Article

IoT-Based Mobile Energy Storage Operation in Multi-MG Power Distribution Systems to Enhance System Resiliency

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Abstract: Multi-microgrids have gained interest in academics and industry in recent years. Multi-microgrid (MG) allows the integration of different distributed energy resources (DERs), including intermittent renewables and controllable local generators, and provides a more flexible, reliable, and efficient power grid. This research formulates and proposes a solution for finding optimal location and operation of mobile energy storage (MES) in multi-MG power distribution systems (PDS) with different resources during extreme events to maximize system resiliency. For this purpose, a multi-stage event-based system resiliency index is defined and the impact of the Internet of things (IoT) application in MES operation in multi-MG systems is investigated. Moreover, the demand and price uncertainty impact on multi-MG operational performance indices is presented. This research uses a popular PG & E 69-bus multi-MG power distribution network for simulation and case studies. A new hybrid PSO-TS optimization algorithm is constructed for the simulations to better understand the contributions of MES units and different DERs and IoT on the operational aspects of a multi-MG system. The results obtained from the simulations illustrate that optimal operation of MES and other energy resources, along with the corresponding energy sharing strategies, significantly improves the distribution system operational performance.

Keywords: microgrid; distributed energy resources; distribution system; mobile energy storage; IoT; optimization

1. Introduction

Electrical energy is an inevitable part of our daily lives, primarily supplied by centralized power plants. The demand growth, technological innovations, and policy-rated constraints drive transformation in electrical power and energy systems by combining decentralized system units with centralized bulk systems. The Internet of Things (IoT) came as a blessing in this modern world for this transformation with some great features. Monitoring the power system network in real time, situational awareness with intelligence and control provided by IoT could shift the conventional power distribution systems into intelligent ones, resulting in an efficient, safe, reliable, robust, and feasible power system network [1]. The decentralized generation systems, called distributed generators (DGs), are normally connected to the distribution networks close to the demand side. Moreover, mobile energy storage is gaining attention in academia and industries as a decentralized energy provider, to reduce the power transmission line losses, system operational costs and environmental emissions. The application of MESs with IoT in power distribution systems can significantly improve the system resiliency during power system disaster events. This paper optimizes mobile energy storage real-time applications using energy management strategies in multi-MG power distribution systems. IoT supports MESs to maintain the generation consumption balance in real time in this research.

Many research articles are available in the literature on power distribution system expansion and operation while considering system resiliency improvement. For instance,

the authors in reference [2] define variable resiliency indices and enhance those indices from the perspective of networked microgrids. This research aimed to increase the network microgrid system resiliency in extreme event situations. The authors in [3] propose a methodology for multi-MG adequate and stable operation to increase system resiliency during extreme events. The authors in reference [4] present a distributed generator-based expansion model in power distribution systems to achieve multiple goals, including annual demand increment, reducing emissions, and overall increasing system resiliency. The authors in reference [5] consider network nano grid rather than microgrid for electric vehicle battery operation using energy management for enhancing the system resiliency. The authors in reference [6] propose a probabilistic optimization model applied in networked multi-carrier microgrids to enhance the system resiliency and minimize the system operating and emissions cost. A control-based energy management system is applied in industrial microgrids with solar photovoltaic (PV) and battery storage systems to improve the resiliency and reduce operating costs [7]. The authors in [8] propose a dynamic home energy management system for residential power scheduling to improve the microgrid resiliency and reduce consumers' electricity cost. The authors in [9] develop a mixed-integer linear programming model for controlling storage devices in PDS to enhance the system resiliency and minimize load shedding. The authors in reference [10] present a methodology based on the unit commitment framework by addressing synchronous issues for operating limitations, power flow distribution assortment, and imposed outages lines. A resilience-oriented proactive methodology is proposed in [11] to enhance the system resiliency by preparing and using multiple energy carrier resources against an approaching hurricane. Multiple MGs have been disregarded in this research, which could benefit from sharing resources based on real-time generation and consumption. A risk-limiting measurement-based strategy is proposed in [12] to restore maximum loads, especially critical loads, after a natural disaster for enhancing the system resiliency of a distribution system. They use stochastic nature intermittent energy resources while skipping energy storage units, which can improve the system resiliency, especially in multi-MGs.

