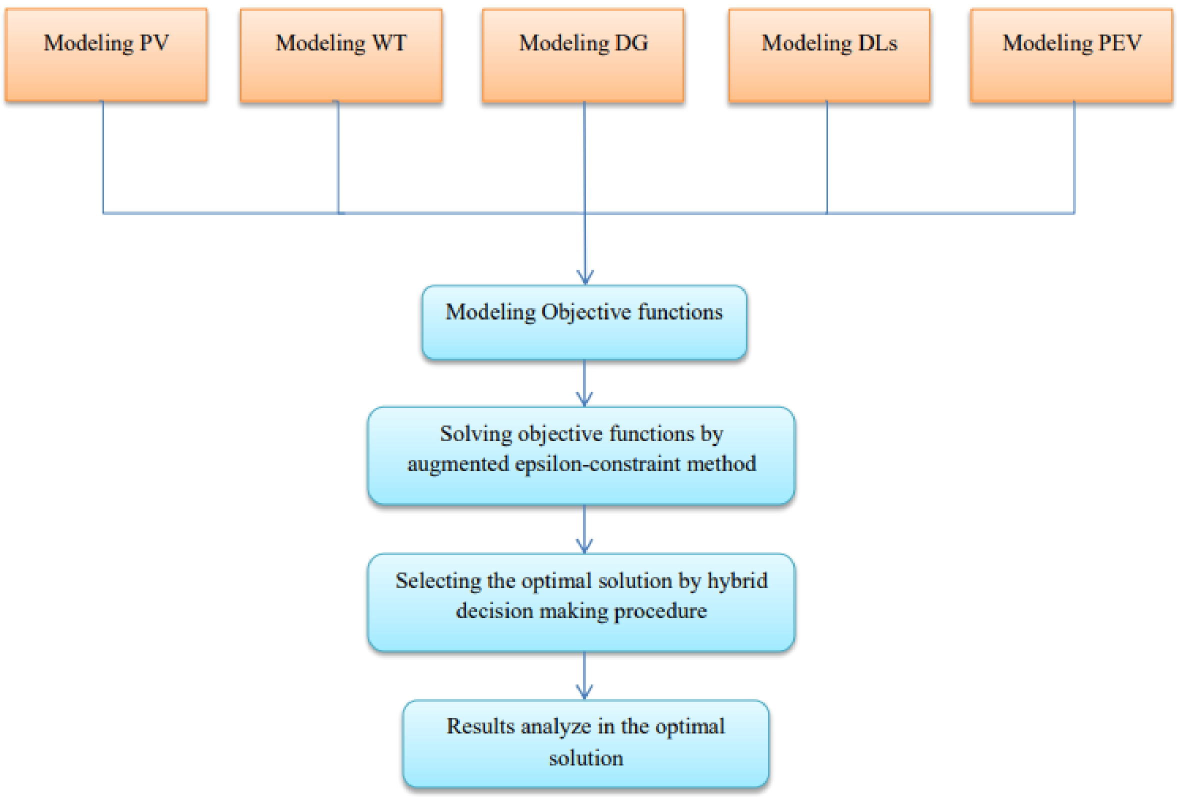

Fig. 4 - Flowchart of the proposed research

5. Results

This section provides an analysis of the numerical findings obtained from the aforementioned case studies. The case studies incorporate the involvement of DLs and PEVs by RCs in the optimal energy planning for day-ahead operations. The outcomes of the study are outlined below:

Case 1) In this particular case study, the involvement of DLs and PEV has not been taken into account. Table 3 illustrates the solutions obtained through augmented epsilon-constraint for objective functions in both Cases 1 and 2. The optimal solution has been determined through a hybrid method, highlighted in bold text format in Table 3. The objectives for Case 1 in Table 3 indicate energy costs and emission in optimal solution have values of $405,332.2 and 5,343.3 kg, respectively. The energy costs of the DGs and UG are $98,454.6 and $306,877.6, respectively. Additionally, the emission of the DGs and UG are 2,467.2 kg and 2,876.4 kg, respectively. Figure 5 shows the energy generated by UG and DERs in Case 1.

Case 2) In Case 2, optimal energy planning is achieved through the simultaneous participation of RCs via PEV and DLs. Figure 6 illustrates the demand with the involvement of DLs, wherein the demand at maximum prices is moved to minimum prices. The implementation of these strategies in Case 2 leads to higher convergence of the objectives as compared to Case 1. Table 3 presents the relevant amounts for energy costs and emissions in the optimal solutions, which amount to $335,250.2 and 4,863.3 kg, respectively. The use of PEV leads to reduced energy generated from the UG, thereby reducing the energy cost and emission of UG. Figure 7 depicts the charging of PEV during hour 1 at minimum prices in UG, while the discharge energy is used by RC at maximum prices.

