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Integration of Community Energy Storage for Congestion Management and Energy Cost Optimization: A TLBO Solution Approach

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ABSTRACT

In the recent years, active distribution systems are exposed to congestion more than in the past. In this regard, different congestion management mechanisms is investigated in the litrature. Adopting sharing framework for Energy Storage Systems (ESSs) to deal with the long pay-back period and high investment cost of Distributed Energy Resources (DERs), can bring a promising solution for relieving congestion. In this paper, a framework for simultaneous energy cost optimization and congestion management by using community energy storage (CES) is proposed. As a case study, a CES within a distribution system, connected to four microgrids (MGs) is considered. The shared storage system enables the MGs to reduce their energy costs by optimizing the operation of the battery using a Heuristic optimization algorithm, specifically the Teaching-Learning-Based Optimization (TLBO) algorithm. Simultaneously, the distribution system operator (DSO) leverages the shared storage to alleviate congestion by purchasing charged power from the CES manager. In the proposed approach, the DSO pays a premium price for the charged power from the CES, surpassing the prevailing electricity price during congested hours. Moreover, to manage uncertainties arising from load variations and intermittent renewable energy resources (RES), Monte Carlo simulation is employed in this study. Through comprehensive simulations and analyses, the proposed approach demonstrates the potential of CES as an effective tool for congestion management and operational cost optimization in distribution systems and providing economic benefits to both the MGs and the DSO.

1. Introduction

In the ever-evolving landscape of distribution systems, the utilization of energy storage has become increasingly crucial for achieving a sustainable and reliable power grid. Initially, the focus was on distributed ESSs, where individual households or businesses would have their own storage units. As the demand for energy storage continues to rise, a new paradigm has emerged -CES which is inspired from shared and cloud economy. This innovative approach involves pooling resources and creating a collective storage infrastructure that benefits multiple participants such as MGs. A schematic of a distribution system connected to MGs and a CES has been illustrated in Fig. 1 [1]. Utilizing CES can bring several benefits for energy communities that are but not limited to optimizing the use of

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renewable energy, balancing supply and demand, and fostering a more resilient and cost-effective energy ecosystem [2]. On the other hand, congestion in distribution systems can be caused by various factors such as high penetration of DERs, load growth, network topology changes, and power quality issues [3-6]. Generally, in modern power systems, congestion occurs when there is limited or inadequate distribution/transmission capacity to accommodate the energy demand. Congestion can lead to voltage violations, line overloading, power losses, and reliability degradation. Ref [7, 8], have delved into the intricate realm of transmission congestion and its management in power system operations. These studies highlight the profound challenges faced by independent system operators worldwide, including the impact of RES integration on congestion and the growing importance of emission reduction. Therefore, congestion management methods are needed to improve the security of distribution systems and how well they operate. The methods used for congestion management in distribution systems are network reconfiguration, OPF-based approaches, demand response, and optimal re-dispatch of DERs, energy resources, and ESSs by using smart meters [2]. The introduction of ESSs has resulted in potential solutions to problems caused by the growing penetration of DERs. By strategically deploying ESSs, uncertainties associated with RES, such as the intermittent nature of wind and solar generation, can be effectively mitigated. These storage units can play a vital role in relieving congestion in power transmission lines by optimally charging and discharging power as needed. The integration of ESSs into power system planning and scheduling enables efficient congestion management, ensuring a reliable and robust grid operation while harnessing the full potential of RES [9]. Due to the cost inefficiency inherent in individual ESS setups on a large scale, CES is introduced by leveraging cost sharing and economies of scale [10-13]. In addition to the investment benefits derived from a shared framework for ESS installation, this approach holds significant value in unlocking greater operational benefits when consumers collaborate. By embracing CES, Distribution System Operator (DSO) can actively participate as consumers and utilize community storage to solve a set of network related problems, such as peak trimming and congestion mitigation. By leveraging shared storage as an integral part of their strategies, DSO can enhance grid reliability, improve system flexibility, and ensure efficient energy distribution throughout their networks. Employing CES fosters synergy among consumers and grid operators, promoting a more integrated and resilient energy ecosystem. More specifically, this shared storage can be used on a larger scale among participants like MGs [14]. As another example of the functionality of shared storage, in Australian apartment complexes, central batteries installed in each unit greatly improved PV self-use, fostered independence, and lowered demand during peak times [15]. CES can offer definite financial advantages when integrated with solar systems in embedding networks or apartment buildings, even though the financial argument for EES is not entirely convincing. Also, in [16], a CES optimal scheduling method is proposed that considers both operational efficiency and reliability cost. The dependability metric of user disruption cost is incorporated into a multiple-purpose schedule. An island partition model accurately calculates the reliability cost, allowing CES integration into the power restoration system. In [17], to maximize the scale and functionality of CES in hybrid power-generating systems, a bi-level model is developed. The results demonstrate reductions in curtailment rates, peak shaving, frequency regulation, and deferred facility upgrades, leading to significant stakeholder benefits of approximately $154M, highlighting the advantages of CES investments in distribution systems.

