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RESEARCH ARTICLE

Cloud Energy Storage Investment by Collaboration of Microgrids for Profit and Reliability Enhancement Considering a TSO-DSO Yearly Reward

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ABSTRACT A shared pool of grid-scale storage resources called Cloud Energy Storage (CES) can bring substantial benefits to the economical and reliable operation of MGs. However, the investment cost of CES may not be affordable for a single microgrid (MG). As a solution, we propose an approach in which neighboring microgrids in a distribution network collaborate and form a multi-microgrid (multi-MG) to install a shared CES to increase their profit and improve their reliability. Different investment scenarios are evaluated by considering the yearly reward from TSO and DSO. For each of the investment scenarios, TSO and DSO give a yearly reward based on the contribution of CES in peak-shaving and distribution network operation yearly cost reduction. Afterward, a decision table is provided in which, for all investment scenarios, profit, reliability index based on expected energy not supplied (ENS), and TSO-DSO yearly reward are determined. Finally, the microgrids select one of the investment scenarios using a multi-attribute decision-making approach. Simulation results of a case study validate the effectiveness of the proposed collaborative decision-making framework in increasing the economic value of CES investment, reliability enhancement in multi-MG, and peak-shaving.

INDEX TERMS Microgrids, energy storage, decision making, cloud energy storage (CES) investment, distribution system, reliability.

NOMENCLATURE

INDICES

i, j	Bus indices.
k	MG index.
t	Time index.
h	Day index.
s	Probability index.

PARAMETERS AND VARIABLES

$P^{s}_{d,jth}$	Active Load power in jth bus at time t in day h (MW).
$P^{s}_{DG,jth}$	Generated power in jth at time t in day h (MW).

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$P^{s}_{bus,jth}$	Injected/exported active power in j[th] bus at time t in day h (MW).
$P^{s}_{up,jth}$	Injected /exported active power from (to) upstream grid in j[th] bus at time t in day h.
$Q^{s}_{bus,jth}$	Injected /exported reactive power in j[th] bus at time t in day h (MVar).
$Q^{s}_{d,jth}$	Reactive Load power in j[th] bus at time t in day h (MVar).
$C_{\mathrm{wt/pv/Bat,max}}$	Maximum number of installed wind turbines / PV panels/batteries.
I_{ref}	The reference to solar radiation ($1000\ \frac{W}{m^2}$).
I_{sol}	The solar radiation ($\frac{W}{m^2}$).
C_T	Temperature factor of PV panel ($1/{}^{\circ}C$).
T_{cell}	The cell temperature (${}^{\circ}C$).
T_{ref}	Reference of cell temperature ($25\ {}^{\circ}C$).
T_{env}	The temperature of the environment (${}^{\circ}C$).
NOCT	Typical cell temperature.
$p_{\mathrm{pv/WT}}$	The output power of each PV panel/wind turbine (MW).
$p_{n,pv/WT}$	PV/Wind turbine nominal power (MW).
$C_{\mathrm{pv/WT}}$	The number of PV panels/wind turbines.
W	Velocity of wind ($\frac{m}{s}$).
$W_{\mathrm{cut-in/cut-out}}$	Cut-in/cut-out speed ($\frac{m}{s}$).
W_{rated}	The speed based on rated power ($\frac{m}{s}$).
$V_j^{\mathrm{min/s/max}}$	Min/Probability/Max of voltage limitation of j[th] bus (v).
P_{Load}	Load demand power of distribution system (MW).
P_{gen}	Generated power by generators (MW).
$\eta_{\mathrm{bc/bd}}$	The efficiency of charging/ discharging.
E_B^{max}	Maximum energy capacity of CES (MWh).
E_B	The amount of battery's energy at time t (MWh).
$P_{B,k}^{\mathrm{max,min}}$	Rated power converter of CES in k[th] MG (MW).
CC_k	Capital cost of k[th] MG ($).
OC_k	Operation cost of k[th] MG ($).
CCP_B	Installation cost of energy capacity ($/MWh).
CCE_B	Installation cost of power converter ($/MW).
λ_{th}	Hourly cost of electricity j[th] bus at time t in day h.
$P_{k,th}$	Injected/exported active power by i[th] MG at time t in day h (MW).
r	Interest rate.
y	Life span (year).
IS_i	Investment scenario i[th].
$\gamma_{p\_DSO/TSO}$	Reward rate according to the peak demand reduction for DSO/TSO ($/KWh).
$RP_{DSO/TSO}$	Reward based on peak reduction for DSO/TSO ($).
$R_{D/T}$	Yearly reward from DSO/TSO ($).
P_i	Average of active power at load point i.
U_i	Ui is the unavailability of load point i.
λ_i	Line outage rate.
r_i	Average outage time of the load point i.

I. INTRODUCTION

A. MOTIVATION

Microgrids (MGs) are small-scale self-sufficient hybrid energy systems that supply loads via distributed energy resources and energy storage. The proliferation of MGs allows more integration of small-scale renewable energy sources (RESs) with a reliability improvement of the power system [7], [8]. Meanwhile, equipping MGs with distributed energy storage systems (DES) can help harvest most of these benefits. However, small-scale discrete energy storage systems cannot respond to high power and energy density. Moreover, the research studies in the literature are mainly focused on improving the uncertainty of renewable energy sources. Energy storage systems operation and management have recently sparked an immense debate. Because the installation of individual energy storage for each end-user needs a high investment cost [11]. Furthermore, overcoming the problem of supply-demand mismatching cannot be easily performed [13]. In addition, the control and maintenance of these discrete energy storage systems are challenging for all MGs' users due to their complexity and DES installation, which may not be affordable for end-users. According to these issues, the need for a Cloud Energy Storage System (CES) is highlighted. CES is a set of different energy storage systems that can provide MGs with energy at a relatively lower price. One of the critical differences between CES and DES is the high capital cost of an energy storage installation and its long investment payback period, which consumers are not inclined to build, so CES is one of the development directions of energy storage in the future to cope with [15]. Different types of energy storage systems with different investment costs and complementary features in a CES enable the CES to meet the demands of the MGs cost-effectively. Energy storage with high-power density, like a super-capacitor, can be applied to meet users' peak energy storage needs. Also, storage with a high-energy density, such as a flow battery, can provide the demand to shift vast amounts of energy [1]. MGs can be joined as a multi-MG to facilitate the CES investment.

Meanwhile, receiving proper support from TSO-DSO can increase the profitability of CES investment from the viewpoint of multi-MGs; also, the operation of the distribution system is improved. However, an appropriate collaborative decision-making mechanism is required to guarantee enough investment budget while maintaining a win-win game between the parties (MGs, DSO, and TSO).

B. LITERATURE REVIEW

In recent years, following the context of the energy transition, energy storage systems (ESS) are gaining increasing attention in smart energy systems all over the globe [2]. To enjoy more operational benefits brought by installing energy storage systems (ESS), some of the recent papers, such as [1], [3], [9], and [20], recommend sharing a framework for ESS. By installing shared ESS, investment costs, required space, and maintenance expenses can be reduced substantially. The sharing framework resolves the cost inefficiency of the individual framework through cost sharing and economies of scale. One of the effective shared ESS is cloud ESS. In the cloud, ESS users can utilize a flexible amount of capacity based on their needs from the storage system. Through this system, the users are enabled to make real-time decision-making for exchanging their power with cloud ESS. Thus, the unused capacity will be minimized, and demand management for all loads can be facilitated for the operator. Some of these benefits have been provided in an empirical analysis that has been performed in Germany and Australia [22]. References [3], [4], and [5] have proposed cloud-based energy storage technology. CES can be defined as a grid-based storage service that enables ubiquitous and on-demand access to a shared pool of grid-scale energy storage resources. CES has an updatable capacity according to the real-time information from end-users. Moreover, cloud storage technologies would make more beneficial use of the shared capacity and can decrease the user's electricity bill cost. The cost-effective architecture of CES, in which applying energy storage technologies with a different investment cost of capacity and energy density, can reduce the total investment cost. Moreover, the CES life span can be maximized by optimizing schedules and coordinating the control of the energy storage facilities, reducing cycling losses, battery space, and maintenance costs [1]. In a CES, all the individual residents can virtually reserve their demand for storing energy by buying power capacity (kW) and energy capacity (kWh) from related operators [3]. Furthermore, distributed generations (DG) can reserve CES capacity to improve reliability and energy storage costs [1], [6]. CES can be utilized in transmission and distribution systems to improve their reliability and even in MGs to provide more reliable and cost-effective power to their end-users [5], [10], [12], [24], [25], [26], [27]. The presence of RESs in MGs brings about uncertainties, and CES can resolve this complication [14]. It should be mentioned that CES could be utilized in various systems, such as ships, single buildings, or large-scale power systems [28]. In [16], in a case study in Germany, shared energy storage for four households was considered. CES has been installed in one of these buildings through the aggregation of extra storage capacities in individual flats, and the results showed the economic benefit of CES. In [17], mathematical models are proposed to investigate optimized planning for shared energy storage in power grids. Moreover, in [18], a planning method for CES is provided based on the charging and discharging load model of five types of distributed energy storage systems. Shared energy storage also can participate in markets for exchanges where in [29], a multi-agent shared energy storage transaction model, aiming at the lack of effective ways for distributed energy to take part in the electricity market and direct transactions with users, is provided. Likewise, a planning framework for CES as a useful resource in the imbalanced band market environment, which is an alternative to traditional market structures, has been proposed in [20] to ensure that system frequency remains within acceptable bounds. Additionally, a dynamic shared energy storage lease model has been developed in [29] to decrease a microgrid's shared energy storage capacity as much as possible. Accordingly, a two-level optimization model of shared energy storage capacity based on multi-energy unit output was introduced. The model maximizes the benefit of shared energy storage and minimizes the total operating cost. One of the most important advantages of multi-MG is functioning collaboratively. In [23], a hybrid energy storage system is introduced, which contains an electrical battery and a heat storage tank. The multiple microgrids can share energy through the hybrid energy storage system collaboratively. An energy optimization problem is formulated to minimize overall energy costs, including energy purchase and hybrid energy storage system operating costs. For households, electricity demand is different due to changes in the balance between supply and demand at certain times. DR can optimize energy consumption to decrease energy costs and limit the influence of infrastructure networks [30]; shared energy storage has been used for the household to reduce energy prices and support low voltage distribution networks to reduce distribution system investment. In [31], shared energy storage has been used among houses to increase the penetration of photovoltaics and to achieve two goals- minimizing energy costs for customers and releasing distribution network constraints for DNOs.

