Energy Optimization Of The Smart Stand-alone Buildings Considering Renewable Energy Resources

Xiaodan Liang[1], Dan Wang[2], and Yalong Liu[1*]

[1] School of Digital Construction, Shanghai Urban Construction Vocational College, Yangpu 200438, Shanghai, China
[2] Shanghai Jianke Architectural Design Institute CO., Ltd. Xuhui 200032, Shanghai, China
[*] Corresponding author. E-mail: lyl731111@163.com

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The utilization of fossil fuels for energy generation leads to the release of harmful emissions, posing a threat to the environment. Therefore, the promotion of energy conservation through the adoption of new energy systems and the utilization of renewable energy resources (RERs) has become a significant focus across various sectors of the energy industry. This study evaluates the economic viability of intelligent residential buildings by optimizing the integration of controllable appliances within an independent electrical residential network. The proposed methodology emphasizes achieving an efficient coordination between controllable appliances and RERs, with the coordination being modeled through the load shifting model (LSM) of the demand side management (DSM) strategy. The power generation from RERs is analyzed using stochastic modeling techniques to address uncertainties. The technical and economic modeling of the stand-alone electrical residential network is formulated as a multi-criteria problem. To solve this problem, the augmented ε-constraint method and fuzzy logic techniques are employed. Finally, numerical simulations are conducted across various case studies to validate and demonstrate the effectiveness of the proposed approach.

Keywords: Smart residential buildings; controllable appliances; stand-alone electrical residential network; load shifting model (LSM); multi-criteria problem

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1. Introduction

1.1. Background and aims

The utilization of renewable energy resources (RERs) is appealing to energy companies due to their avoidance of fossil fuels, resulting in reduced pollution emissions and the ability to meet demand reliably [1]. Among the well-known RERs, wind turbines (WT) and photovoltaic (PV) panels are particularly valuable in remote residential areas [2]. However, power generation through RERs can be intermittent and unpredictable within electrical networks [3]. To address these challenges, various modern technologies have been developed, including smart grid technology and storage systems [4]. Additionally, RERs provide a reliable source of energy that is not subject to the fluctuations in price and availability that can occur with fossil fuels [5]. This stability can help energy companies better plan for the future and ensure a consistent supply of energy to meet the needs of their customers [6]. Furthermore, investing in RERs can also provide economic benefits for energy companies, as governments and consumers increasingly prioritize clean energy solutions [7]. By diversifying their energy portfolio to include RERs, companies can position themselves as leaders in sustainability and attract environmentally conscious customers [8]. Overall, the appeal of RERs to energy companies lies in their ability to provide a cleaner, more reliable, and economically viable alternative to traditional fossil fuels [9]. By embracing RERs, companies can not only reduce their environmental impact but also position themselves for long-term success in a rapidly changing energy landscape [10].

Through the implementation of smart grid technology, demand side management (DSM) emerges as a crucial strategy for effectively meeting energy demand under different circumstances [11]. DSM encourages consumers to regulate their energy consumption during critical periods [12]. Moreover, DSM is not limited to critical times and can also optimize the coordination between RERs and controllable appliances, thereby reducing energy generation costs and promoting the integration of RERs [13]. Smart grids, which enable controlled and intelligent transmission of electrical energy from production to consumption, play a pivotal role in this process [14]. By adjusting their consumption patterns based on information from manufacturers, incentives, and certain limitations, consumers actively contribute to reducing manufacturing costs and enhancing grid reliability. The development of smart grids has also led to a greater focus on improving demand-side management programs [15]. While residential areas consume the majority of energy compared to commercial and industrial sectors [16], energy management in residential settings is a relatively new platform for enhancing technical and economic performance through the control of loads within electrical systems [17]. In Fig. 1, energy management in a stand-alone smart building is shown. In this figure, there are several components for implementing energy management:

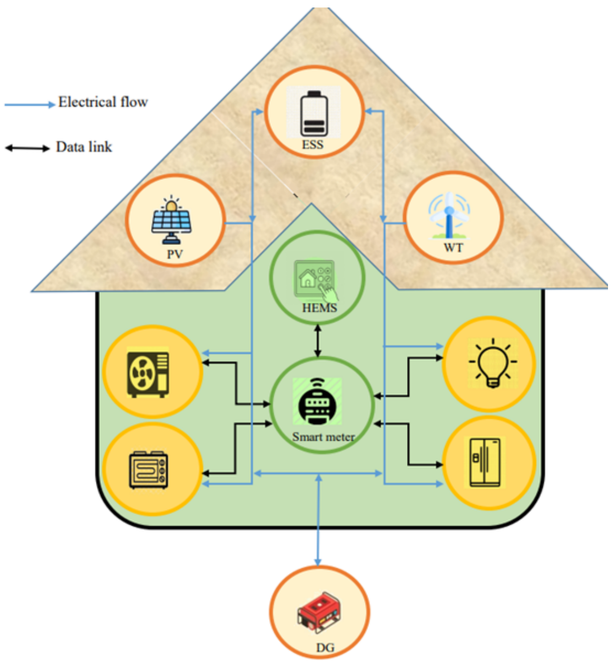

Fig. 1. Overview of the stand-alone smart building

Controllable loads: The controllable loads are appliances with a manageable nature. These loads can be controlled and used at various times of day. These loads include dryers, optional lighting, air conditioners, etc [18].

Generators: The RERs, electrical storage systems (ESS), and diesel generators (DGs) are the main electrical generators. The electrical generation by RERs is dependent on climate conditions like solar irradiance and wind speed. As well, DGs are fed by fossil fuels for electrical generation [19].

Home energy management system (HEMS): The HEMS plays a crucial role in the efficient management of energy in smart buildings by coordinating the controllable loads and generators using data collected from smart meters. By taking into account the forecasted climate data, consumers can utilize the controllable loads at their optimal state [20].

1.2. Related studies

The energy management in the residential section has been investigated using different approaches and optimization modeling in previous studies. In Zhang et al. [21], the optimal operation of the plug electric vehicles (PEVs) in smart buildings is studied in order to reduce consumers' bills. In Chamandoust [22], co-optimization modeling is implemented to decrease greenhouse gases and costs in residential sections. The lifecycle modeling of the energy consumption by appliances in residential sections is investigated in Tribioli and Cozzolino [23]. In Babaei et al. [24], focused on energy scheduling of the cooling and heating appliances to increase energy-saving and consumers' comfort in smart buildings. In Xie et al. [25] efficiency and design of the RERs are studied in smart buildings with attention to electrical price. The energy scheduling in residential sections with optimal operation of the ESS and RERs is investigated in Patel and Singal [26]. In Thiaux et al. [27], optimal participation of the generators in electrical microgrids and smart buildings is proposed in Babaei et al. [28], without consideration of the RERs penetration. The power management of the appliances is studied under risk modeling and energy price uncertainly [29]. In Rivera-Niquepa et al. [30], the day-ahead operation of the energy hub system is reported with consideration of the greenhouse gases and costs in the smart buildings.

1.3. Novelties

This study presents a research for the functioning of independent smart buildings, focusing on economic and technical factors in the day-ahead operation. The main objectives include minimizing operational costs and maximizing the integration of renewable energy resources (RER). To achieve this, a multi-criteria modeling approach is adopted.

The coordination between the electrical demand, managed through the load shifting model (LSM), and the power generation from RER is emphasized. The multi-criteria problem is addressed using augmented ε-constraint and fuzzy methods. Consequently, the article highlights the key novelties and innovations as follows:

The multi-criteria problem of the stand-alone smart buildings is proposed.

The LSM is used as a DSM strategy to maximize RER penetration and minimize operation costs.

The augmented ε-constraint method is employed to solve multi-criteria problems.

The fuzzy method is utilized to maximize trade-offs between objective functions.

1.4. Paper arrangement

The arrangement of this investigation is proposed as follows: In section 2, modeling RER is done. The ESS modeling is presented in section 3. The modeling multi-criteria issue is proposed in section 4. In section 5, the solution procedure is introduced. In sections 6 and 7, simulation and conclusion are presented, respectively.

2. RERs modelling

The climate conditions greatly impact the power generation of renewable energy resources (RERs). Wind speed as well as solar irradiance play a crucial role in generating power through wind turbines (WT) and photovoltaic (PV) systems, respectively [31]. However, the behavior of wind speed and solar irradiance is uncertain when it comes to energy generation. Therefore, the modeling of WT and PV systems is as follows:

2.1. WT modelling

The power generation by WT based on uncertain behavior is as follows [31]:

$$f^{WT}(v) = \begin{cases} \frac{k}{c} \times \left(\frac{v}{c}\right)^{k-1} \times e^{-\left(\frac{v}{c}\right)^{k}} & v \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

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

Eqs. (1) and (2) are Weibull probability density functions (PDF) for modeling uncertain behavior of wind speed and power generation by WT, respectively.