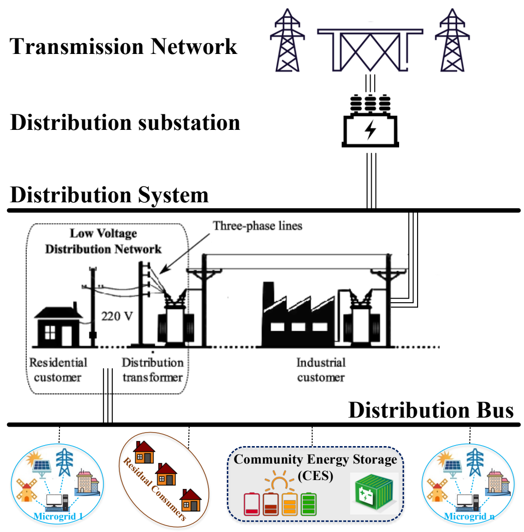

Fig. 1. Topology of the distribution system connected to MGs and a CES.

Moreover, market-based approaches and direct control methods are the two primary categories into which several ways to control congestion can be divided in terms of execution. Market-based approaches to managing congestion include dynamic tariffs, distribution capacity markets, shadow prices, and flexible service markets. These approaches provide financial incentives and pricing mechanisms. Conversely, physical changes to the network are made in order to reduce congestion when using direct control methods including network reconfiguration, reactive power control, and active power control [18]. In [19], a novel approach is presented for mitigating congestion in distribution systems by employing a centralized coordinated home energy management system based on market principles by utilizing daily power-based networking tariffs and variable tariffs. As another study of congestion management, model of a local flexibility market is introduced in [20] that encourages MGs to offer flexibility services, thereby addressing issues like congestion in an active distribution system. Additionally, authors in [21] proposed a strategy to address the issue of electricity congestion resulting from peer-to-peer energy transactions among MGs under uncertain conditions. This strategy involves a rolling horizon optimization framework that operates based on specific events. Furthermore, in [22], the authors investigated the efficient functioning of a virtual energy storage system consisting of multiple carriers such as batteries, thermal energy storage, power to hydrogen, hydrogen to power, and electric vehicles. The study focuses on the integration of demand response programs and takes into account market participants and price uncertainties.

This paper focuses on the integration of a CES system within a distribution system, specifically a distribution system connected to MGs. The increasing adoption of DERs and the challenges posed by congestion in distribution systems necessitate efficient solutions for managing congestion and reducing energy costs. This

CES optimization approach contributes by addressing the following issue:

- Proposing an optimization mechanism of CES as a valuable tool in managing congestion in distribution systems.

Also, Efficacy of the proposed method in reducing energy costs for MGs and managing congestion in the distribution system has been examined in case study.

The remainder of the essay is structured as follows: in Section 2 the mathematical formulation is given, in Section 3, the solution approach is proposed, in Section 4, a case study has been presented and finally in Section 5 conclusion remarks are given.

2. Mathematical Model

We have introduced a model for the CES scheduling in distribution systems connected to MGs along with their associated constraints. The model's objective function incorporates the operational expenses of the CES, aiming to optimize its performance.

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

Subject to:

$$P^{s}_{up,jth} + P^{s}_{l,jth} + P^{s}_{DG,jth} + P_{B,jth} = \sum_{i=1}^{bnj} V^{s}_{jth} V^{s}_{ith}\, Y^{s}_{ij}\, cos(\Theta_j - \delta^{s}_{ith} - \delta^{s}_{jth}) \tag{2}$$

$$Q^{s}_{up,jth} - Q^{s}_{l,jth} = -\sum_{i=1}^{bnj} V^{s}_{jth} V^{s}_{ith}\, Y^{s}_{ij}\, sin(\Theta_j - \delta^{s}_{ith} - \delta^{s}_{jth}) \tag{3}$$

$$V_j^{min} \le V^{s}_{jth} \le V_j^{max} \qquad j \in \{1,2,\dots,bn\} \tag{4}$$

$$P_j^{min} \le P^{s}_{up,jth} \le P_j^{max} \qquad j \in \{1,2,\dots,bn\} \tag{5}$$

$$p_{pv}(t) = p_{n,pv} \cdot \left(\frac{I_{sol}}{I_{ref}}\right) . \left[1 + C_T\left(T_{cell} + T_{ref}\right)\right] \tag{6}$$

$$T_{cell} = T_{env} + \left(\frac{I_{sol} \cdot (NOCT - T_{Amb})}{si}\right) \tag{7}$$

$$P_{pv}(t) = p_{pv}(t). C_{pv} \tag{8}$$

$$\begin{cases} p_{WT}(t) = 0 & V(t) < V_{cut-in} \\ p_{WT}(t) = C_1 . V^3(t) - C_2\, p_{n,WT} & W_{cut-in} \le W(t) < W_{rated} \\ p_{WT}(t) = p_{n,WT} & W_{rated} \le W(t) < W_{cut-out} \\ p_{WT}(t) = 0 & W(t) \ge W_{cut-out} \end{cases} \tag{9}$$