Mobile energy storage can play a significant role in distribution systems from different operational perspectives. A day-ahead energy management system is applied in [13] for mobile storage operation to minimize the cost of the power imported from the grid. However, real-time operations seem to assume here which need to be identified. The authors in [14] propose a model for integrating a high level of renewable energies by supporting mobile storage to minimize the total investment and maintenance costs. The cost of RESs and mobile energy storage, system operating costs, and emission costs together are considered in their research. This research did not consider multi-MGs to enhance system resiliency through joint renewables and mobile energy storage planning. A mobile generator and fuel tanker-based energy management scheduling is proposed in [15] for boosting the power distribution system resiliency. For benefited would be possible by considering multi-MGs while considering joint scheduling of available energy resources. While much research has been conducted with the aim of system resiliency improvement, there are still possibilities to significantly improve resiliency by using more advanced technologies like IOT for avoiding any time delay in operation of power distribution systems. If multi-MGs present in power distribution systems, the delay issue will be more visible for generation and load forecasting. The authors in reference [16] propose an algorithm to connect the demand response program with the present demand-controlled energy management system considering the IoT technology as a data communication platform. This research did not consider energy storages management within the demand response mechanism in the energy management system. The authors in reference [17] present a methodology for event-based power and load management solution for prosumer MGs by considering real-time communication platform-based IoT technology. This research has limitations for not viewing multi-MGs while improving system resiliency in the presence of external energy sources.

With the transformation of electrical power systems by combining decentralized system units with the centralized bulk systems, mobile energy storage has great potential to improve the system resiliency. Multi-MGs operation within the distribution system without any time delays are required to have a more efficient energy system, and IoT is delivering the concept of such advanced technological opportunities. This research considers mobile energy storage optimal planning and operation inside multi-MGs during special events to maximize system resiliency. The developed model promotes the investment in the optimal generation facilities among profit-oriented entities, utilities, or system operators, as well as the consumers. IoT is considered to make sure no delay is occurring for energy generation and load balance. Due to the multi-MGs structure, regular consumers will experience less power loss as critical loads will be recovered instantaneously, in the system. Furthermore, this research considers a resiliency index to measure system resiliency during extreme events to achieve early recovery of consumers. The main contribution of this paper is summarized as follows:

(1) Defining a multi-stage power system resiliency index for mobile energy storages operation during extreme events in multi-MGs;
(2) Optimizing operation of mobile storage in terms of their locations and capacities during multistage extreme events to improve system operational performances;
(3) Formulating the problem of mobile energy storage planning and operation in the presence of renewable energies inside multi-MGs distribution systems;
(4) Performing different case studies of IoT and load uncertainty analysis while considering multistage system resiliency.

The rest of the paper is organized as follows: Section 2 describes the resiliency and IoT in power system and mobile storage. Section 3 describes the system modelling for both dispatchable and non-dispatchable generators as well as loads. Problem formulation and the optimizing solution algorithm is presented in Sections 4 and 5, respectively. Multi-MGs power distribution systems are analyzed in Section 6, and the results and simulation are presented in Section 7. The impact of IoT and the load generation uncertainty is discussed in Section 8; finally, the conclusion of this paper is presented in Section 9.

2. Resiliency, IoT and Mobile Storage in Power Distribution Systems

Power system resilience is the capability of a power system to protect itself during an extreme event using adequate preparation, responding, and recovering quickly from the significant disruptions [2]. Resilience may depend on the event type and its action of recovering the system. In this research, the system has been supported during extreme events for power system resiliency improvements using mobile energy storage in the presence of renewables inside multi-MGs. Different stages have been considered based on event formulation and coordination happens between mobile energy storage along with renewable and nonrenewable generators. The variation of energy storage capacities and locations based on stages could positively impact the system resiliency in various quantities. At the same time, different renewable and nonrenewable generators supported for optimal power system operations impacted the system resiliency performance. This section will describe the system resiliency assumption chosen for this research and how the different stage-based resiliency indices have performed for resiliency improvement.

In this research, the well-known PG & E 69 bus power distribution system along with some DGs (gas turbine, PVs, and wind turbine) is considered for enhancing the system's resiliency. Since multi-MGs enhance the power system performance, especially during extreme events, both dispatchable and non-dispatchable generators have been considered here in this research. The main contributors for enhancing the system resiliency are energy storage and distributed generators. Since the existing system may already have some installed generators, the operations are based on energy storage and the existing DGs inside the system. Some critical load points are considered for the grid operations, and prioritized assumptions are made for the rest of the loads.