2.2. PV modeling

The PV modeling is as follows [31]:

$$f^{PV}(si) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} si^{\alpha-1}(1-si)^{\beta-1} & 0 \leq si \leq 1, \alpha \geq 0, \beta \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$P_{PV}(si) = \eta_{PV} \times S_{PV} \times si \tag{4}$$

Eqs. (3) and (4) represent the Beta PDF and the PV output, respectively. Conversely, RERs can be integrated at any given moment to ensure optimal coordination with controllable loads. Therefore, merged energy generation by RERs is modeled by Eq. (5) [31]:

$$P_{PW}(t) = P_{PV}(si,t) + P_{WT}(v,t) \tag{5}$$

3. ESS modelling

The discharge power and charge power of ESS are modeled by Eq. (6) [32]:

$$\begin{cases} P_{ESSS}^{\mathrm{did}}(t)/\eta_{\mathrm{dis}} \leq P_{ESS}^{\mathrm{max}_{ESS}} & P_{ESS}(t) \geq 0 \\ P_{ESS}^{ch}(t) \times (-\eta_{ch}) \leq P_{ESS}^{\mathrm{max}} x_{ESS} & P_{ESS}(t) \leq 0 \end{cases} \tag{6}$$

4. Multi-criteria problem modeling

The modeling multi-criteria problem is formulated as follows:

4.1. Operation costs

The first objective is minimizing the costs, which is modeled as follows:

$$\begin{aligned} \min f_1 = & \sum_{t=1}^{T} \left[\sum_{d=1}^{D} \left\{ \sigma P_d^2(t,d) + \omega P_d(t,d) + \lambda \right\} \right] + \\ & \sum_{t=1}^{T} \left[\sum_{ess=1}^{ESS} \left\{ C_{OP}^{ess} \times P_{ESS}^{dis}(t,ess) \right\} \right. \\ & \left. + \sum_{ess=1}^{ESS} \left\{ C_{OP}^{ess} \times P_{ESSS}^{ch}(t,ess) \right\} \right] \end{aligned} \tag{7}$$

In objective Eq. (7), the first term is the operation cost of the DG, and the second term is the ESS operation cost in discharge and charge modes, respectively.

4.2. RERs penetration

Maximization of the RERs penetration is the second objective function, which is given by Eq. (8). In this objective, optimal coordination of the RERs with controllable loads is provided.

$$\max f_2 = 1 - \left\{ \sum_{t=1}^{T} \cdots \frac{\left[\left| \sum_{cl=1}^{CL} D_{CL}(t,cl) - P_{PW}(t) \right| \right]}{D_{CL}(t,cl) + D_{NRC}(t,ncl)} \right\} \tag{8}$$

Where:

$$D_{CL}(t,cl) = \sum_{t'} \sum_{cl=1}^{cL} D_{CL}\left(t,t',cl\right) - \sum_{t'} \sum_{cl=1}^{cL} D_{CL}\left(t',t,cl\right) \tag{9}$$

$$0 \leq \sum_{t'} \sum_{cl=1}^{CL} D_{CL}\left(t,t',cl\right) \leq \Upsilon(t) \times \sum_{cl=1}^{CL} D_{CL}(t,cl) \tag{10}$$

Here Eqs. (9) and (10) are demand shifted of the controllable loads at t to t', and the level of the controllable load's participation in LSM, respectively.

4.3. Constraints

The multi-criteria problem is optimized while considering the constraints outlined below:

$$\left\{ \sum_{d=1}^{D} P_d(t,d) + \sum_{b=1}^{B} P_{ESS}^{dis}(t,b) - \sum_{b=1}^{B} P_{ESS}^{ch}(t,b) + \sum_{pw=1}^{PW} P_{PW}(t) \right\} = \left\{ \sum_{cl=1}^{CL} D_{CLs}(t,cl) + \sum_{ncl=1}^{NCL} D_{NRC}(t,ncl) \right\} \tag{11}$$

$$0 \leq P_d(t) \leq P_d^{\max} \tag{12}$$

$$\mu^{\mathrm{on}}(t,d) + \sum_{\tau=t+1}^{\min\left(T,t-1+M^U\right)} \mu^{off}(\tau,d) \leq 1 \tag{13}$$

$$\mu^{\mathrm{off}}(t,d) + \sum_{\tau=t+1}^{\min\left(T,t-1+M^D\right)} \mu^{on}(t,d) \leq 1 \tag{14}$$

$$\sum_{t=1}^{T} P_d(t,d) - \sum_{t=1}^{T} P_d(t-1,d) \leq RU \tag{15}$$

$$\sum_{t=1}^{T} P_d(t-1,d) - \sum_{t=1}^{T} P_d(t,d) \leq RD \tag{16}$$

The constraint Eq. (11) is power balance each time. The power limit of the DGs, minimum uptime of the DGs, minimum downtime, ramp up, as well as ramp down of DGs are constrained in Eqs. (12) to (16), respectively.