$$C_1 = \frac{p_{n,WT}}{(V^3_{rated} - V^3_{cut-in})} \tag{10}$$

$$C_2 = \frac{V^3_{cut-in}}{(V^3_{rated} - V^3_{cut-in})} \tag{11}$$

$$P_{WT}(t) = p_{WT}(t). C_{wt} \tag{12}$$

$$e_B(t) = e_B(t-1) + \eta_{bc} \sum_{d=1}^{D} P_{B,d} \qquad d \in \{1,2,\dots,D\} \tag{13}$$

$$e_B(t) = e_B(t-1) + \sum_{d=1}^{D} \left(\frac{P_{B,d}}{\eta_{db}}\right) \qquad d \in \{1,2,\dots,D\} \tag{14}$$

$$P_{B,min} \le P_{B,i}(t) \le P_{B,max} \tag{15}$$

Where:

$$BO = \sum_{s=1}^{ns} U_s . \left(\sum_{d=1}^{D} \sum_{t=1}^{T} \sum_{h=1}^{H} \left(Y_{th} . P_{d,th}\right)\right) \tag{16}$$

$$d \in \{1,2,\dots,D\}, s \in \{1,2,\dots,ns\}, t \in \{1,2,\dots,T\}$$

The objective function that includes the CES's operational cost is represented by equation (1). Equations (2) and (3), which represent a power flow limitation, are used to account for these needs. Equations (4) and (5), respectively, explain the preservation of voltage within acceptable bounds and the required injected power.

The power that is generated by each photovoltaic panel is described by equation (6), where $p_{pv}(t)$ signifies the generated energy of any PV panel, and$p_{n,pv}$ denotes the PV nominal power. Additionally, the variables I_{sol} , I_{ref} , C_T, T_{cell} and T_{ref} correspond to the radiation from the sun, the reference for radiation from the sun, the PV panel's temperature variable, the temperature of the cells, and the reference temperature of the cells, in that order.

In equation (6), the cell temperature can be determined using equation (7), which takes into account the environmental temperature T_{env}, typical cell temperatures (NOCT), solar irradiance (si=800 mW/cm2), and ambient temperature I_{Amb}. Lastly, the total electricity generated by the PV panels at a given time t can be computed by considering how many PV panels there are (C_{pv}) and utilizing equation (8).

The output power of wind turbines is prone to vary because wind speed varies. The power generated by wind energy can be determined using equation (10). Each wind turbine's power generation is referred to P_{WT} in equation (9). Additionally, $V(t)$, V_{cut-in} , $V_{cut-out}$ and V_{rated} represent the instantaneous wind velocity, cut-in speed, cut-out speed, and rated power speed, respectively. Equations governing the coefficients C_1 and C_2 are given by (10) and (11). The entire amount of power produced by wind turbines can be computed using equation (12), where C_{wt} denotes the total number of wind turbines.

The state of charge and state of discharge of the CES at time t, which depend on the remaining energy from the previous time step (t-1), can be determined using equations (13) and (14). These equations involve the charging efficiency η_{bc} and discharging efficiency η_{db} of the CES, respectively. Furthermore, equation (15) establishes the charge and discharge limitations enforced by the converter. The capacity of the converter is expressed in equation (15).

Equation (16) represents the operational expenditure of the CES at time t and day h, taking into account the electricity price (Y_{th}) and the exchanged power to the CES ($P_{d,th}$). For each uncertainty scenario , this equation is calculated (U_s).

3. SOLUTION APPROACH

In this study, a CES system that is especially connected to MGs is integrated into a distribution system as part of CES. Maximizing the use of the CES is intended to alleviate the issues of congestion and high energy prices. In order to address these issues, the proposed approach leverages a CES system within a distribution system. In this paper's model, we have two parties, consumers and DSO. Each of them tries to use CES for their own criteria. To investigate, two scenarios have been considered:

In the first scenario, the TLBO technique is used by the shared storage manager to optimize its operation. In this scenario, the objective is the MGs energy expenses that are decreased as a result of this optimization's effective management of the battery's charging and discharging processes. The effectiveness of this strategy is proven through in-depth simulations and analysis, which indicate a notable decrease in the energy costs for the MGs.