A general assumption is made in this research. Initially, it is considered that the system operator will be notified regarding extreme events in real time and will take appropriate actions for the completion of resiliency improvement. In this case, there should be pre-existing forecasting data present regarding the extreme events. As a result, system resiliency improvement happens by using both mobile energy storage and distributed generator coordination based on their availability. The total number of operation stages for coordination between mobile energy storage and distributed generators is selected based on considering or ignoring the forecasted event data. In this case, the total number of resiliency improvement operational stages will be four; namely, the planning and avoidance stage, operational and survival stage, reconfiguration and recovery stage, and post-recovery stage, which is described in detail in upcoming sections of this paper.

The resiliency enhancement stages are shown in Figure 1. According to Figure 1, the operational cycle starts from t_0 and will finish at t_n in the last stage. Where t_0 and t_n have highest operation performance (100%), i.e., the power supply is available for all the loads. On the contrary, t_{esp} and t_{er} have the lowest operation performance, i.e., the minimum power supply is available to support the loads.
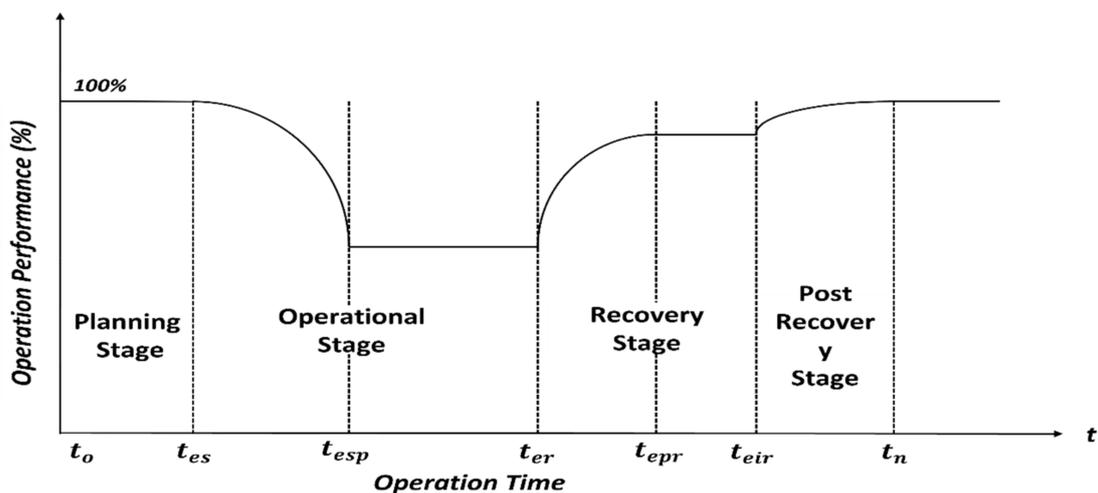
Figure 1. Different power system resilience stages where the operation performance expressed as time varying function.

The IoT in power distribution systems provides a sustainable solution to enhance the operational performance. In this research, the goal of the IoT and energy management is to utilize MES and distributed generators for their optimal operations in real time to minimize the system operating costs and reduce environmental emissions while enhancing system resiliency. Multi-MGs are present in this research to optimize the power flow so that maximum power is drawn from the MGs and minimum power is taken from the primary grid if there is availability during extreme events. The target is to shift the energy dependency from the primary grid more toward MGs, especially by energy management for mobile energy-storage operations. When the event enters operational stages, the available energy will support critical loads first, defined as priority-based loads. When the energy needs for critical loads are fulfilled, MGs' excess energy generation can be used based on their priority to the less critical loads. The power exchanges to and from the multi-MGs are performed based on real-time use of IoT rates. The power distribution system will become more efficient, cost-effective, and resilient with IoT, especially during extreme events. Since extreme events include several stages, i.e., planning and avoidance stage, operational and survival stage, reconfiguration and recovery stage, and post-recovery stage, coordination between generation and load in real time is crucial. Moreover, the IoT in power distribution systems provides feedback to the utilities and multi-MG energy resources, including mobile storage in real time, which better serves critical customers

by controlling functionalities [18]. Due to this real-time feedback provided by the IoT to multi-MGs, the support for the customers and ultimately of multi-MGs power distribution systems will be enhanced.