In [32], the superiority of Lithium-ion-Batteries (LiBs) and the Vanadium Redox Flow Battery (VRFB) technologies have been proved for both CES ownership scenarios (individual ownership and shared ownership between DSO and aggregator). Also, [4] and [33] confirms this result by comparing the performance of Li-ion batteries, lead-acid batteries, nickel-cadmium batteries, sodium-sulfur, and redox flow batteries for CES architecture. To attract all benefits from CES investment, like any ESS, proper subsidy policies and investment decision-making mechanism is a must and can be ensured for the investment value of the microgrid and reduce the initial cost of such a capital-intensive component as reported in [34]. Various energy storage subsidy policies for both businesses and consumers are developed throughout

TABLE 1. Taxonomy table (included: ✓ not included: –).

Ref.	Storage in … network		Profit enhancement	Collaborative	TSO and DSO collaboration	Operation (O)/ Planning (P)	Distribution system constraints	Reliability evaluation and enhancement	A supportive mechanism for CES investment
	Distribution system	Microgrid							
[1]	✓	-	✓	-	-	O	-	-	-
[2]	✓	-	✓	-	-	O	-	-	-
[3]	-	✓	✓	-	-	O	-	-	-
[4]	-	✓	✓	-	-	O	-	-	-
[5]	✓	-	✓	-	-	O & P	-	✓	-
[6]	✓	-	✓	-	-	O	-	✓	-
[8, 9]	-	✓	✓	-	-	O	-	-	-
[10]	✓	-	✓	-	-	O & P	✓	✓	-
[12]	-	✓	-	-	-	O	-	✓	-
[14]	-	✓	✓	-	-	O	-	-	-
[16]	✓	-	✓	-	-	O	-	-	-
[17]	✓	-	✓	-	-	O & P	-	-	-
[18]	✓	-	✓	-	-	O	-	-	-
[19]	-	✓	✓	-	-	O & P	-	-	-
[21]	✓	-	✓	✓	DSO	O	-	-	-
[23]	-	Multi-Microgrid	✓	-	-	O	-	-	-
This paper	✓	Multi-Microgrid	✓	✓	✓	O & P	✓	✓	✓

the globe. For instance, in the US, at the federal level, a bill under investigation through the Energy Storage Association would extend eligibility for an investment cost of energy storage [35]. As another example of this policy, budget allocation in Germany for houses can be a real-world example of this policy to support the investment cost of battery storage [36].

C. CONTRIBUTION, HIGHLIGHTS, AND ORGANIZATIONS

Despite the benefits, CES brings to MG operation, the main challenge in front of CES investment is its high capital cost. Among all of the papers which have been devoted to CES, none of them has considered this matter and provided a practical plan for the MGs to tackle the high investment cost of CES. As a contribution to the existing literature, this paper proposes a novel CES planning framework to make the investment of CES more affordable and feasible for MGs. A shared ownership investment framework for the MGs is proposed in this paper. Also, based on the benefits brought by the CES for the DSO and TSO, a yearly reward is included in the proposed investment mechanism to increase the economic viability of the CES planning. Moreover, non of the existing literature considered the impact of CES on reliability. in some of the previous investment studies of conventional energy storage, reliability is considered in the proposed optimization models as an objective function [37], or a constraint [38]. However, to the best of our knowledge, none of the previous works has been devoted to considering reliability in CES studied. For the first time, we have developed a novel decision-making framework to tackle the high investment cost of CES, in which ENS (as a reliability index) is considered. The proposed methodology of this paper is designed to consider both profit and reliability in the collaborative CES investment of MGs. To this end, we considered distribution network topology in our model. In summary, the novel contributions of the proposed CES planning scheme are as follows:

- Proposing a CES planning method considering the collaboration of MGs and receiving yearly rewards from TSO and DSO to tackle the high investment cost of CES.
- Considering reliability as a decision-making criterion of MGs in CES planning for the first time.

Involving all affected actors (MGs, DSO, and TSO) in the investment decision-making procedure.

To show the novelty of this paper and the research gaps that have been filled, a taxonomy table has been provided in Table 1. Numerous studies conducted in the area of CES have been reviewed, and their features have been compared with our work. As has been shown that various networks have been considered for installing shared energy storage. It is evident that most of them have worked on traditional distribution systems, and one of the papers has considered multi-MG as their network to install CES like our study. Moreover, the increase in profit has been one of the common goals among previous works and our study.

Different levels of the power system, such as the distribution and transmission systems, can collaborate to fulfill their needs. As can be seen from Table 1, just the model in one of mentioned works, i.e. [21], has provided a collaborative framework among CES investors and DSO. The ability to capture energy at one time for use later, which CES can save

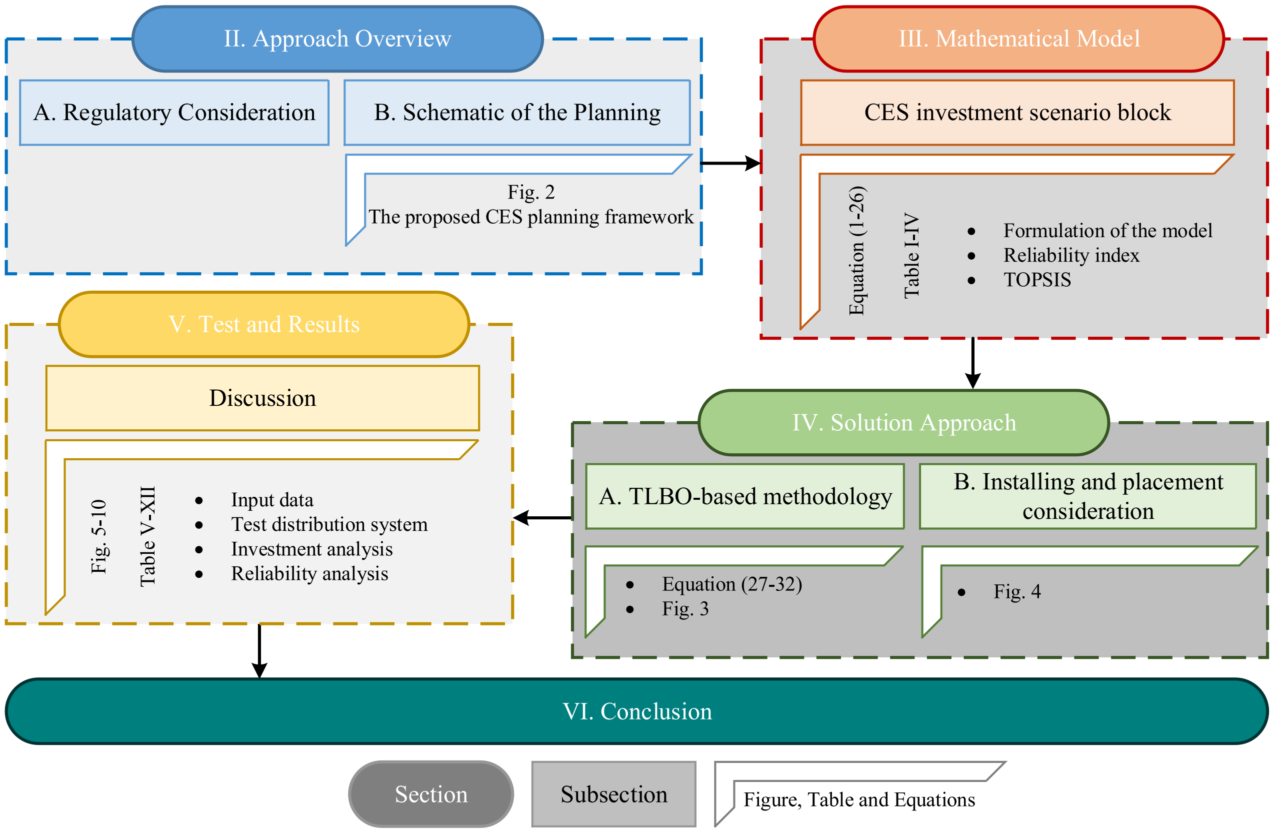

FIGURE 1. **Paper structure and affinities.**

energy in many forms (e.g., chemical, kinetic, or thermal) and convert them back to useful forms of energy like electricity. Apart from this, CES's importance and attractiveness as an integral part of the electrical supply, transmission, and distribution systems are receiving increasing attention from a wide range of stakeholders, including utilities, end-users, and grid system operators, planning is an indispensable aspect of the investigation of CES. Planning is a feature that has been common among a few previous studies and our work. As mentioned in none of the earlier works, the CES optimization models among microgrids have been considered. Just in [10], CES has been considered a distribution system. Reliability is considered to be one of the most important indexes in the power system, which is studied papers a few numbers of them have had this index in their model, like our work. The most important issue about CES is its high capital cost, for which previous studies have not provided a practical method to be implemented. Providing a supportive mechanism for CES investment has been the most important contribution of this study, which has been shown in Table 1.

The remainder of the current paper is organized as follows (Fig. 1). After presenting the introduction in the first section, Section II introduces the regulatory considerations and the proposed schematic of the CES planning framework. Afterward, in section III, the formulation of the mathematical model is presented. After that, the solution approach is presented in section IV. In section V case study, test, and its result are discussed. Finally, in section VI, the conclusion of this study will be expressed.