In the second scenario, the CES system is used to reduce congestion when it develops in the distribution system. The storage manager sells charged power to DSO, even though the price is higher than the going rate for electricity during peak times. Congestion is successfully managed by using CES, which benefits both the MGs and the DSO financially. By demonstrating its effectiveness in lowering energy prices for the MGs and controlling congestion in the distribution system, the research emphasizes the significance of CES as a crucial instrument in tackling congestion- and cost-related concerns in distribution systems. In both cases, the manager of the CES tries to schedule charging/discharging in a way that is financially advantageous compared to paying the electricity bill without the battery. Due to the different reasons described in the first section, there is occasionally congestion. In this situation, the CES manager makes an effort to work with the DSO during scheduling to reduce congestion while simultaneously generating more revenue for the MGs by selling energy at a higher price than the price during congestion hours. Fig. 2 illustrates the entire procedure while taking congestion into account by the red color. In addition, to address uncertainties stemming from fluctuations in load and renewable energy sources that are sporadic, this study utilizes Monte Carlo simulation.

3.1. Optimization approach

TLBO, one of the most recent heuristic optimization methods, is inspired by the method of education and learning. For studying and teaching, TLBO takes into account a theoretical framework. The connected system is optimized as a result of its implementation in two parts. The best population member is chosen as the first instructor, representing the mean attitude of the population toward itself. The best new member is then chosen as the best instructor among the freshman students Equation (17). In the actual world, a competent teacher is responsible for carrying out that mission.

$$mm_{new,i} = mm_{old,i} + r_i(M_{new} - (T_F \times M_i)) \qquad (17)$$

Another stage of the population's development is trying to advance together and learn more. Two students, mm_i and mm_j, are selected at random for this step. Equation (18) determines the location for that member if the target function for that member is less than the target for member j; else, Equation (19), determines the position for it. By comparing each member's objective function inside a given iteration, the optimal solution is thus discovered. Because it has the fewest parameters, one of this algorithm's most significant characteristics is its independence from parameters [23].

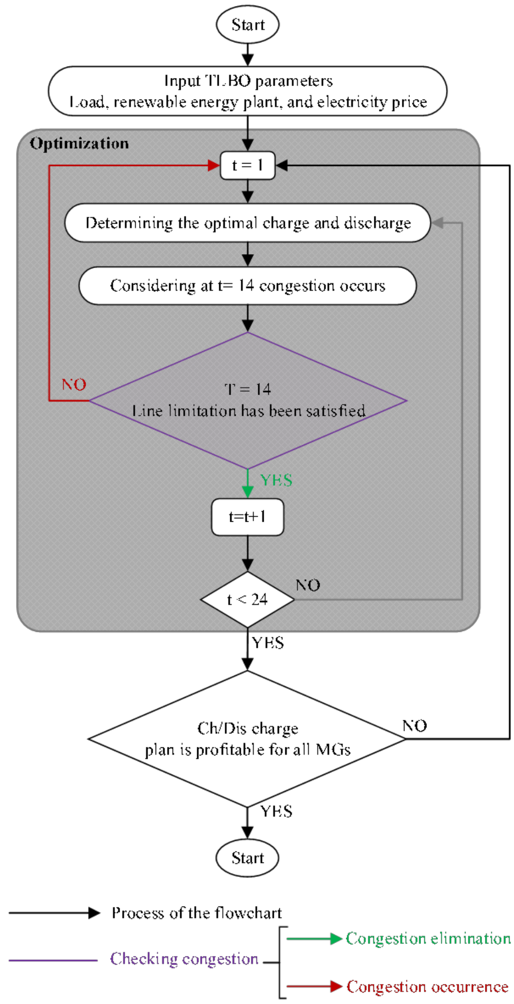

Fig. 2. Problem-solving process.

$$mm_{new,i} = mm_{old,i} + r_i(mm_i - mm_j) \qquad (18)$$

$$mm_{new,i} = mm_{old,i} + r_i(mm_j - mm_i) \qquad (19)$$

The issue is nonlinear and non-convex in the suggested optimization (equations (1)–(16)) because power flow-related imposed limitations are taken into account. Heuristic algorithms are promising methods for locating the best solution in such power system problems [21]. As a result, this study employs a heuristic algorithm in the research. It should be mentioned that similar problems can be solved using genetic algorithm (GA), particle swarm optimization (PSO), and other heuristic methods. The population size and maximum iteration are the only algorithmic parameters required for the TLBO technique to function, which is its main advantage. In addition, the algorithm requires less memory than others like GA and PSO and is simple to implement [24], see [25, 26].

To ensure transparency and reproducibility, we provide a comprehensive description of the simulation methodology and parameter settings employed. The parameters of TLBO, including population size, and number of iterations, were carefully selected based on preliminary experiments and domain knowledge to best optimize CES allocation within MGs.

3.2. Uncertainty consideration

The unpredictable nature of the input variables—wind speed, solar irradiation, and load demand—is taken into account in this study. The Weibull, Beta, and Normal distribution functions, respectively, model these parameters. The variance and mean may be used to compute the load uncertainty. State prediction methods, stochastic load flows, and load probability density functions may all be made using these parameters. A Normal distribution function is being used in statistical loading analysis [27]. The Weibull probability distribution function, widely used to forecast the wind speed frequency distribution, has been employed in this instance to estimate the wind speed dispersion [28]. We used a Beta distribution approach to model solar radiation on a global scale. When used to represent global solar radiation, the Beta distribution offers a reliable, adaptable method that allows for the addition and deletion of independent variables as needed and can be interpreted using conventional inferential statistics [29].