5. Solution procedure

In this section, we present a proposed solution procedure for solving multi-criteria problems. The augmented ε-constraint procedure is a well-known approach for obtaining non-dominated Pareto solutions in such problems. The modeling of the augmented ε-constraint procedure is outlined as follows [33]:

$$\min \left[f_1(x) - \delta \sum_{n=1}^{N} \frac{s_n}{r_n} \right] 10^{-6} \leq \delta \leq 10^{-3} \tag{17}$$

Where:

$$f_n(x) + s_n - \varepsilon_n^z \quad n = 2,3,\ldots,N; s_n \in R^+$$
$$\varepsilon_n^z = f_n^{\max} - \left[\frac{f_n^{\max} - f_n^{\min}}{q_n - 1} \right] \times z \quad z = 0,1,\ldots,q_n \tag{18}$$

Here x, δ, and n are the decision variable, slack variable, and nth objective function, in that order. The sn, $f_n^{\min}$ and $f_n^{\max}$ are the slack variable, and ranges of nth objective, respectively. And rn, qn, and εzn are the objectives range, the equal range, and the zth interval of nth objective, in that order.

5.1. Fuzzy approach

In this subsection, the fuzzy approach is introduced for opting for the best trade-off solution in non-dominated Pareto solutions. In this approach, using Eq. (19) extracted non-dominated Pareto solutions from the augmented ε-constraint procedure are normalized. Then, by Eq. (20), the maximum rate is chosen as the best trade-off solution [34].

$$\vartheta_n^m = \begin{cases} 1 & f_n^m \leq f_n^{\min} \\ \frac{f_n^{\max} - f_n^m}{f_n^{\max} - f_n^{\min}} & f_n^{\min} \leq f_n^m \leq f_n^{\max} \\ 0 & f_n^m \geq f_n^{\max} \end{cases} \tag{19}$$

$$\vartheta^m = \frac{\sum_{n=1}^{N} \omega_n \cdot \vartheta_n^m}{\sum_{m=1}^{M} \sum_{i=1}^{I} \omega_n \cdot \vartheta_n^m} \sum_{n=1}^{N} \omega_n = 1, \quad \omega_n \geq 0 \tag{20}$$

Here n and m are a number of objectives and the solutions, respectively; fmn and ϑ mn are the objectives value and membership function, respectively. The ωn is the weight rate of the nth objective.

6. Case studies and simulation

The two cases are considered in simulation modeling to verify the proposed approach based on numerical simulation. The cases are assumed as follows:

Case A) Coordination of the controllable loads with RERs output is not considered.

Case B) Coordination of the controllable loads with RERs output is considered.

The RERs such as PV WT and, also ESS are considered for each node (consumer). The random variables are generated by Monte Carlo simulation to model the wind speed and solar irradiance as well as load demand at day-ahead, which is provided in Table 1. The data of the RERs, ESS, and DGs are given in Table 2. The level of the demand shifting for each consumer is 25%. As well, we used four DGs with the same information and data.

6.1. Discussion and results

The outcomes analysis of the cases has been discussed in this section. In Case A, optimal coordination between controllable loads and RERs output is not taken into account. Hence, the first objective function (operation cost) in Case A is optimized.

In Case A, the total expenditure is $587,686.32, with 97.9% of this expenditure being assigned to DGs. The

Table 1. Demand, Solar irradiance, and wind speed at day-ahead

Hour	Electrical demand (kW)	Solar irradiance (kW/m^2)	Wind speed (m/s)
1	100.3	0	11.9
2	100.5	0	11.4
3	110.5	0	11.8
4	100	0	10.6
5	120.5	0	9.3
6	140.5	0.03	4.6
7	140.9	0.1	4
8	170	0.2	4.1
9	180.5	0.34	4.9
10	190.5	0.51	4.36
11	200.5	0.62	4.93
12	230.5	0.67	3
13	220.5	0.66	3.1
14	190.5	0.54	2.89
15	180	0.42	5.67
16	200	0.37	3.1
17	230	0.2	4.6
18	290.5	0.09	7.84
19	250.5	0.02	7.2
20	270	0	5.6
21	280.5	0	6.57
22	340	0	9.87
23	320	0	10.6
24	200	0	10.1