II. APPROACH OVERVIEW

A. REGULATORY CONSIDERATION

In this sub-section, we show that the regulatory consideration of this paper is adapted to reality. To this end, we bring real-world evidence to support our assumptions. This paper considers a yearly reward mechanism for supporting the CES project. As mentioned in [39], even a prosumer inside an energy community can increase its profit by providing ancillary services for DSO and TSO. Hence, it is normal that we assume that a grid-scale CES project can receive a yearly reward. Moreover, establishing such a mechanism is adapted to what is done in many countries because energy storage technologies are still cost-inefficient [34]. As an example, we can refer to the compensation mechanism for energy storage proposed by the Guidelines on Energy Storage Technology and Industry Development announced by the National Development and Reform Commission (NDRC) of China in 2017. Also, in Zhejiang province, China, a model to guide ESS subsidy policies for microgrids has been applied, and its importance has been illustrated [34]. In this work, microgrids are connected to the distribution system, and they can interact with it. Apart from this, because of the impact that power supply in microgrids can have impacts on TSO through received power from DSO. So TSO even

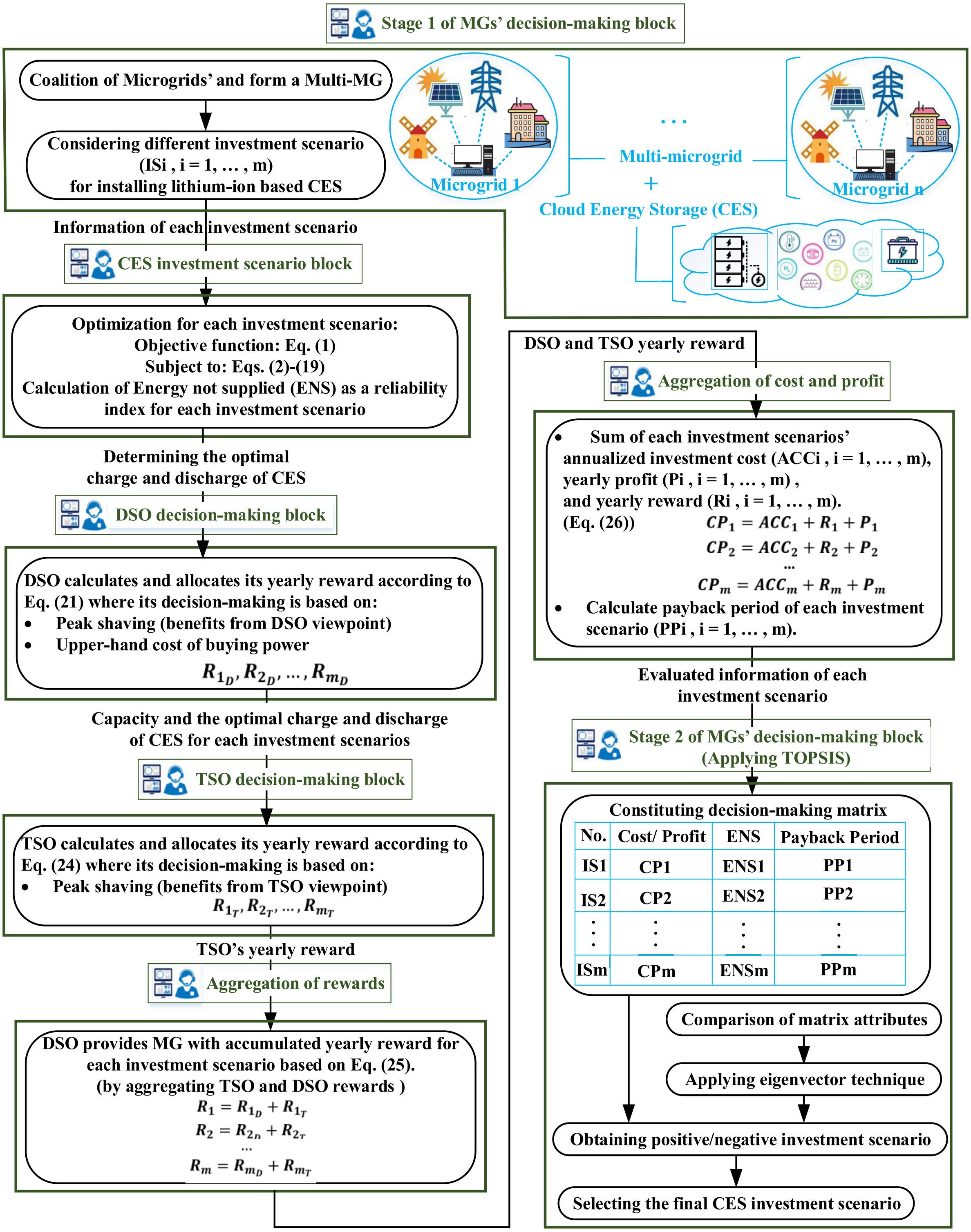

FIGURE 2. The proposed CES planning framework.

will give subsidies to MGs. As a case study, [40] reports assigning subsidies to an energy storage project in China with a 5 MWh lithium and a 20 MWh lead-acid energy storage system. In our study, peak shaving and annual electricity cost reduction have been considered factors for allocating the budget to the CES investment. This policy consideration is also adapted to support mechanisms in the real world. For instance, increasing the system's flexibility and the stability of the network is considered a goal of Spain's government to support energy storage [41]. Another example of real-world supporting battery storage can be referred to [36], where a case study has been introduced in Germany.

The collaboration of MGs, DSO, and TSO for CES investment has been considered in our study. The collaboration of MGs led to the creation of a multi-MG, which is designed to facilitate CES investment despite its high investment cost. MGs-DSO collaborative decision-making is what has been rooted in previous credible literature such as [42], where DSO and MGs collaborate on making operational decisions to utilize more potential benefits of MGs in improving local electricity services or in another study in which a collaborative framework is introduced among DSO, users, and a manager to use energy efficiently [21].

B. SCHEMATIC OF THE CES PLANNING

The proposed planning framework for CES investment is shown in Fig. 2, in which a bottom-up collaborative interaction between multi-MG, DSO, and TSO is designed. As shown in this figure, TSO-DSO supporting mechanism is also included to enhance the economic viability of CES planning. In the first stage, a multi-MG is formed by a coalition of MGs to support the high investment of CES. The multi-microgrid controls the CES, which uses these CES technologies to fulfill load demands optimally.

In the next step, MGs consider different CES investment scenarios ($IS_i, \forall i = 1, \ldots, m$) with different capacities. The CES investment cost includes batteries, inverters, cables, and communication modules. The investment cost of each scenario is obtained by a coalition of all MGs. After the investment, based on the budget a MG devoted to CES investment, it can book its required capacity from the CES. It is noted that MGs choose the CES facility based on lithium-ion battery technology, which is the most cost-effective battery due to investigations in [4] and 32. Due to the privacy of information, MGs do not have access to the distribution system's technical data. Hence, traditional planning models (such as what has been done in [43]) in which the investment and operation costs are minimized subject to a set of technical constraints are not applicable here. In this regard, MGs choose a set of feasible CES investment scenarios ($IS_i, \forall i = 1, \ldots, m$). Afterward, for each of the investment scenarios, the optimization model (1)-(22) of section III is solved by DSO to obtain the best state of charge and discharge of CES over a year (CES investment scenario block of Fig. 2). Using the optimal solution of each investment scenario, the profit of each investment scenario is obtained. Also, the reliability of each investment scenario is analyzed based on the energy not supplied (ENS) index as one of the main criteria for the decision-making of MGs. Following the CES investment scenario block, DSO assesses each scenario based on peak shaving and the impact on the total cost reduction of the distribution system and assigns yearly rewards (R_{i_D}) to each of the CES investment scenarios according to equation (39).

Meanwhile, DSO shares the information on capacity and optimal charge and discharge of each investment scenario with TSO. Turning to the TSO decision-making block, as shown in Fig. 2, TSO evaluates each scenario based on its contribution to peak-shaving and allocates the yearly reward (R_{i_T}) based on equation (42). Eventually, the annual rewards from TSO and DSO assigned to each CES investment scenario are accumulated in the aggregation of the rewards block according to equation (43). Then, the aggregated yearly reward is communicated to MGs. In this step, MGs calculate annualized investment cost (ACC) from the total cost of installation for each scenario according to equations (20) and (21). Also, the payback period (PP) is calculated using engineering economics relevant equations, as shown in section III.

Finally, the yearly profit of each CES scenario is calculated. Also, these cost-oriented terms are used to analyze the cost ($CP_i, \forall i = 1, \ldots, m$) of each investment scenario (Aggregation of Cost and Profit Block in Fig. 2).

In stage 2 of the MGs' decision-making block, MGs use all this information to choose the most preferred investment scenario by applying the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). To this end, a decision-making matrix consisting of each investment scenario's technical and economic benefits is constituted. The details about the application of TOPSIS are referred to relevant multi-attribute decision-making studies such as [44].

Moreover, the communication module of the CES enables the exchange of information among the microgrids, TSO, and DSO. Microgrids should be able to access the CES consumer interface using apps online wirelessly to set their charging and discharging schedules [1]. So it can help reduce the demand for the installation of extra cables. Just some cables are needed for the transmission of energy .focus of this paper is to provide a mechanism to support the investment cost of CES. Microgrids themselves decide about the expenses and whether they like to participate or not. This decision is made based on a decision-making matrix.

III. MATHEMATICAL MODEL: CES INVESTMENT SCENARIO BLOCK

In this sector, the CES operation model and grid-based formulations and their constraints have been presented. The objective function of the proposed model contains the operation cost of CES:

$$\text{Min } Total\ Cost = OC \tag{1}$$

$$\text{Subject to: } P^s_{up,jth} + P^s_{d,jth} + P^s_{DG,jth} + P_{B,jth} = \sum_{i=1}^{bnj} V^s_{jth} V^s_{ith} Y^s_{ij} cos(\theta_j - \delta^s_{ith} - \delta^s_{jth}) \tag{2}$$

$$Q^s_{up,jth} - Q^s_{d,jth} = -\sum_{i=1}^{bnj} V^s_{jth} V^s_{ith} Y^s_{ij} sin(\theta_j - \delta^s_{ith} - \delta^s_{jth}) \tag{3}$$

$$V_j^{min} \leq V^s_{jth} \leq V_j^{max} \quad j \in \{1, 2, \ldots, bn\} \tag{4}$$

$$I_l^{min} \leq I^s_{lth} \leq I_l^{max} \quad l \in \{1, 2, \ldots, ln\} \tag{5}$$

$$P_j^{min} \leq P^s_{up,jth} \leq P_j^{max} \quad j \in \{1, 2, \ldots, bn\} \tag{6}$$

$$Q_j^{min} \leq Q_{up,jth}^{s} \leq Q_j^{max} \quad j \in \{1, 2, \ldots, bn\} \tag{7}$$

$$(V)_{jth})^2 (I_{ljth}^{s})^2 = (P_{ijth}^{s})^2 + (Q_{ijth}^{s})^2$$
$$j \in \{1, 2, \ldots, bn\} \tag{8}$$

$$E_B(t) = E_B(t-1) + \sum\nolimits_{k=1}^{g} (P_{B,k}) .\eta_{bc}$$
$$k \in \{1, 2, \ldots, g\} \tag{9}$$