The probability distribution functions listed above have been utilized to produce samples using Monte Carlo simulation. The task is made extremely complex and difficult by the enormous number of samples. The fast-forward technique was used in our study to minimize the number of situations, resulting in the reduction of scenarios to S. Running a random scenario-generating technique produces scenarios that effectively depict the uncertainty present in a decision-making problem. However, because these situations are typically rather vast, an optimization model may be produced that is impractical to use. After performing further simulations, it is found that there are not any differences between 1000 and 10000 samples, so to reduce the simulation time 1000 samples for the model have been considered. In this way, a scenario reduction method has been used named the Kantorovich distance [11, 30].

4. Case Study and Results

4.1. Case study

The IEEE 33-bus system serves as the foundation for the test system used in this work, which exhibits radial characteristics. It consists of 32 lines, with the slack bus designated as bus number 1. The base voltage for the system is set at 12.66 kV, and the power base is defined as 10 MVA [31]. Both reactive and actual power for the system is recorded as 3.71 MW and 2.31 MVar, respectively, while the voltage is limited to 1.00 p.u. The data pertaining to the distributed generations within this test and to establish the connection with four MGs, specific data for each MG is provided in [11]. A comprehensive overview of the single-line illustration is presented in Fig. 3. Technical specifications for the wind turbine and solar panels used in the system can be found in Table I.

Moreover, other technical data has been given in Table II and III. It is assumed that all energy storage devices have 96% charging and discharging efficiency. Each energy storage device has a minimum and maximum state of charge (SOC) of 10% and 90%, respectively. For wind turbines and solar panels, the rated power is considered as one KW. Fig. 4 shows the load profile and the environmental data (wind speed and solar radiation) for 24 hours [30].

Table I. Technical Data.

Parameters	Values	Units
PV modules		
Rated power	1	Kw
Solar radiation	1000	W/m2
PV panel temperature factor	$-3.7 \times 10\text{-}3$	1/°C
Typical cell temperatures	43	°C
Temperature reference for cells	25	°C
Wind turbines		
Rated power	1	kW
Cut-in wind speed	3	m/s
Cut-out wind speed	17	m/s
Rated wind speed	8	m/s

Table II. 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 III. MGs Loads

System	Load bus No.	Total active load (MW)	Total reactive load (MVar)
MG1	34,35,36,37,38,39,40	0.37	0.0705
MG2	41,42,43,44,45,46,47	0.275	0.0603
MG3	48,4,50,51,52,53	0.338	0.0750
MG4	54,55,56,57,58,59,60,61, 62,63,64,65,66,67,68	0.675	0.1205

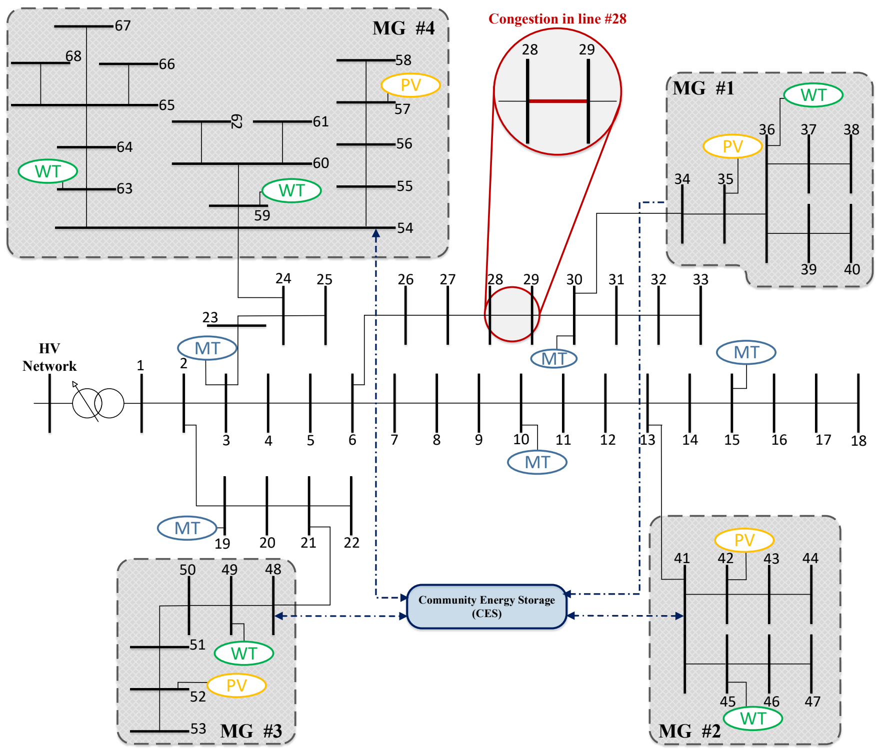

Fig. 3. Test distribution system along with several MGs and CES.