MES storage has been gaining popularity for power system engineers in recent times. One of the significant advantages of MES rather than conventional energy storage is that MES is portable and easy to relocate to the required places during extreme events. MES is typically used as a backup resource for non-dispatchable wind turbines and PVs in any power system network [19]. In this research, their operation is different from the traditional one. Since the goal of this research is to improve the system performance along with system resiliency, mobile energy storage operation will be adjusted according to the resiliency stages. For instance, before the extreme event starts, mobile storage will be relocated in the system based on real-time data for available expected generation and the location of the critical loads in the system. MES can work in both load and generation mode operations, depending on the power system planners. In this research, especially during extreme events, mobile energy storage will operate as a generator. For special cases that all the critical loads have been covered during those periods, it may become charged and operate as a load to support the priority-based loads in the future. An energy management system using IoT decides whether or not to take power from MES during different power system operating conditions.

3. System Modelling

This section discusses the modeling for gas turbines, PVs, wind turbines, and mobile energy storage in detail.

3.1. Dispachable Generators

For the construction of multi-MG distribution systems, it is essential to use both dispatchable and non-dispatchable generators. Gas turbines are used as dispatchable distributed generators in this research, ensuring continuous energy support if the fuel is available. They have been modeled as active power sources, which can provide a certain amount of power for the loads. Due to sustained power availability, the operational costs from these dispatchable generators can be measured per kWh using (1) [20].

$$C_0^{MT}\left(P_{MT}^{(t)}\right) = \frac{C_{ng}}{K} \sum \frac{P_{MT}^{(t)} \times \Delta t}{\eta_{MT}} \tag{1}$$

where C_{ng} represents the cost of natural gas, K is the co-efficient, and η_{MT} is the efficiency of the gas turbine.

It should be noted that the initial investment costs of each dispatchable distributed generator have been ignored in this research since it will not affect the operational performance, e.g., energy management in the system. The energy sharing between dispatchable and non-dispatchable generators happens within the multi-MGs by considering tertiary controls of these DGs for optimizing operational goals.

3.2. Non-Dispachable Generators

In this research, the non-dispatchable wind turbine and solar PV are used for the multi-MGs application and to support the critical loads during extreme events. Such resources are not usually controllable, and the critical loads obtain maximum capacity based on the load's priorities. Wind and solar PV energy can be used to charge the mobile storage as required to make sure continuous power is supplied to the critical loads during the extreme-event time periods.

The wind turbine distributed generators have non-dispatchable characteristics due to their uncertain output power for different times during a 24 h period. The reason for uncertain power from wind turbines is mainly the wind speed and its variation and the turbine module too while delivering its output power. In this case, it is essential to

model these distributed generators with their uncertain behavior. The model for obtaining output power from the wind turbine is performed hourly using Weibull probability density function (PDF) from reference [21].

$$
Pv_w(v_{aw}) = \begin{cases} 0 & 0 \leq v_{aw} \leq v_{ci} \\ P_{rated} \times \frac{v_{aw} - v_{ci}}{v_r - v_{ci}} & v_{ci} \leq v_{aw} \leq v_r \\ P_{rated} & v_r \leq v_{aw} \leq v_{co} \\ 0 & v_{co} \leq v_{aw} \end{cases} \tag{2}
$$

where v_{ci} represents the wind's cut-in speed, v_r and v_{co} are the rated speed and cut-out speed of the wind, respectively. Pv_w and v_{aw} are the wind's output power and average wind speed for the state w.

Like wind turbines, solar PV is also considered for non-dispatchable generators in this research that are not controllable. Solar PV is also used for the multi-MGs application and support of the critical loads during extreme events. It also shows uncertainty, and the PV's output power mainly depends on the outside whether, solar irradiance and the PV module itself.

The model for obtaining output power from the solar PV is performed hourly using Weibull PDF from reference [21].

$$
f_b(s) = \frac{\tau(\alpha + B)}{\tau(\alpha)\tau(\beta)} \times s^{(\alpha-1)} \times (1-s)^{\beta-1} \qquad 0 \leq s \leq 1; \ \alpha, \beta \geq 0 \tag{3}
$$

where s is the solar irradiance and $f_b(s)$ is the beta distribution function. The beta distribution function parameters α and β can be calculated by Equation (4).

$$
\alpha = \frac{\mu \times B}{1 - \mu} \times s^{(\alpha-1)} \ and \ \beta = 1 - \mu \times \left(\frac{\mu \times (1 + \mu)}{\sigma^2} - 1 \right) \tag{4}
$$

3.3. Loads

The load data considered in this paper have been taken from the IEEE RTS [22]. In this research, the priority-based critical load has been assumed from the load bus position. Even the priority-based critical load changes will not affect the modeling process, and the modeling can be performed with the same approach. The load in the peak time of the day is used to create a 24 h load by simply multiplying the percentages of that peak load. The probabilistic nature of the load has also been considered in a 24 h load period to obtain more accurate results. It should be noted that the priority-based critical load has been assumed in this research, which can be residential or industrial demands. The type of load, whether residential or industrial, will not affect the formulations and modeling process and can only affect the values of hourly load data.