$$E_B(t) = E_B(t-1) + \sum\nolimits_{k=1}^{g} (\frac{P_{B,k}}{\eta_{db}})$$
$$k \in \{1, 2, \ldots, g\} \tag{10}$$

$$P_{B,min} \leq P_{B,i}(t) \leq P_{B,max} \tag{11}$$

$$P_{B,\mathrm{k},24h} \leq P_{B,0} \tag{12}$$

$$p_{pv}(t) = p_{n,pv} \cdot \left(\frac{I_{sol}}{I_{ref}}\right) . \left[1 + C_T \left(T_{cell} + T_{ref}\right)\right] \tag{13}$$

$$T_{cell} = T_{env} + \left(\frac{I_{sol} . (NOCT - T_{Amb})}{si}\right) \tag{14}$$

$$P_{pv}(t) = p_{pv}(t) .C_{pv} \tag{15}$$

$$\begin{cases} p_{WT}(t) = 0 \\ \qquad V(t) < V_{cut-in} \\ p_{WT}(t) = C_1 . V^3(t) - C_2 p_{n,WT} \\ \qquad W_{cut-in} \leq W(t) < W_{rated} \\ p_{WT}(t) = p_{n,WT} \\ \qquad W_{rated} \leq W(t) < W_{cut-out} \\ p_{WT}(t) = 0 \\ \qquad W(t) \geq W_{cut-out} \end{cases} \tag{16}$$

$$C_1 = \frac{p_{n,WT}}{(V_{rated}^3 - V_{cut-in}^3)} \tag{17}$$

$$C_2 = \frac{V_{cut-in}^3}{(V_{rated}^3 - V_{cut-in}^3)} \tag{18}$$

$$P_{WT}(t) = p_{WT}(t) .C_{wt} \tag{19}$$

$$CC = (\sum\nolimits_{k=1}^{g} CCP_B P_{B,k}^{max}) + CCE_B E_B^{max}$$
$$k \in \{1, 2, \ldots, g\} \tag{20}$$

$$ACC = \frac{r}{1 - (r+1)^{-y}} .\mathrm{CC} \tag{21}$$

where:

$$OC = \sum\nolimits_{s=1}^{ns} \rho_s . (\sum\nolimits_{k=1}^{m} \sum\nolimits_{t=1}^{T} \sum\nolimits_{h=1}^{H} (\lambda_{th} . P_{k,th}))$$
$$k \in \{1, 2, \ldots, g\}, \quad s \in \{1, 2, \ldots, n\},$$
$$h \in \{1, 2, \ldots, H\}, \quad t \in \{1, 2, \ldots, T\} \tag{22}$$

Equation (1) as the objective function includes the operation cost of the CES device. In each power system, active and reactive loads should be supplied through the active and reactive powers generated by different resources at each time. This constraint is considered a power flow constraint in equations (2) and (3). Moreover, the voltage constraint and the injected power are regarded as equations (4)-(8).

The state of charge and state of discharge of CES at the time t, which depends on the amount of remained energy of CES from the time t-1, is calculated by the equation (9) and (10) where, η_{bc} and η_{db} are charging and discharging efficiency, respectively. In equation (11) where the amount of charge and discharge limitation, in other words, the capacity of the converter is determined by multi-MG managers [45]. Equation (12) provides us with information about the rest of the power in the CES at the last hour of the day.

The output power of each photovoltaic panel is considered by equation (13) which, here $p_{pv}(t)$ and $p_{n,pv}$ are as the output power of each PV panel and the PV nominal power, and also, I_{sol}, I_{ref}, C_T, $T_{cell}(-3.7 \times 10^3 1/{}^\circ C)$ and T_{ref} are the solar radiation, the reference of solar radiation, the temperature factor of the PV panel, the cell temperature, and the reference of cell temperature in the given order.

In equation (13), the cell temperature is calculated by equation (14), where T_{env}, NOCT, si (800 mW/cm2), I_{Amb} are the environment, typical cell temperatures, solar irradiance, and ambient temperature. Finally, the whole output power of the PV panels at the time t is calculated through the number of PV panels numbers (C_{pv}) by equation (15).

Due to the variations in the quantity of wind speed quantity, the wind turbine output power can be changeable. The power generated by wind energy is calculated by equation (16) [45]. In equation (16), P_{WT} is the output power of each wind turbine. Moreover, $V(t)$, V_{cut-in}, $V_{cut-out}$ and V_{rated} are the velocities of wind at the moment t, cut-in speed, cut-out speed, and the speed based on rated power. Equations related to C_1 and C_2 are described by (17) and (18). Equation (19) calculates the total power generated by wind turbines. In this equation, C_{wt} is the total number of wind turbines.

Also, in equation (20), the total investment cost (CC), including the power capacity and energy storage capacity of CES, is described. Note that in this study, $\frac{r}{1-(r+1)^{-y}}$ in equation (21) is a coefficient to convert the present value into annualized value, which is used to calculate annual investment cost (ACC). In equation (22), the operation cost of CES at time t, on day h is represented, where λ_{th} is the price of electricity and $P_{k,th}$ is exchanged power to CES. This equation is calculated for each uncertainty scenario (ρ_s). It should be mentioned that this procedure is applied to each investment scenario of CES.

Another criterion for choosing the best capacity is reliability. The distribution system reliability improvement or decrease of users' ENS is described regarding the load point and its energy consumption. The power in some load points might be cut off because of a line outage. So, according to the probability of the network topology line outage, the power lost by network customers is defined as ENS, which aims to reduce this index and improve network reliability. Power system reliability is an important criterion in the long-term planning for system capacity expansion in the future to

TABLE 2. Matrix of normalized attributes.

CES capacity (MWh)	Cost / profit	Sum of ENS (MWh)	Payback period (year)
4	Y_{11}	Y_{11}	Y_{11}
6	Y_{12}	Y_{12}	Y_{12}
7	Y_{13}	Y_{13}	Y_{13}
8	Y_{14}	Y_{14}	Y_{14}
12	Y_{15}	Y_{15}	Y_{15}
20	Y_{16}	Y_{16}	Y_{16}

TABLE 3. Decision-making matrix by the attributes' weights.

CES capacity (MWh)	Cost / profit	Sum of ENS (MWh)	Payback period (year)
4	V_{ij}	V_{ij}	V_{ij}
6	V_{ij}	V_{ij}	V_{ij}
7	V_{ij}	V_{ij}	V_{ij}
8	V_{ij}	V_{ij}	V_{ij}
12	V_{ij}	V_{ij}	V_{ij}
20	V_{ij}	V_{ij}	V_{ij}

ensure that the total capacity is adequate for consumption. The planning procedure uses reliability indexes as criteria to determine the new investments. Reliability is evaluated by employing various indices. In this paper, ENS is simulated to assess the system's reliability which is defined below [46]:

$$\mathrm{ENS} = \sum_{\mathrm{i}=1}^{\mathrm{nl}} \mathrm{P_i.U_i} \tag{23}$$

$$U_i = \lambda_i.r_i \tag{24}$$

where *nl* is the load point, Pi is the average of active power at load point *i*, λ_i represents the line outage rate, *Ui* is the unavailability of load point *i*, and ri indicates the average outage time of the load point *i*. The decision matrix attributes are cost, payback period, and ENS for each investment scenario. The decision-making matrix should be normalized to have a matrix with a standard scale. This is done by equation (25) as below:

$$Y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{IS} x_{ij}^2}} \tag{25}$$

where Y_{ij} is each normalized attribute for each investment scenario, x_{ij} is the attribute of each investment scenario, and also IS is the number of scenarios. The matrix can be like Table 2.

In our work, criteria have been attributes which are the cost of investment, ENS, and payback period in this step; their weights are determined by using the eigenvector technique from the matrix of attributes, and a matrix like Table 2 is created here *Y* is a normalized attribute of each investment scenario. The next stage is calculating the positive/negative ideal scenarios. These weights (W) are multiplied by each related column (Y) by the following equation:

$$V_{ij} = W_{ij}.Y_{ij} \tag{26}$$

According to this equation, a new matrix is created, which is shown in Table 3. Throughout the next stage, the best ideal

TABLE 4. Effective scenarios' table.

CES capacity (MWh)	SS_j^+t	SS_j^-
4	S^+	S^-
6	S^+	S^-
7	S^+	S^-
8	S^+	S^-
12	S^+	S^-
20	S^+	S^-

scenario (V_j^+) and the worst ideal scenario (V_j^-), which are the highest and lowest numbers in each column, respectively, are obtained from the V matrix in Table 3 according to their value.

Thence The next step is calculating the distance from each best ideal scenario (V_j^+) and the worst ideal scenario (V_j^-) by the following equations:

$$SS_j^+ = \left[\sum_{j=1}^{f} V_{ij} - V_j^+\right]^{0.5} \tag{27}$$

$$SS_j^- = \left[\sum_{j=1}^{f} V_{ij} - V_j^-\right]^{0.5} \tag{28}$$

where j is the number of attributes. A matrix can be formed as shown in Table 4. In the next step, the similarity index is calculated.

$$P_{ij} = \frac{S_i^-}{S_i^- + S_i^+} \tag{29}$$

In the final step, the best investment scenario is calculated. The scenario whose p is near 1 is considered to be the best scenario.

IV. SOLUTION APPROACH

The proposed model (equations (1)-(22)) is non-linear and non-convex. In this section, we proposed two methods for solving this problem. Subsection IV-A presents a convexification approach for the model and Subsection IV-B presents an evolutionary-based approach using the Teaching-Learning-Based Optimization algorithm (TLBO). Finally, a few installation and placement considerations are brought in Subsection IV-C.