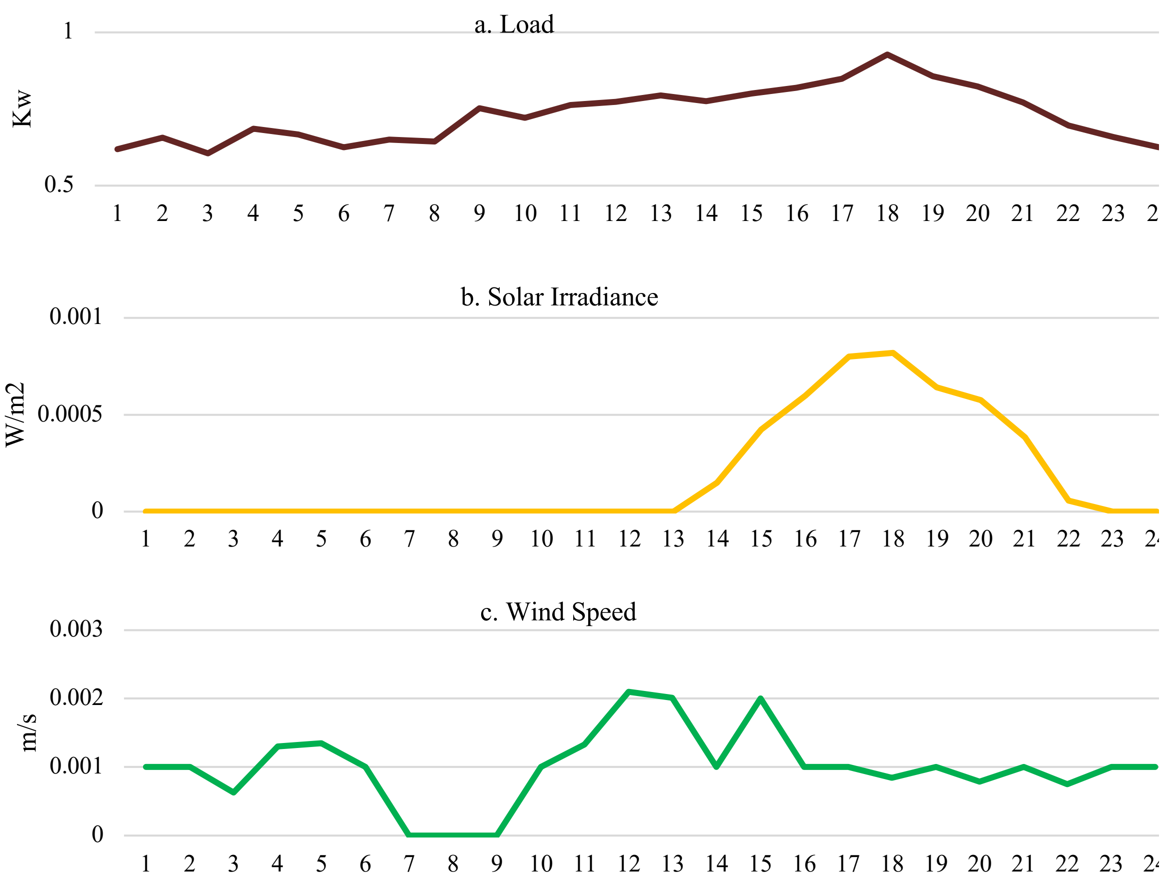

Fig. 4. Input data.

The simulation is carried out hourly, the load profile used is drawn from a true household load profile received from the Alberta Electric System Operator, and a real market energy price, given by the electrical market operator, is incorporated [31].

The optimization process based on the TLBO method discussed in Subsection 3.1, utilizes a maximum of 50 iterations and a population size of 500. The teaching factor and learning factor have been chosen between 1 and 2. To account for uncertainties related to load profiles and environmental data, a Monte Carlo simulation method is employed, generating 1000 samples. These samples are subsequently reduced to 5 representative samples with probabilities of occurrence set at 0.6037, 0.118, 0.1048, 0.092, and 0.08, respectively.

4.2. First scenario: cost optimization

In the first scenario, the shared storage system plays a crucial role in optimizing the operation of the battery within the MGs, leading to notable reductions in energy costs. This optimization process is accomplished by leveraging the power of the TLBO algorithm, a sophisticated heuristic optimization technique specifically designed for energy management.

By employing the TLBO algorithm, the shared storage system intelligently determines the most optimal charging and discharging strategies based on various factors such as electricity prices, load demands, and available DERs. Through comprehensive simulations and rigorous analyses, the proposed approach showcases its remarkable effectiveness in minimizing energy costs for MGs.