Table 3 - Obtained solutions in cases 1 and 2

Solutions	**Case 1**		**Case 2**	
#	**Generation cost ($)**	**Emission polluting (kg)**	**Generation cost ($)**	**Emission polluting (kg)**
1	483324.3	0	396571.3	0
2	453574.3	4587.8	376542.3	4054.7
3	**405332.2**	**5343.3**	359876.3	4565.6
4	398765.3	6544.3	**335250.2**	**4863.3**
5	355474.2	7254.2	302476.3	5132.3
6	0	7565.4	0	5563.5

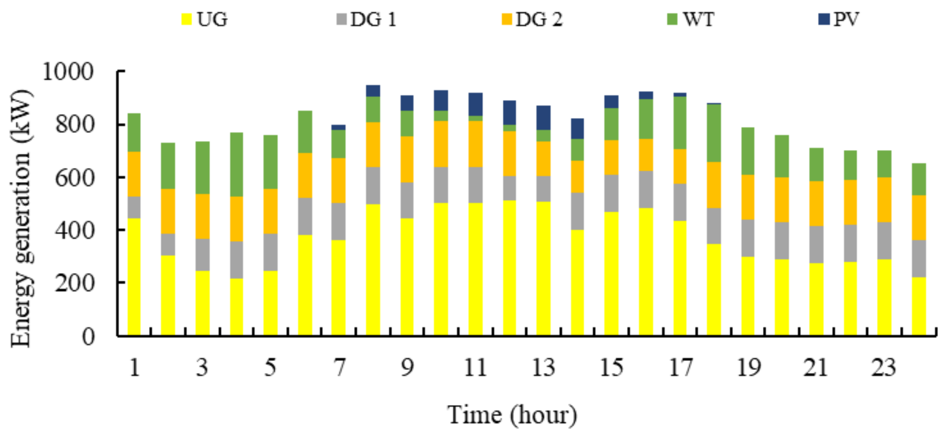

Fig. 5 - Power generated in case 1

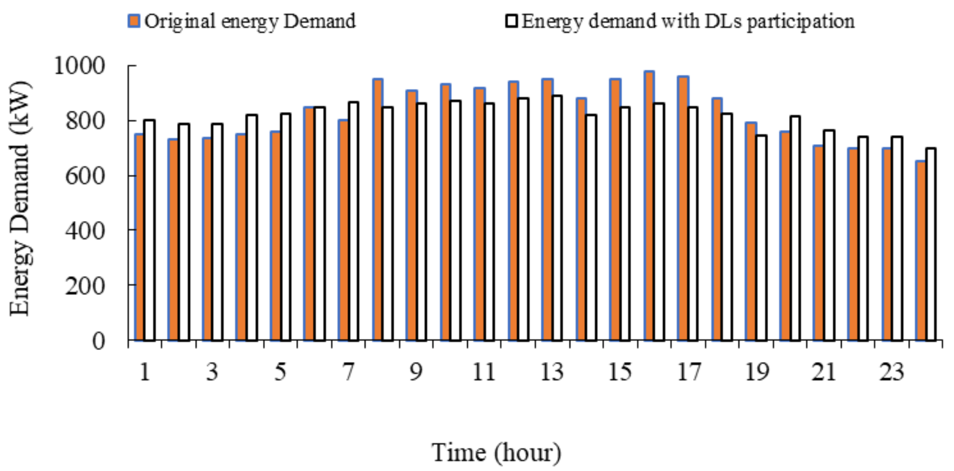

Fig. 6 - Energy demand with DLs

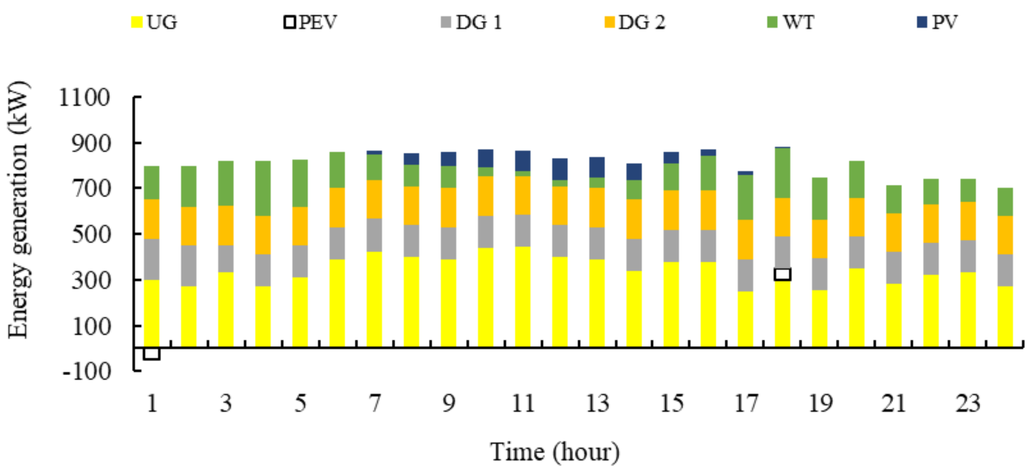

Fig. 7 - Power generated in case 2

6. Conclusion and Future Scope

This paper examines the energy scheduling of buildings with the participation of demand. The RCs play an active role in the grid by demand shifting and generating power through the use of PEVs. Consequently, energy demand is optimized through the participation of DLs in smart homes, based on day-ahead energy prices. This approach aims to reduce peak demand during operation time, thus minimizing costs and reducing emissions. The inclusion of PEVs and DLs in energy generation has resulted in a better level of objective functions, including a decrease in energy generation from the utility grid. Also, this study can be expanded with new optimization algorithms, new objective functions in the various energy systems.

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