Table 2. Data of the RERs, ESS, and DGs

Parameters	Value	Unit
	PV data	
SPV	10	m^2
η PV	32	%
PN, PV	5	kW
	WT data	
VCi	1	m/s
VCo	12	m/s
VR	4	m/s
PN, WT	5	kW
	DGs data	
σ	95.2	k/kW^2
ω	30.2	$ kW
λ	240.2	$
Pmax	100	kW
MU	10	hour
MD	15	kW
RU	100	kW
RD	100	kW
PESS	ESS data	%
η ch	90	%
dis	95	$
ESSOP	90	8

power generation by DGs, RERs, and ESSs in case A is shown in Table 3. The table clearly demonstrates that the surplus power produced by the RERs during hours 1-4 and 7 is stored in ESS, resulting in an increase in the cost of charging and discharging the ESS. Additionally, the power discharged from the ESS during peak hours or hours 20-24 is scheduled accordingly.

Fig. 2 displays the non-dominated Pareto solutions and the operation of electrical generation in case B. Table 4 presents the Pareto solutions derived through the augmented ε-constraint method, with the optimal trade-off solution obtained by setting equal weights $\omega1 = \omega2 = 0.5$. The operation cost and RER penetration values in the chosen trade-off solution are $569, 324.2 and 45.1%, respectively. In Scenario B, the costs of DGs and ESS are $565, 384.1 and $3, 940.1, respectively. However, by aligning controllable loads with RER power output, the operational cost in case B is reduced by 3.12% compared to Scenario A, due to the absence of RER operational costs to meet demand. The reduction percentages in the costs of DGs and ESS in case B compared to case A are 1.73% and 68.1%, respectively.

Table 4 presents the power generation schedule in case B. In this table, the excess power from RERs in hours 1 and 2 is utilized to meet demand. The electrical demand during peak hours using LSM is shifted to hours 1-4, resulting in

Table 3. Energy scheduling in Case A

Hour	DG 1	DG 2	DG 3	DG 4	PW	ESS
1	0	0	0	0	180	-80
2	0	0	0	0	150	-50
3	0	0	0	0	160	-40
4	0	0	0	0	170	-60
5	18	0	1	0	100	0
6	50	0	2	0	80	0
7	10	30	40	0	75	-20
8	30	50	40	0	50	0
9	0	0	45	50	80	0
10	0	30	50	40	70	0
11	50	56	30	10	50	0
12	10	50	50	50	65	0
13	40	50	30	15	86	0
14	12	20	30	40	85	0
15	0	10	20	60	90	0
16	0	20	45	40	88	0
17	10	40	50	50	76	0
18	20	60	50	70	84	0
19	40	50	60	10	87	0
20	30	28	50	50	110	5
21	20	60	56	50	90	10
22	50	55	40	55	100	40
23	30	20	60	40	110	60
24	0	0	0	20	120	60

Table 4. Data of the RERs, ESS, and DGs

Hour	DG 1	DG 2	DG 3	DG 4	PW	ESS
1	0	0	0	0	180	0
2	0	0	0	0	150	0
3	0	0	0	0	160	-10
4	0	0	0	0	170	-20
5	18	0	1	0	100	1
6	50	0	3	0	80	2/5
7	10	30	40	0	75	-20
8	30	50	40	0	50	0
9	0	0	45	50	80	0
10	0	30	50	40	70	0
11	50	56	30	10	50	0
12	10	50	50	50	65	0
13	40	50	30	15	86	0
14	12	20	30	40	85	0
15	0	10	20	60	90	0
16	0	20	45	40	88	0
17	10	40	50	50	76	0
18	20	30	20	70	84	0
19	40	50	60	10	87	0
20	30	28	50	50	110	0
21	20	60	40	30	90	0
22	50	35	42	20	100	0
23	30	20	60	40	110	-30
24	0	0	0	20	120	60

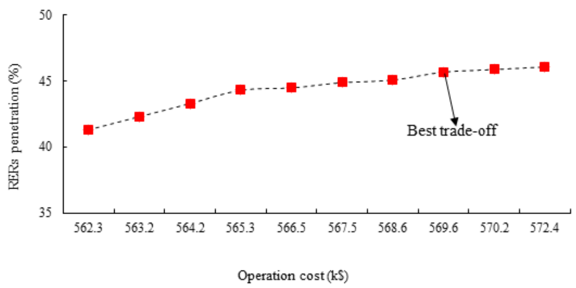

Fig. 2. Non-dominated Pareto solutions in Case B

an increased RER penetration. The RER penetration rates for cases A and B to meet demand are 40.3% and 45.1%, respectively.