Fig. 5 shows the operation of the CES by the storage manager to ensure that MGs costs will decrease. As can be seen, during lower prices like hours 1 to 3 or 7 to 9 it has tried to save energy in storage, on the other hand, in hours like 17 to 19 the energy of the storage has been discharged for the MGs in order not to use the electricity from the distribution system. As a result of this scheduling for charge and discharge, in Fig. 6, it is clearly evident that in a 24-hour day existence of the energy storage has been profitable, and more than 100$ the cost to be paid for the electricity has decreased. Moreover, through Fig. 7, it is revealed that individual MGs have benefited from CES.

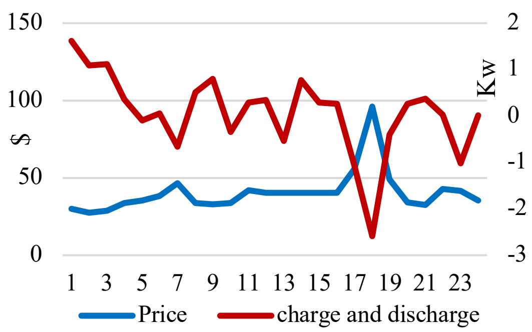

Fig. 5. Storage charge and discharge by MGs.

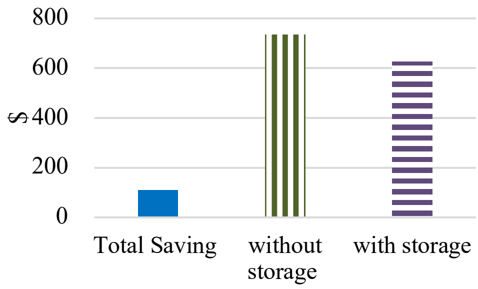

Fig. 6. Total cost and saving obtained by shared storage in a day.

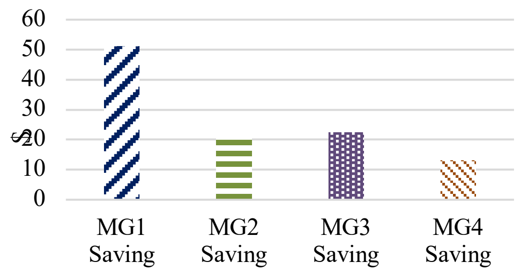

Fig. 7. Saving obtained by MGs individually compared to without storage.

4.3. Second scenario: cost optimization plus congestion management

According to the second scenario, the distribution system gets congested at time t=15:00, and the CES system is employed to manage and relieve this congestion. In this situation, DSO still purchases the charged power even if the storage manager's offer is more than the usual rate for electricity during congestion hours. Through this method, which lessens congestion, the shared storage system economically benefits both the MGs and the DSO.

Once again with the occurrence of congestion at a given time, the storage manager has been able to schedule storage's charge and discharge successfully, ensuring that the use of storage is profitable as can be seen in Fig, 8, but with lower profit compared with Fig. 6, when there was not any congestion in distribution system lines. However it was profitable, and simultaneously storage manager has been able to cooperate with DSO to alleviate the congestion that has happened. As can be seen in Fig. 9 the line limitation considered is 290 Kw for the line between bus 28 and 29 at 16.00 because of the congestion. In this condition, DSO has shared the energy storage from the storage manager and has bought the charged energy of the shared storage 1.5 times more than the price of electricity in that hour. Consequently, as can be seen in Fig. 9, the passing power from the considered line has decreased.

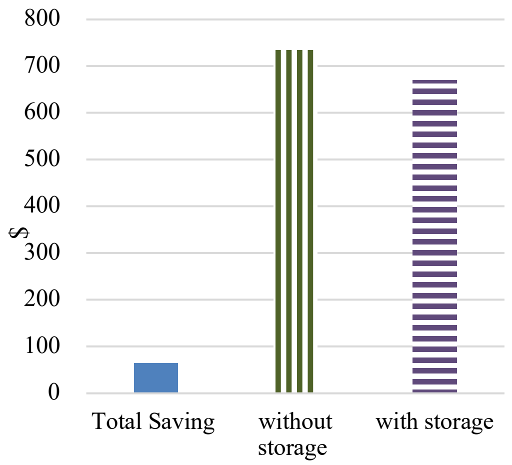

Fig. 8. Total cost and saving obtained by shared storage in a day when congestion occurs.

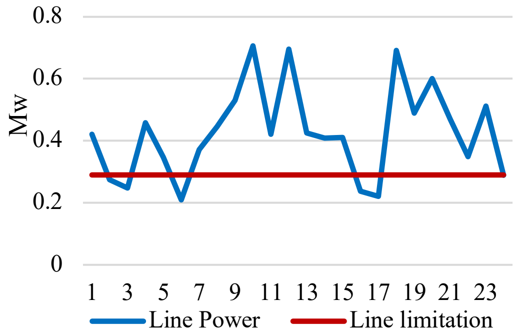

Fig. 9. Passing power between bus 28 and 29 in 24 hours of a day considering congestion.