4. Problem Formulation

This section describes the problem formulation for system resiliency multi-stage coordination for optimal mobile storage operations. In addition, the energy management objective function using IoT for the mobile storage operations inside the multi-MGs has been discussed. At the end of this section, constraints are summarized for solving the optimization problem.

4.1. Multistage Coordination for System Resilience Enhancement

The main stages for the system resiliency improvement in any power distribution system is the operational/survival stage and recovery stage. However, this research considers multistage actions by considering planning stages before the extreme event and post recovery stage after the event finish to improve the resiliency by using stages coordination.

4.1.1. Stage 1: Planning and Avoidance Stage

This stage will consider the assumption made for this research, and there is forecasting related to this stage. The objective in this stage is to make a planning problem based on optimal mobile storages location to supply the critical load. The mobile storage application may consider by coordinating with multiple energy resources located within multi-MGs to fulfil the objective function. The duration of this stage is from t_0 to t_{es}. This stage is also considered as a normal stage just before the extreme event starts. The resiliency $Res_{S,1}$ in this stage is calculated for the optimal mobile generator location-based critical loads, as shown in the following equations:

$$Res_{S,1} = \int_{t_0}^{t_{es}} F_1(t)dt \tag{5}$$

$$F_1(t)dt = \sum_c L_{ct}.P_{ct}.C \tag{6}$$

where the system performance $F_1(t)$ is evaluated as the total electrical energy supplied to consumers based on the critical load. L_{ct} is the distribution load status, and P_{ct} is the active power of mobile storage.

4.1.2. Stage 2: Operational Stage–Survive Stage

This stage is the operational stage, where its objective is to minimize the loss based on priority-based loads by coordinating mobile energy storage and available energy resources. This will also consider different combinations of mobile storage negotiating with different energy generators with different capacities to enhance the system resiliency. The operation of such energy storage along with energy generators will operate based on defined objectives in this stage. Since this stage is considered operational during extreme events, there will be an issue with the operation of the existing generator, and it will be optimized to enhance the system's resiliency. The resiliency $Res_{S,2}$ in this stage is calculated for a priority-based load, as shown in the following equations:

$$Res_{S,2} = \int_{t_e}^{t_r} F_2(t)dt \tag{7}$$

$$F_2(t)dt = \sum_t \sum_l c_l.u_{t,l}.\tau - MS - G \tag{8}$$

where the system performance $F_2(t)$ is evaluated as the total electrical energy supplied to consumers based on the priority-based load. MS is the power of mobile storage that will be used in the operational stages, and G is the generator that exists in the system.

4.1.3. Stage 3: Reconfiguration Stage-Recovery Phase

The main advantage in the reconfiguration or recovery stage is that the system can utilize its resources based on its experience during the event period. The objective in this stage is to minimize the loss based on priority-based loads and considering MS reconfiguration. The different capacities of the mobile energy storages and distributed energy generators could affect the multi-MG system during the stages; the detailed analysis of their operations will be investigated by using this stage.

$$Res_{S,3} = \int_{t_r}^{t_{ir}} F_3(t)dt \tag{9}$$

$$F_3(t)dt = \sum_t \sum_l c_l.u_{t,l}.\tau - MS - G \tag{10}$$

4.1.4. Stage 4: Normal Stage–Post Recovery Phase

This stage is the normal stage, and the system will go back to its normal operations. The resiliency $Res_{S,4}$ in this stage is calculated for a regular load, as shown in equations:

$$Res_{S,4} = \int_{t_{ir}}^{t_n} F_4(t)dt \tag{11}$$

$$F_4(t)dt = \sum_t \sum_l c_l . u_{t,l} . \tau \tag{12}$$

After defining four different stages, the total system resiliency $Res_{S,B}$ can be calculated by simply adding those stages.

$$Res_{S,B} = Res_{S,1} + Res_{S,2} + Res_{S,3} + Res_{S,4} \tag{13}$$

Then, this research defines a new resiliency index,

$$R = \frac{Res_{S,B}}{\int_0^{t_n} F(t)dt} \tag{14}$$

Thus, the resiliency index should be the proportion of total resiliency for four different stages to the entire system performances evaluated during the same period. The resilience index is based on accumulated loss in post degradation stages: the system resilience concerning the extreme event can be quantified as the reciprocal of the system's loss of performance [18].