6.2. Sensitivity analysis

To indicate the validation and superiority of the suggested energy optimization, the mentioned case studies are assessed by using a sensitivity analysis approach via increasing and reducing ESS capacity and increasing and reducing load demand. In Table 5, the results of the sensitivity analysis in the mentioned case studies are provided.

By comparing results of the Case B with Case A, participation of the LSM leads to lessening operation costs in the stand-alone smart buildings.

6.3. Comparative analysis of solution procedure

In this subsection, the proposed solution procedure for solving objective functions in Case B is compared with the genetic algorithm (GA). In Fig. 3, Convergence characteristics of the augmented ε-constraint procedure and GA in Case B are shown. In this figure, 10 iterations are considered for both methods. The augmented ε-constraint procedure shows better performance than GA.

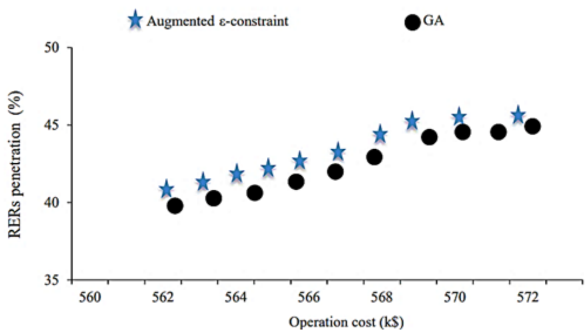

Fig. 3. Convergence characteristics of the augmented ε-constraint procedure in Case B

7. Conclusion

This article delves into the operation of independent intelligent buildings that utilize the Load Shift Management

Table 5. Sensitivity analysis

Case studies	Case A	Case B	
Sensitivity analysis / Objectives	Operation cost ($)	Operation cost ($)	RERs penetration (%)
15% increasing ESS capacity	586645.41	565332.41	43.55
15% decreasing ESS capacity	587853.84	570876.38	45.62
10% increasing demand	592532.13	571463.33	44.58
10% decreasing demand	580143.33	560433.54	46.66

(LSM) technique to efficiently coordinate controllable loads with renewable energy resources (RERs). The primary goal of this system is to reduce operational costs and increase the integration of RERs. In order to achieve this objective, a multi-criteria problem is defined with objective functions for the optimal operation of the system in day-ahead planning. Numerical simulation modeling is performed using fuzzy and augmented ε-constraint procedures. Two case studies are carried out to confirm the efficacy of the proposed approach. The outcomes of the case studies regarding the implementation of LSM are as follows:

Case A) Optimization without LSM. In this case, operation costs and power output of the RERs to meet demand are $587686.32 and %40.3, respectively.

Case B) Optimization with LSM. The RERs penetration rate and operation costs are %45.1 and $569324.2, respectively.

Based on the findings from the case studies, it can be inferred that the implementation of LSM effectively facilitates the efficient management of the demand side. This, in turn, ensures that the system achieves the desired state in terms of both economic and technical indicators.

nomenclature

Decision variables

μ_{ESS} Binary variable for ESS
$C^{ess}{}_{OP}$ ESS' Operation cost, $
$P^{dis}{}_{ESS}$ Discharge power of ESS, kW
P_d Power of DG, kW
P_{ESS} Power of ESS, kW
P_{PV} PV power, kW
P_{WT} WT power, kW
Pch $_{ESS}$ Charge power of ESS, kW

Index

cl,CL Controllable appliances index
d,D Diesel generators index
ESS Electrical storage system index
t,T Time index, Hour

Parameters

η^{ch}, η^{dis} Efficiency of discharge and charge states in ESS, %
η_{pv} PV Efficiency, %
σ, ω, λ DGs fuel cost, $\$/kW$
D_{CL}, D_{NCL} Load of the Controllable appliances and non-Controllable appliances, kW
M^D, M^U Minimum down and up times for DG, Hour
$P_{N,WT}$ WT power rate, kW
R^U, R^D Ramp up and down for DG, kW
S_{PV} PV area, m^2
si Irradiance of Solar, kW/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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