A. CONVEXIFICATION APPROACH

In the proposed model (equations (2)-(22)), the objective function (equation (1)) is linear, a few constraints (equations (9)-(22)) are linear and the other constraints (equations (2)-(8)) are non-linear. Moreover, there are a few binary variables in the model which makes the optimization problem a nonconvex mixed-integer nonlinear programming (MINLP) problem. We inspire by the convexification approach of [47]. The active and reactive power balances on each system bus are ensured by these constraints, which can be expressed as equations (30) and (31). These equations have

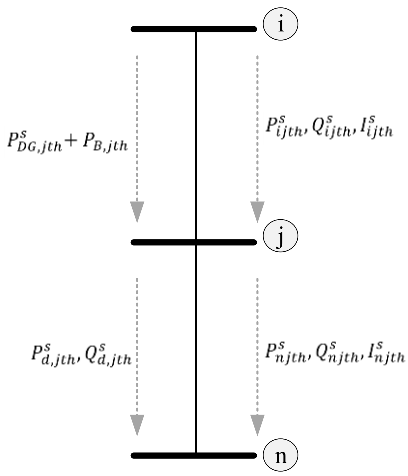

FIGURE 3. Illustration of a radial distribution network.

been described the Kirchhoff's current law (KCL) as shown in Fig. 3.

$$\sum_l [P^s_{ijth} - R_{ij}(I^s_{ijth})^2] - \sum_l \left[P^s_{njth}\right] + P^s_{DG,jth} - P_{B,jth} = P^s_{d,jth} \tag{30}$$

$$\sum_l [Q^s_{ijth} - X_{ij}(I^s_{ijth})^2] - \sum_l \left[Q^s_{njth}\right] = Q^s_{d,jth} \tag{31}$$

The non-linear and quadratic variables in these equations turn the problem into a non-convex and non-linear one. The following new variables are defined as the initial step in linearizing these constraints

$$f^s_{ijth} = (I^s_{ijth})^2 \tag{32}$$

$$u_{jth} = (V_{jth})^2 \tag{33}$$

Constraints (2)–(8) are rewritten using these new-defined variables, respectively:

$$\sum_l [P^s_{ijth} - R_{ij} f^s_{ijth}] - \sum_l \left[P^s_{njth}\right] + P^s_{DG,jth} - P_{B,jth} = P^s_{d,jth} \tag{34}$$

$$\sum_l [Q^s_{ijth} - X_{ij} f^s_{ijth}] - \sum_l \left[Q^s_{njth}\right] = Q^s_{d,jth} \tag{35}$$

$$(V_j^{min})^2 \le u_{jth} \le (V_j^{max})^2 \quad j \in \{1, 2, \ldots, bn\} \tag{36}$$

$$(I_l^{min})^2 \le f^s_{ijth} \le (I_l^{max})^2 \quad l \in \{1, 2, \ldots, ln\} \tag{37}$$

$$u_{jth}.f^s_{ijth} = (P^s_{ijth})^2 + (Q^s_{ijth})^2 \quad j \in \{1, 2, \ldots, bn\} \tag{38}$$

As can be seen, constraints (2) and (8) are linearized by providing additional variables. The only nonlinear constraint remaining at this point is (38), which causes the microgrid optimum scheduling problem to be a nonconvex MINLP problem. It is possible to achieve convexity by relaxing the equality constraint (38) in the following ways:

$$u_{jth}.f^s_{ijth} \ge (P^s_{ijth})^2 + (Q^s_{ijth})^2 \quad j \in \{1, 2, \ldots, bn\} \tag{39}$$

It should be noted that this relaxation had no effect on the optimal solution obtained. In other words, the best answer to the microgrid scheduling problem will be the same when both the equality requirement (38) and the inequality constraint (39) are taken into consideration. This is because reducing the objective function also minimizes the magnitude of the current flow in distribution lines ($f^L_{mn,t}$), which includes the cost of energy losses. The mathematical model can be made more tractable by using the relaxation mentioned. As can be observed, the model changed into a convex non-linear problem when (39) was expressed as the second-order conic constraint.

B. EVOLUTIONARY-BASED TLBO APPROACH

In this section, we introduce the methodologies that are applied to solve the optimization model of the CES investment scenario block of Fig. 2 (equations (1)-(22)) and the multi-attribute decision-making tool (TOPSIS) that has been used in Stage 2 of MGs' decision-making block of Fig. 2. Since the mathematical model of the proposed method (equations (1)-(22)) is non-linear and non-convex for which classic approaches can not be applied, and a proper solution approach based on evolutionary algorithms can be adopted. For this purpose, the TLBO has been used and adapted as the optimization tool for solving the mathematical model of Section III. Since the CES is shared storage among MGs, there should be a time horizon for financial clearance between the MGs. It is assumed that this horizon is for 24 hours. Hence, in Fig. 4, the optimization of equations (1)-(22)) has been solved daily for over a year. The CES state of the charge at the end of each day is calculated and considered as the initial state of the charge of the next day. Since TLBO is a type of population-based algorithm, the optimization has been run several times each day to ensure a near-optimal solution. It is worth mentioning that other evolutionary algorithms, such as GA and PSO, can be applied instead of TLBO. TLBO is based on a teacher's influence on students' results in a class [48]. In the proposed optimization model (equations (1)-(22)), because of considering power flow-related constraints, the problem is nonlinear and nonconvex. In such problems in the area of power systems [49], Heuristic algorithms are promising approaches for finding the optimal solution. Hence, we decided to use a heuristic algorithm in our study. We agree with the esteemed reviewer that GA, PSO, and other heuristic algorithms can be used to solve such problems. However, the main merit of TLBO method is working without a lot of parameters of the algorithm for its operation except for the population size and maximum iteration, moreover, the algorithm can be easily implemented and needs less memory when compared with algorithms like GA, PSO, ACO see [50] and [51]. In this algorithm, the input variable contains an n × 24 matrix, which figures the optimal operation of CES.

As it is shown in Fig. 1, stage 2 of the MG decision-making block is TOPSIS, which is used to determine the best investment scenario. To constitute the decision matrix, three attributes have been considered: cost, payback period, and ENS for each investment scenario. These attributes have

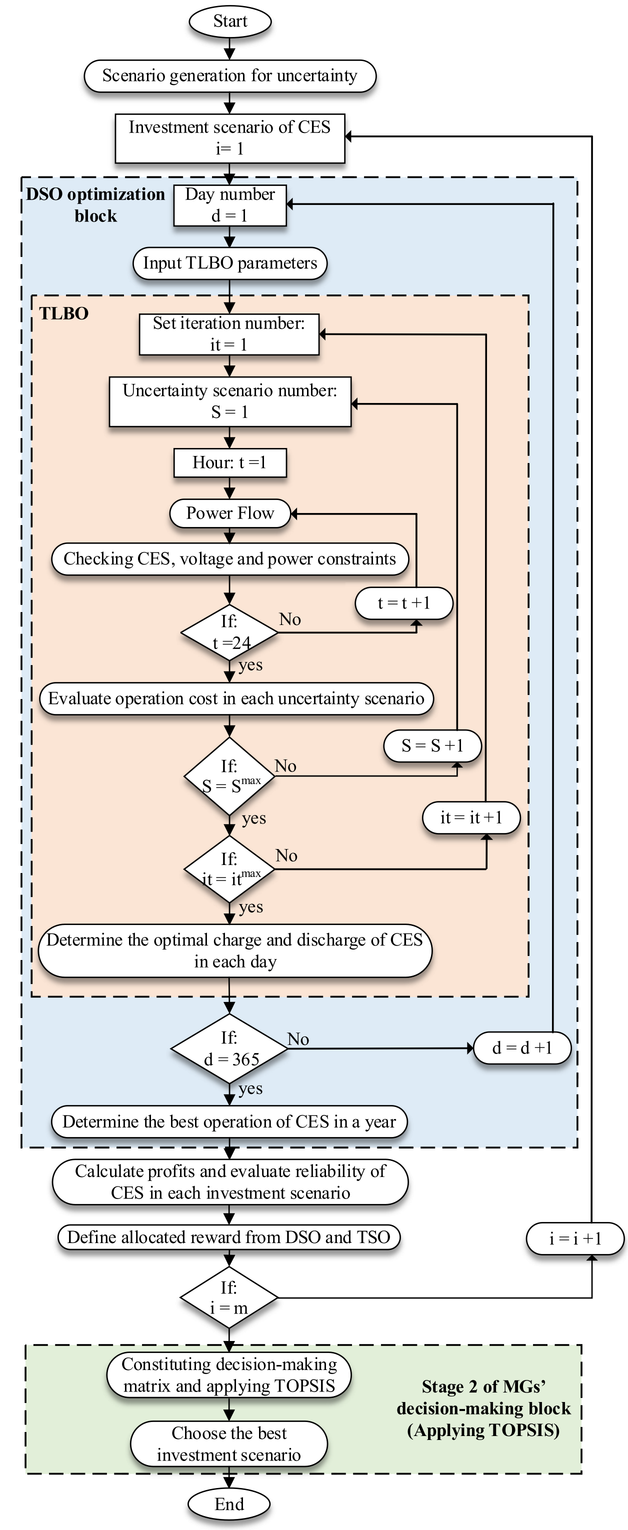

FIGURE 4. Solution approach.

different values for decision-makers, and their values are determined according to the comparison matrix of attributes using the ''eigenvector technique'' [44]. As can be seen at the end of the flowchart in Fig. 4, TOPSIS is applied to the results of the simulation to find the best solution.

As it is shown in Fig. 2 in the CES investment scenario block, DSO receives information on each investment scenario and MG's load data, which is explained in the optimization block (blue color) in Fig. 4.

This study considers the uncertainty of input variables, wind speed, solar irradiance, and load demand. These variables are modeled by the Weibull, Beta, and Normal distribution functions, respectively. This study considers the uncertainty of input variables, wind speed, solar irradiance, and load demand. Load uncertainty could simply be given by variance and mean. These parameters are the key to constructing any load probability density functions probabilistic load flow, and state estimation programs can apply. Current practice in statistical loading analysis adopts a Normal distribution function [52]. There are some approaches to predicting Weibull parameters, but there are many different approaches to be used, and here, the wind speed dissemination has been modeled by employing the Weibull probability distribution function, which is a two-parameter function commonly used to predict the wind speed frequency distribution. Reference [53] We have used a beta distribution approach for modeling global solar radiation. The beta distribution provides a robust, flexible modeling approach for predicting global solar radiation that allows for the addition and removal of independent variables as appropriate and can be interpreted using standard inferential statistics [54].