$$Res_{A,1} = \frac{1}{loss_A + loss_B} \tag{15}$$

This index represents the system behavior until the system goes to the full-degradation stage. This period has been considered for this index due to the performances of energy storage inside the grid. Performance loss can be calculated by the integration of the relative deviation after the duration of performance degradation, as shown below:

$$Loss_A = \gamma \times \int_{t_r}^{t_{ir}} \left[\frac{Q_0 - Q(t)}{Q(t)} \right] dt \tag{16}$$

The parameter γ is used to convert energy into its equivalent dollar value. $loss_B$ represents the loss in the rest of the period rather than the areas from t_r to t_{ir}.

4.2. Mobile Energy Storage Energy Management Objective Functions

The objective function for finding the optimal locations of mobile energy storage in the pre-event stages is to minimize the PDS losses, and it can be formulated as follows by Equation (17):

$$Minimize\ OF = \sum_{h=1}^{24} \sum_{i=1}^{N} P_{loss}{}^i \tag{17}$$

Since inside multi-MG PDS there are non-dispatchable DGs with an uncertain nature, the power losses of the system are calculated by:

$$P_{loss} = \sum_{n=1}^{N_{st}} P_{loss} \times \rho_n \times h_n \tag{18}$$

where represents the total number of mobile energy storages uses in the multi-MGs. N_{st} is the total number of uncertainty states. ρ_n and h_n works for only dispatchable distributed generators and for dispatchable DGs, and ρ_n and h_n will be equal to 1.

4.3. Multi-MGs System Performances Assessments

In this research, multi-MGs power distribution system operational performances have been identified for optimal mobile energy storage operations. If the multi-MGs power distribution system already has some installed generators, the operational cost can be calculated from (19) for a 24 h period considering the operating costs of such DGs. DGs considered in this research are both dispatchable and non-dispatchable types.

$$
\begin{aligned}
OC_b = \sum_{h=1}^{24} (P_{s\_h} + \quad P_{s\_l\_h}) \times C_{spu\_h} \\
- \sum_{h=1}^{24} \sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} \\
+ \sum_{h=1}^{24} \sum_{j=1}^{N_{DG}} E_{DG,d\&nd}
\end{aligned}
\tag{19}
$$

where P_{s_h} represents the total power generating from the system, $P_{s\_l\_h}$ represents the system loss and C_{spu_h} is the cost of power at time h. $P_{DG\_j\_h}$ and $C_{DGpu\_j\_h}$ is the power and per-unit costs of power for j^{th} base DG at time h, and N_{DG} is the total number of base DGs. $E_{DG,d\&nd}$ is the generation from the dispatchable and non-dispatchable generators.

System operational cost: multi-MG power distribution system operational costs (OC) can be calculated by (6) for the energy storage charging period, generally before the extreme event.

$$
\begin{aligned}
OC = \sum_{h=1}^{24} (P_{s\_h} + \quad P_{s\_l\_h}) \times C_{spu\_h} - \sum_{h=1}^{24} \left(\sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} \right) \\
+ \sum_{h=1}^{24} \sum_{m=1}^{N_{MESS}} P_{MESS_h} \times C_{MESS_h}
\end{aligned}
\tag{20}
$$

On the other hand, the common scenarios of mobile energy storage applied in this research is in a discharging state where it will relocate during the extreme event. The operational cost (OC) of multi-MGs power distribution systems can be calculated by Equation (21) for the energy storage discharging period, which will be normally operational for the recovery stage during the extreme event.

$$
\begin{aligned}
OC = \sum_{h=1}^{24} (P_{s\_h} + \quad P_{s\_l\_h}) \times C_{spu\_h} - \sum_{h=1}^{24} \left(\sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} \right) \\
- \sum_{h=1}^{24} \sum_{m=1}^{N_{MESS}} \eta P_{MESS_h} \times C_{MESS_h}
\end{aligned}
\tag{21}
$$

where P_{NMESS_h} represents the real power from MES in kW, C_{MESS_h} represents the per-unit costs for the mth, MES, and N_{MESS} is the total MES number reforms inside the multi-MG power distribution system. η represents the efficiency for MES discharging operation.

System emission cost: the emissions from the generators in the distribution system can be measured by [20]:

$$
C_E = P \times \sum_{j=1}^{m} E_p^j \times S
\tag{22}
$$

Here, E_p represents the costs for environmental emission USD/kg, and S is the corresponding emission coefficient in kg/kwh.