4.4. Aaassas ;

Fig. 10 provides valuable insights into the application of energy storage in two different states, namely CES and discrete, to address congestion in a distribution system. The diagram demonstrates that employing CES between MGs proved to be effective in managing congestion in the distribution system's line. Conversely, when MGs attempted to install energy storage individually, the capacity limitations of the discrete energy storage hindered effective congestion management. In Fig. 11, a comparative analysis is presented, showcasing the performance of two heuristic algorithms, namely the Grey Wolf Optimizer (WGO) and TLBO, in terms of cost reduction in a distribution system involving four MGs. The results indicate that TLBO outperformed WGO in achieving cost reduction. This finding highlights the effectiveness of TLBO as a heuristic algorithm in optimizing the distribution system, leading to enhanced cost efficiency.

The utilization of the TLBO algorithm resulted in a more substantial reduction in costs compared to the WGO algorithm. The distribution system, consisting of four MGs, benefitted significantly from the optimization capabilities of TLBO, enabling more efficient resource allocation and utilization. The superior performance of TLBO suggests that it is a promising approach for reducing costs and improving the overall operational efficiency of distribution systems in scenarios similar to the one considered in this study.

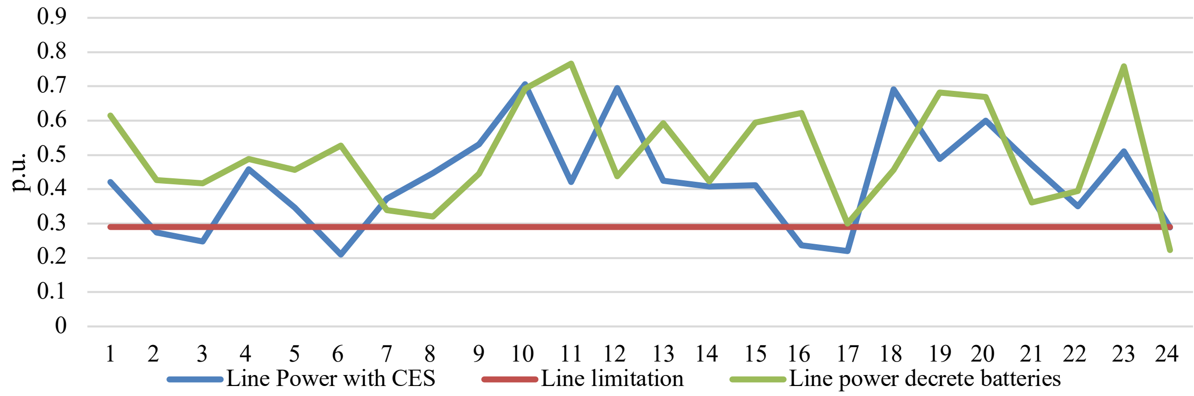

Fig. 10. Application of energy storage in two different states, namely CES and discrete, to address congestion in a distribution system.

5. Conclusion

This study presented a comprehensive solution approach for managing congestion and minimizing energy costs in distribution systems through the integration of a CES system. By leveraging the shared storage system and applying the TLBO algorithm, the operation of the battery within MGs was optimized, resulting in a decrease in energy costs for the MGs. The effectiveness of this approach was validated through extensive simulations and analysis, which consistently demonstrated satisfactory results.

Furthermore, the CES system proved instrumental in addressing congestion in the distribution system. During congestion hours, DSO purchased charged power from the storage manager, even at a premium price exceeding the prevailing electricity rate. This mechanism effectively alleviated congestion and provided economic benefits to both the MGs and the DSO. The successful management of congestion and the reduction in energy costs underscored the importance of CES as a valuable tool in tackling congestion and cost-related challenges in distribution systems.

Moreover, the results highlight the importance of a coordinated and centralized approach, such as CES, in

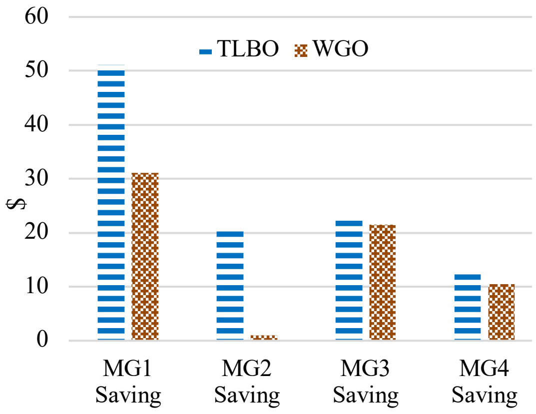

Fig. 11. The performance of two heuristic algorithms WGO and TLBO in terms of cost reduction.

tackling congestion issues within a distribution system. The utilization of CES between MGs enables efficient sharing and distribution of energy resources, effectively alleviating congestion and maintaining a smooth operation. In contrast, individual installations of discrete energy storage systems by MGs lack the necessary capacity to effectively manage congestion, emphasizing the benefits of a centralized and collaborative energy storage approach. A potential direction for future research based on this paper is to explore the booking strategy of CES in a peer-to-peer energy trading context.

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