Monte Carlo simulation has been used to generate samples by the mentioned probability distribution functions. This large number of samples causes the problem to be excessively complex and complicated. In our study, the fast-forward algorithm was utilized to decrease the number of scenarios, and scenarios were reduced to S. A scenario set that properly represents the uncertainty involved in a decision-making problem, which is obtained by running a random scenario generation process, is typically large, resulting in an optimization model that may be intractable. In a scenario reduction problem, it is possible to reduce a large scenario set to a simpler set that is close to the original one if measured by a probability distance. It can be seen that the optimal value of the simpler problem (considering the reduced scenario set) is close to the value of the solution to the original problem (considering the original scenario set) if the scenario sets are sufficiently close in terms of the probability distance. In this study, a probability distance method was used, which is common in stochastic optimization and is called the Kantorovich distance [55], Dk defined between the two probability distributions s and ś by the problem [56]:

$$D_k\left(\mathrm{s},\acute{\mathrm{s}}\right)=inf\left\{\int_{\Omega\times\Omega}c\left(\mathrm{O},\acute{\mathrm{O}}\right)\eta\left(\mathrm{dO},d\acute{\mathrm{O}}\right):\int_{\Omega}\eta\left(.,\mathrm{d}\acute{\mathrm{O}}\right)\right.$$
$$\left.=S\int_{\Omega}\eta\left(O,.\right)=\acute{\mathrm{S}}\right\}\tag{40}$$

This problem is known as Monge–Kantorovich mass transportation problem. Further details on this problem are provided in [57]. In this problem $c\left(\mathrm{O},\acute{\mathrm{O}}\right)$ is a nonnegative, continuous, symmetric function, often referred to as cost function, and the infimum is taken over all joint probability distributions. Also for scenario reduction as can be seen in [58], there is not much difference between reduced scenarios in terms of cost in the negatively and positively correlated wind and load. Fig. 5 has been provided to show the scenario reduction algorithm.

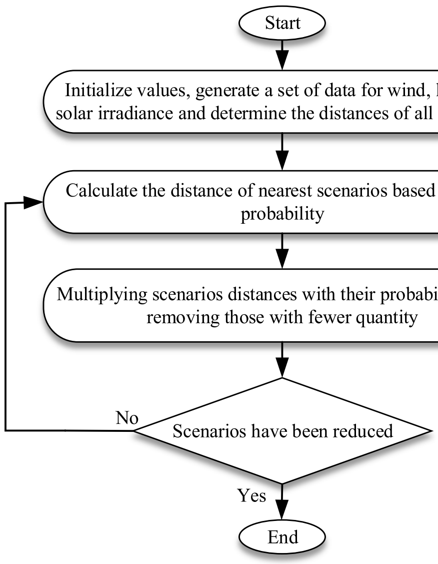

FIGURE 5. Scenario reduction.

The assigned reward by TSO and DSO will be calculated from the operation of CES over one year. In the flowchart of Fig. 4, the following equations are used to calculate the yearly reward:

$$R_D = RP_{DSO} + S_{upperhand} \tag{41}$$

$$S_{upperhand} = 0.8upper_{profit} \tag{42}$$

$$RP_{DSO} = \gamma_{p\_DSO}.peak_R \tag{43}$$

$$R_T = \gamma_{p\_TSO}.peak_R \tag{44}$$

$$R_i = R_{i_D} + R_{i_T} \quad i \in \{1, \ldots, m\} \tag{45}$$

$$CP_i = ACC_i - R_i - P_i \quad i \in \{1, \ldots, m\} \tag{46}$$

where R_D in equation (41) is the allocated reward by DSO, including the cheaper power from CES ($S_{upperhand}$ in equation (42)), and the reward for demand reduction in peak hours (RP_{DSO} in equation (43)) with the rate of γ_{p_DSO}($/KWh). Also, in equation (44) where R_T is the dedicated reward by the TSO. This is calculated through γ_{p_TSO}($/KWh) as a peak demand reduction budget rate. Then, R_i as the aggregated reward will be calculated in equation (45). According to equation (46), the total cost of each investment scenario will be calculated, where P_i is the profit of installing CES. Eventually, information on evaluated scenarios is sent to MG, as can be seen in the decision-making block of Fig. 4 (green color). MGs choose the best investment scenario by using TOPSIS.

C. INSTALLING AND PLACEMENT CONSIDERATION

Besides batteries, a CES system has a few technical assets such as a communication module, energy transmission corridors (cables), monitoring and measurement systems, as seen in Fig. 6. Since MGs should be able to access the CES consumer interface using online apps wirelessly to set their charging and discharging schedules, in a CES system data-related assets have a more critical role in comparison to the other storage systems. The wireless capability of this interface leads to a reduction in investment costs for data cabling [1]. Generally, CES facilities can be categorized into data-related and energy-related assets. As one of the data-related assets, the communication module of CES facilitates information exchanges among the MGs, TSO, and DSO.

Regarding energy-related assets, some cables are required to share the power of the CES during the charge and discharge among MGs and CES since MGs are connected through the distribution system to transfer power. An optimal location for installing CES should be determined to reduce the extra cables for transmitting the power between microgrids and CES.

From a grid stability perspective, having a considerable CES capacity for supporting multi-microgrid systems would be beneficial. One of the benefits, this can help each MG in the cluster in case such MG encounters a power imbalance. This can help provide services to the cluster of connected MGs, such as ancillary services for supporting frequency and voltage. Additionally, the system strength of multi MGs with CES would be enhanced using advanced coordination techniques for utilizing the energy capacity of the CES. It is to emphasize that CES would bring benefits to the system stability since having a cluster of MGs operated together and helping each other is better than individual MG because the MGs can help stabilize each other in case of any stability issues. However, the stability of such systems is one of the attractive topics that need further investigation and research.

V. TEST AND RESULTS

The test system is the IEEE 33-bus system. The overall features of the radial test system are the number of lines = 32, slack bus number = 1, base voltage = 12.66 kV, and power base = 10 MVA [59]. The total real power = 3.71 MW, reactive power = 2.31 MVar, and limited voltage = 1.00 p.u. Distributed generations' data of the test system has been presented in Table 5. This radial system is connected to four MGs, and the related data of these MGs have been described in Table 6 [60]. The whole single-line diagram is shown in Fig. 7. The technical data of the wind turbine and PV panels are indicated in Table 7. All energy storage devices' charging and discharging efficiencies are assumed to be 96%. Each energy storage device's minimum state of charge (SOC) is considered at 10%, while its maximum SOC is regarded as 90%. The rated power of wind turbines and solar panels has been considered to be one KW. The time interval for the entire simulation is 1 hour. The hourly calculations are based on a realistic residential load curve extracted from the Alberta Electric System Operator. A real market energy price calculated by the electricity market operator is taken from [61]. The CES capital costs are 60 USD/kW and

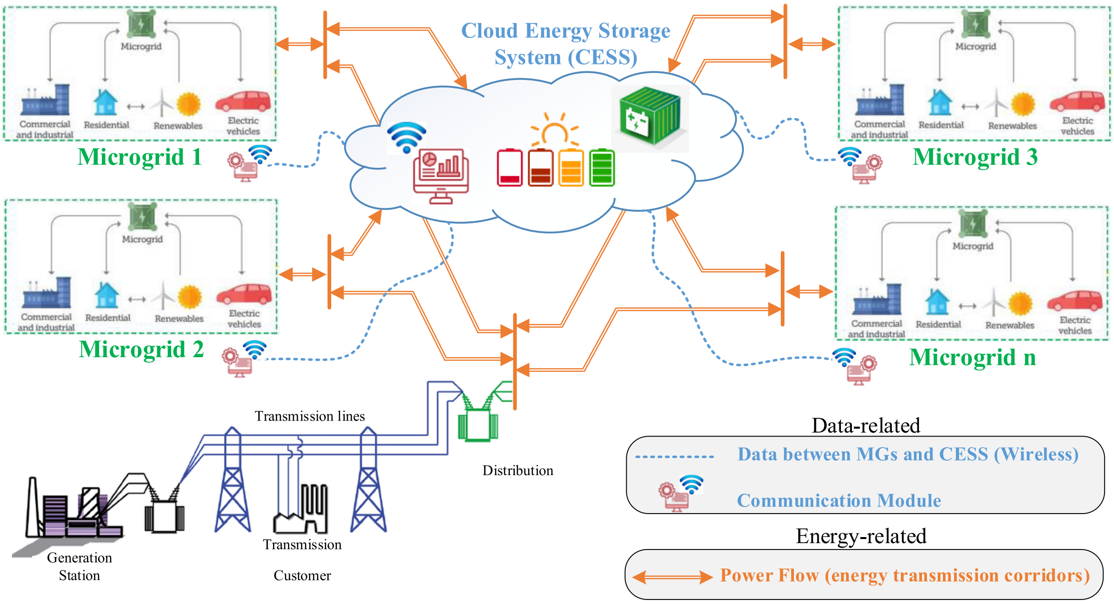

FIGURE 6. Framework of cloud energy storage and its connections.

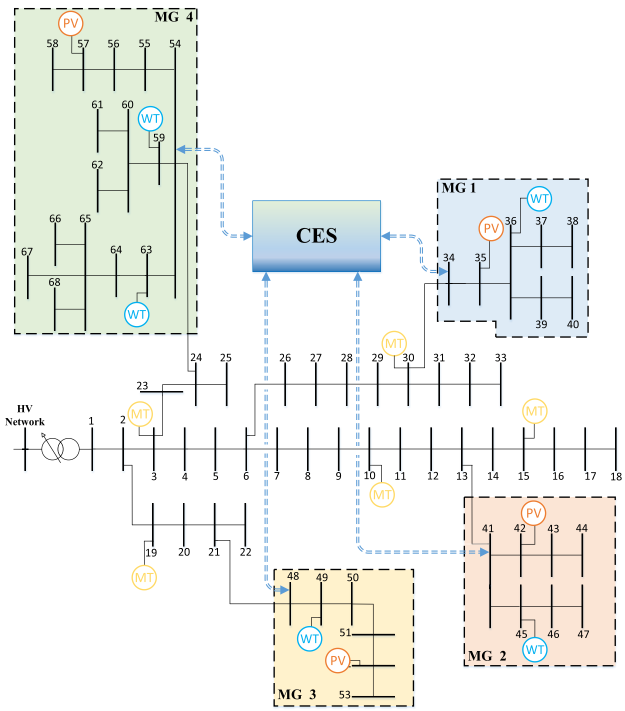

FIGURE 7. Test distribution system with multi-microgrids and CES.

180 USD/kWh [3]. The maximum number of iterations and population size for the TLBO-based optimization method, which was discussed in Subsection IV-A, are 50 and 500, respectively. 1000 samples for the uncertainty of the load profile and the environmental data have been generated by the Monte Carlo simulation method, and it has been reduced to 5 samples with probabilities of 0.6037, 0.118, 0.1048, 0.092, and 0.08, respectively.

TABLE 5. Distributed generations' data.