4.4. Optimization Constraints

The are several significant constraints used in this research for solving the optimization problem, summarized as follows [20]:

Modification has been performed for the power flow equation to include real and reactive power from the energy sources used in this research.

$$P_{Sub_t} + \sum P_{DG_t} - \sum P_{Load_t} = \sum_{i=1}^{nbus} V_{t,i} \times V_{t,j} \times Y_{i,j} \times \cos(\theta_{i,j} + \delta_{i,j} - \delta_{t,i}) \quad \forall_{i,t} \tag{23}$$

$$Q_{Sub_t} + \sum Q_{DG_t} - \sum Q_{Load_t} = -\sum_{i=1}^{nbus} V_{t,i} \times V_{t,j} \times Y_{i,j} \times \sin(\theta_{i,j} + \delta_{i,j} - \delta_{t,i}) \quad \forall_{i,t} \tag{24}$$

The power limit for MES integrated into the power network should be maintained with constraints.

$$MESs_{min} \leq MESs_{t,i} \leq MESs_{max} \; \forall_{t,i} \neq 1 \tag{25}$$

Another constraint is the integration level of various energy resources (ERs) such as gas turbines, wind turbines, and PV solar capacities.

$$\sum_{i=1}^{n} P_{ERs\_i} = \% \; ERs_i \; \text{of feeder capacity} \tag{26}$$

Two important considerations are for the voltage limit and the current limit maintained.

$$V_{min} \leq V_{t,i} \leq V_{max} \; \forall_{t,i} \neq 1 \; I_i \leq I_{max,i} \; \forall_{t,i} \neq 1 \tag{27}$$

5. Optimization Solution Algorithm

There are two different algorithms used for mobile storage operation in this research: hybrid Particle Swarm Optimization-Tabu Search (PSO-TS) optimization algorithm and Newton Raphson's load flow method. These methods look at the best storage places and their corresponding capacities before extreme events. The next stage is performing energy management and applying IoT technology for finding the optimal schedule and coordination between dispatchable and non-dispatchable DGs and mobile energy storage for a 24 h period. The 24 h period is divided into a couple of stages based on improving multi-MGs power distribution system resilience.

Particle swarm optimization (PSO) and Tabu Search (TS) are usually conventional metaheuristic algorithms used for vital research to solve optimization problems in different areas. Those methods can look for optimal solutions and global solutions even in complex problems [21]. TS can look for a good solution using a neighboring searching strategy and use various memory forms to make solution space more economical and practical. Those memory forms try to look for answers from the attractive regions and avoid revisiting solutions found earlier. The solution that is not changing to a better shape TS considers those solutions run from optimal local feels for discrete and non-discrete areas.

The PSO algorithm uses various decision variables in the searching space. There are two primary considerations for the PSO updates during its operation: position at the bus number and the velocity. Those places are selected randomly at the program's first iteration, and the initial velocity is considered as zero in this stage. In the following steps, PSO will update the position and velocity by using a simple concept based on data collected from particles past own best, which may have few random perturbations. PSO will follow the same procedure and confirm near-optimal global solutions in the iterations while finding places with the best solution. The limitations with these two metaheuristics algorithms PSO and TS are their limitation on finding the global best optimal solution, especially in the high network distribution system [21,23]. Consequently, this research uses a hybrid PSO-TS optimization algorithm, which has a better capability to ensure global optimum solutions even in the high degree network distribution system.

In this hybrid PSO-TS optimization algorithm, initial positions and velocities are chosen inside the PSO, and the result is transferred to TS to obtain more robust results.