System	PV		Wind		Micro Turbine
	Unit number	Total capacity (MW)	Unit number	Total capacity (MW)	Maximum capacity (MW)
MG 1	100	0.1	100	0.1	0.4
MG 2	50	0.05	100	0.1	0.4
MG 3	100	0.1	50	0.05	0.4
MG 4	100	0.1	200	0.2	0.4

TABLE 6. MGs' demand.

System	Load bus No.	Total active load (MW)	Total reactive load (MVar)
MG 1	34,35,36,37,38,39,40	0.38	0.075
MG 2	41,42,43,44,45,46,47	0.285	0.063
MG 3	48,4,50,51,52,53	0.348	0.075
MG 4	54,55,56,57,58,59,60,61, 62,63,64,65,66,67,68	0.665	0.125

TABLE 7. Technical parameter.

Parameter	Value	Unit
PV module		
Rated power	1	Kw
Solar radiation	1000	W/m2
Temperature factor of PV panel	- 3.7 × 10-3	1/◦C
Typical cell temperatures	43	◦C
The reference of cell temperature	25	◦C
Wind turbine		
Rated power	1	kW
Cut-in wind speed	3	m/s
Cut-out wind speed	17	m/s
Rated wind speed	8	m/s

Consumers inside MGs could book their required capacity from CES to reduce their electricity bills under variable

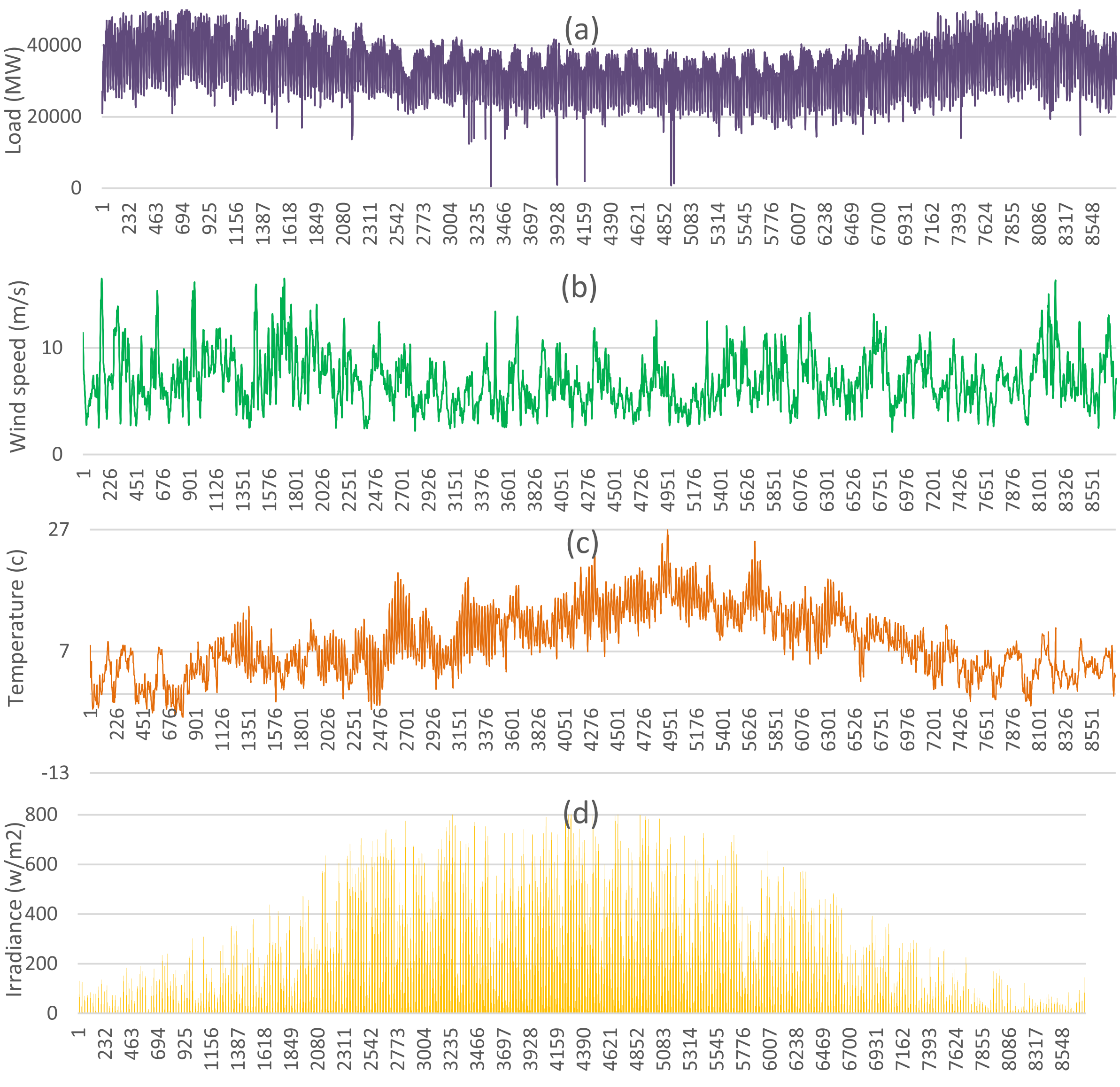

FIGURE 8. Input data [60].

electricity prices, which is considered the budget that MGs want to allocate to the chosen investment cost of CES through this procedure (Fig. 2 stage 1). In this study, each MG book its demand and, according to it, allocates its budget.

After trial and error, we found that there are not any differences between 1000 and 5000 samples, so we decided to consider 1000 samples for our model to reduce the simulation time. There are many methods for the reduction of samples. We have used the Kantorovich distance technique for our model in order to reduce the simulation time. According to preview works, this number has had a good result for uncertainty [37], [38], [58]. These samples have been considered as input data for considering uncertainty in each investment scenario (IS) in Fig. 2 (stage 1). All simulations have been done on a PC in Rasht, Gilan, Iran, with an Intel Core i7 CPU @ 3.20 GHz and 32 GB RAM using MATLAB 2021a.

Fig. 8 shows the load profile and the environmental data (wind speed, solar radiation, and ambient temperature) for 8760 h (over one year). The analysis is based on the investment cost for the capacities of 4, 6, 7, 8, 12, and 20 MWh to provide more choices from which consumers would be able to choose the best option. The capacity of converters is the same, 0.6 MW, for each MG. We have turned each scenario's overall investment of capacity and converters into annualized figures to compare the simulation result. The booked capacity of CES by each MG can be seen in Fig. 9.

To show the economic benefit of various CES capacities in Fig. 10, the investment cost, obtained profit, and operation cost for each investment scenario have been compared to the cost of the grid operation without CES in the power system. One of the barriers to CES is its investment cost, and even it should be mentioned that investments in CES

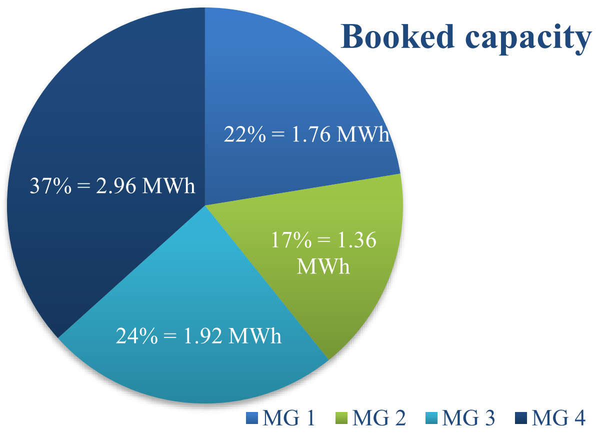

FIGURE 9. Booked capacity by each MG.

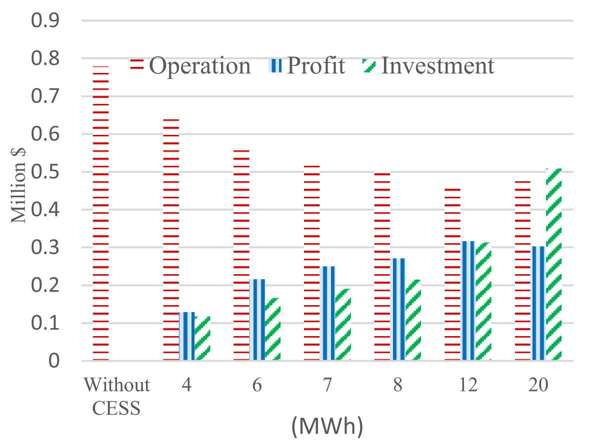

FIGURE 10. CES operation and investment cost ($).

TABLE 8. Budget from DSO and TSO.

CES capacity (MWh)	DSO yearly reward ($)		TSO yearly reward ($)
	Reward from Upper-hand cost reduction	Reward for peak reduction	Reward for peak reduction
4	27830.7	2011.39	106.5
6	33240.023	2159.26	92.64
7	61804	4040.3	134.97
8	64558.437	3349.387003	102.72
12	88554	1949.4	68.431
20	56376	4014.7	88.126

provide inflation protection by the nature of the asset class. From Fig. 10, it is obvious that the operation cost of the MGs has decreased with the presence of CES. Moreover, CES with more capacity brings about more profit. In addition, the increase in capacity is profitable to some extent. For example, in Fig. 10, it can be seen that after the capacity of 12 Mw which is 20 Mw, not only is it evident that the investment cost will go up remarkably but also there has not been any change in operating profit.

Turning to the operation in each capacity, the MGs receive their yearly reward from the upper stream. So DSO allocates its reward based on the obtained profit from installing CES.

This reward is considered according to the reduced demand during peak hours and exchanging power with CES. The reward rate of peak demand reduction for DSO is 0.023 $/KW [62]. DSO dedicates 80% of its operating profit, which is obtained from buying cheaper electricity from CES in expensive times. Furthermore, TSO allocates its reward to MGs based on peak reduction. Its reward rate of peak demand reduction is assumed to be 0.08 $/KW. Table 8 presents the allocated reward from DSO and TSO by the capacity of CES in $.

The allocated reward by TSO and DSO as was mentioned will be calculated through the operation of CES over one year. In Table 8 the yearly reward by DSO is calculated by equations (41)-(43). Furthermore, the yearly reward that will be allocated by TSO is calculated by equations (44). All of these yearly rewards are calculated during the process in Fig. 2, in DSO and TSO decision-making blocks separately.

Table 9 describes the results of the proposed approach in detail. The annualized cost of investment in each scenario has been calculated from equations (20) and (21) by $(Annualized\_Inv_{cost} = Inv_{Cost}.(\frac{A}{P}, 0.06, 10))$. The investment cost column is an accumulation of the annualized cost, operation profit, and total yearly reward for one year in each investment scenario. By comparing costs for each investment scenario, it is evident that the largest capacity, 20 MWh, is not profitable and has no economic value. By comparing other candidates, it can be seen that the higher the capacity, the more profit can be obtained by MGs.

Fig. 11 shows the economic analysis of each candidate. According to this figure, MGs should pay the cost of the interesting scenario from the start of the first year. After that, at the end of the first year, they benefit from reducing operating costs. The profit is the difference in operating costs with and without CES. Moreover, the yearly reward from DSO and TSO is paid to MGs at the end of each year. The figure shows the trend of paying and gaining money.

In terms of CES, the payback period measures the time to recover the cost of the investment from the saved energy or reduction in energy bills. One of the best ways to compare the different capacities of CES is when CES with a certain capacity can compensate for its investment cost. Also, this criterion has been one of the attributes in TOPSIS that the best investment cost is determined. Fig. 12 presents the lifetime of all capacities and their payback period from the profit of operation and reward. Any plan that is in the green zone is beneficial and it is economical, like 4, 6, 7, 8, and 12 MWh capacities. On the other hand, the 20 MWh year of return is 16.5, which means that this capacity is not economical and is not worth investing in because it can not be profitable in its lifetime (10 years).

To evaluate the reliability of the model, four scenarios, and in each scenario, six capacities, 4, 6, 7, 8, 12, and 20 MWh, have been evaluated. Each scenario has its specific parameters, namely the failure day, the hour of failure start, the outage period, the line of failure, and the probability as

TABLE 9. Economic analysis.

No.	CES capacity (MWh)	Available Investment Budget ($)	Investment cost ($)	Annualized Inv. Cost ($)	Operation cost ($)	Operation cost without CES ($)	Profit ($)	DSO yearly reward ($)	TSO yearly reward ($)	Cost/Profit of CES investment
1	4	100000	864000	117380	649678.92	778972.97	129294	29842.09	106.5	-41862.63947
2	6	1250000	1224000	166302	562645.1		216330.81	35399.283	92.64	-85520.74
3	7	1500000	1404000	190804	528917.24		250058.7	65844.7	134.97	-125234.37
4	8	1700000	1584000	215265.6	507769.122		271243.148	67907.82	102.72	-123988.08
5	12	2500000	2304000	313039	462124.13		316864.33	90503.4	68.431	-94397.161
6	20	4000000	3744000	508689	476426.25		302546.72	91390.7	88.126	114663.4540

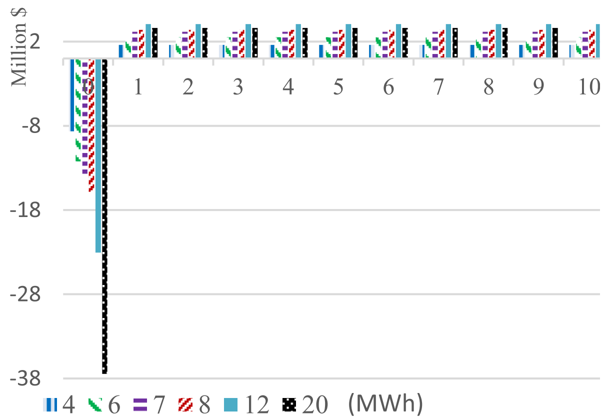

FIGURE 11. Economic analysis of each candidate.

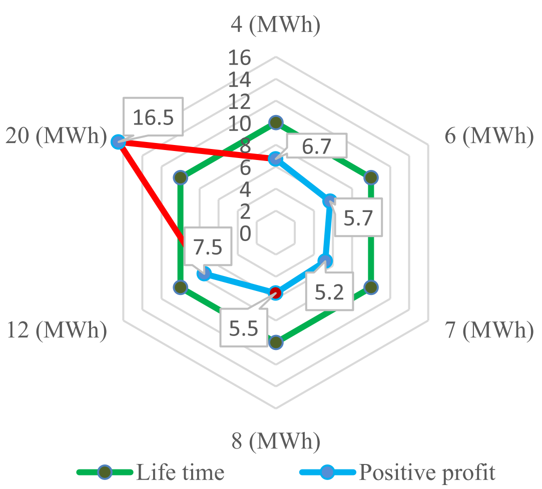

FIGURE 12. Payback period of each investment scenario (years).

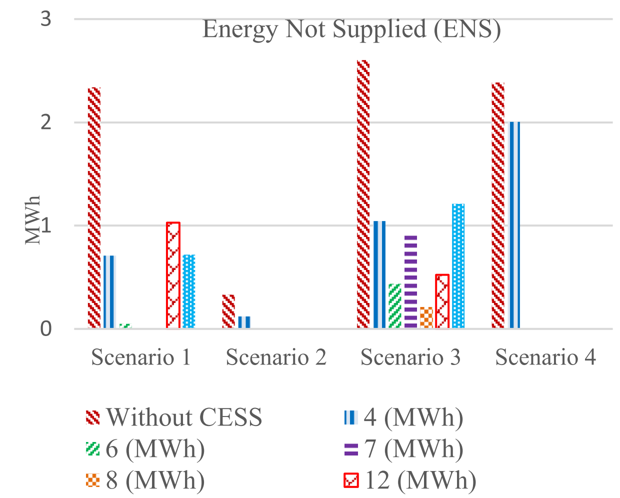

FIGURE 13. Energy not supplied in each scenario of failure.

TABLE 10. Reliability scenario information.

Failure	Number of scenario							
	S 1		S 2			S 3		S 4
Day of failure	40	23	3	90	41	7	101	98
Hour of failure starts	14	5	22	6	13	2	10	3
Outage period	10	3	1	6	3	16	7	9
Line of failure	29	28	12	11	40	19	20	23
Probability	0.4	0.6	0.2	0.35	0.45	0.85	0.15	1
Microgrid's failure	MG 1		MG 2			MG 3		MG 4

TABLE 11. Reliability results.

Number of Scenario	Energy Not Supplied (ENS) in MW.						
	Without CES	CES with capacity of E (MWh)					
		E = 4	E = 6	E = 7	E = 8	E = 12	E = 20
S 1	2.3381	0.7086	0.05	0	0	1.0274	0.717
S 2	0.3308	0.1201	0	0	0	0	0
S 3	2.6031	1.045	0.4376	0.9212	0.21	0.52529	1.212
S 4	2.3875	2.0037	0	0	0	0	0
Total ENS	7.66	3.877	0.48814	0. 9212	0.21	1.553	1.93

shown in Table 10. Either of these figures has randomly been determined. Turning to Fig. 13 and the resulting figures in Table 11, it is evident that the presence of CES in four scenarios has decreased the energy not supplied (ENS). Based on scenarios, with the more capacity of the CES, the system's reliability has been improved.

CES with the capacity of 6, 7, 8, 12, and 20 MWh had fewer ENS than when the capacity was 4 MWh. As evident, when ENS has been considered, there is a bit of difference between the results for the capacity of 12 and 20 MWh. The main reason for this is the difference in the remaining energy in the battery at failure time.

Eventually, by using TOPSIS, the best investment scenario will be chosen. Table 12 is the decision-making table described in Fig. 1 in stage 2 of MG's decision-making block. In this study, as it was mentioned, TOPSIS has been used to

TABLE 12. Decision-making table.

CES capacity (MWh)	Cost / profit	Sum of ENS (MWh)	Payback period (year)
4	-41862.63947	3.877	6.7
6	-85520.74	0.48814	5.7
7	-125234.37	0. 9212	5.2
8	-123988.08	0.21	5.5
12	-94397.161	1.553	7.5
20	145663.454	1.93	16.5

TABLE 13. Comparison of Simulation results.

Profit of installing CES in 24 hours in $.	
Heuristic optimization (TBLO)	Mathematical optimization (“fmincon” solver)
178.63	**180.3**

determine the best capacity to be invested. In this method, some criteria should be considered to choose the best option. In our work, criteria have been attributes which are the cost of investment, ENS, and payback period. Each of these criteria should have a certain weight according to their value, and there are some methods to determine these weights, which here weights are determined by using the eigenvector technique from the matrix of attributes, which are 0.335, 0.199, and 0.466, respectively. Finally, the best investment scenario is a capacity of 7 MWh.

Finally, to evaluate the performance of the implemented method (TLBO-based optimization of Subsection IV-B), a 24-hour simulation has been done on a standard IEEE 33-bus system using the convexification approach in Subsection IV-A. The convexified problem has been solved by the YALMIP toolbox in Matlab with the “Fmincon” solver. Results of both mathematical optimization and heuristic optimization (TBLO) for 24 hours of operation have been illustrated in Table 13. It is conceivable that there is a small difference between the proposed method of this study and the mathematical model. It shows us that the TLBO-based optimization method has been designed effectively.

VI. CONCLUSION

This paper has investigated the concept of Cloud Energy Storage on a distribution network by considering multi-MGs. Moreover, we have applied a collaborative approach between MGs, DSO, and TSO to develop a CES planning scheme for the feasible investment of CESIn this study, the distribution system has been studied in detail with the presence of renewable resources, micro-turbines, MGs, and CES. As a result of this investigation, the proposed framework covered its installation costs and improved the system’s reliability indices. In addition, the practicality of the presented model proved to be a good solution for the high capital cost of CES. Finally, the MGs, by applying TOPSIS, can make the best decision to reduce their future energy costs with the provided decision table.

CES has a significant influence on the improvement of reliability and reducing the electricity bills of MGs compared to when CES has not been installed. Also, it allows the DSO to buy power from CES at a lower price and reduce its operating costs. However, our analysis shows that over-investment or increasing the capacity of CES cannot be profitable necessarily. Also, the small size of the CES would decrease the profit and the system’s reliability. Hence, a proper sizing scheme for CES should be adopted, similar to what we did in this paper.

Future work can be on considering end-users as decision-makers for their charge and discharge schedule. Also the number the impact of CES on loss reduction can be investigated. Moreover, a collaborative decision-making procedure in which the CES is privately funded by an investor. In this suggested model, some changes will happen to our framework. First, the profit earned from the sold power to the end-user is considered for the investor. Second, MG’s power bought from the upper system is separated from the power bought by CES. The results can be compared to our study in which no investor exists.

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