Depending on the system resiliency stages in the problem, PSO will select the size or location or both the size and location before sending to the TS. There are both dispatchable and non-dispatchable DGs inside multi-MGs, so PSO will consider with Newton Raphson whether to take the number of uncertainty states or not. After TS obtains the initial PSO results based on resiliency and uncertainty states, the PSO-TS algorithm will finalize the solution after bringing back the best results from TS. The results from TS are further sent to PSO to confirm its near best local and global best optimal results. Details of each step applied for constructing the hybrid PSO-TS algorithm and its application for optimal mobile storage operation in multi-MGs power distribution to enhance the power distribution system resilience are illustrated in Figure 2.
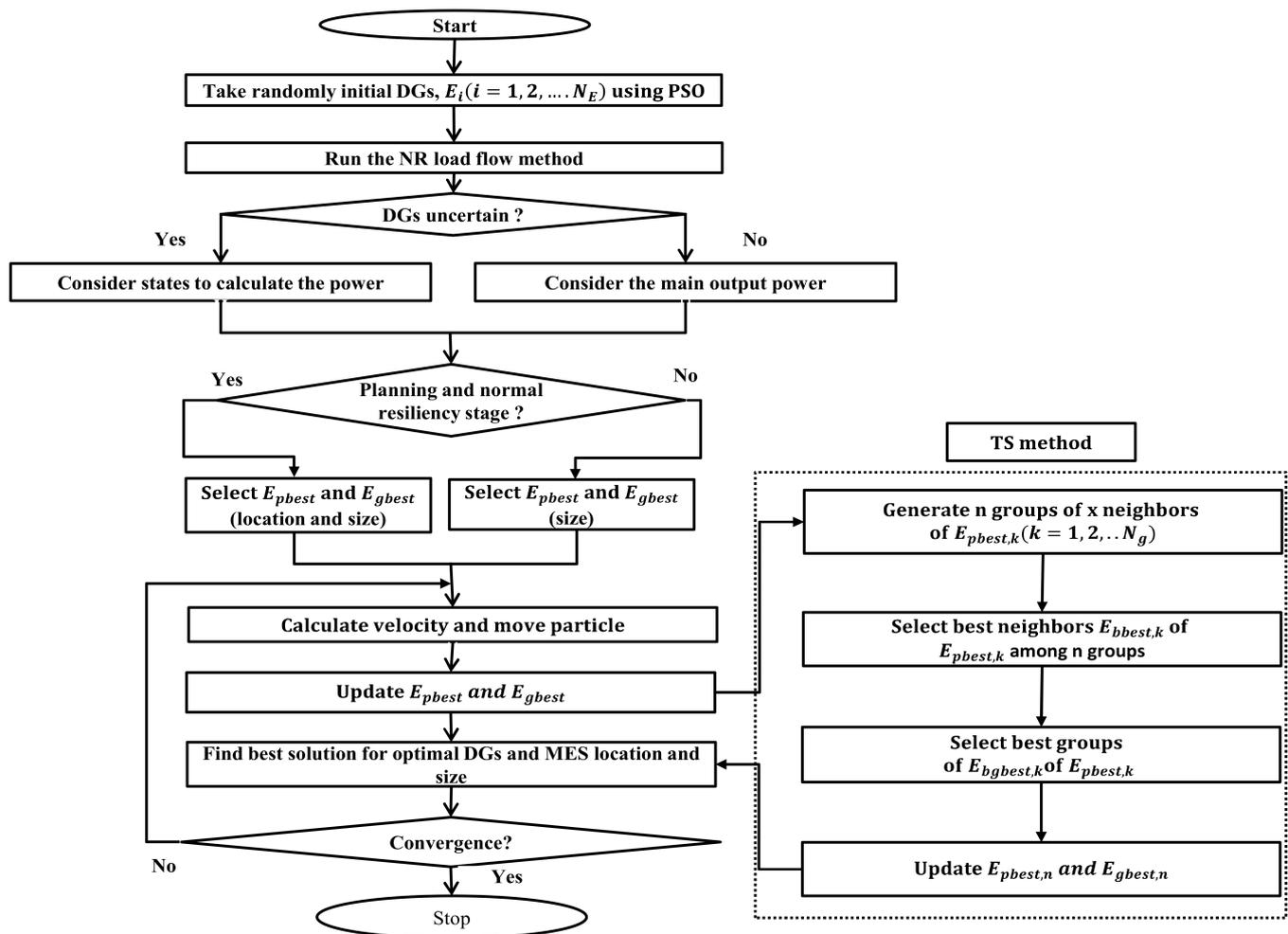

Figure 2. Multi-stage resiliency-based hybrid PSO-TS solution algorithm.

6. Multi-MG Power Distribution System under Study

The well-known PG & E 69-bus power distribution system with five different microgrids inside it is selected for simulations and case studies for mobile energy storage operations. Since MGs should have their own sufficient distributed generators inside them, in this research, different gas turbines, PVs, and wind turbines are considered inside microgrids to make the system a more practical case. When the microgrids operate between themselves and share their energy based on energic economy, available generations, etc., it is called a multi-microgrid. There are four switch positions between the microgrids and located between the bus number 11–12, 15–16, 23–24, and 43–44. The multi-MGs power distribution system normal operational costs can be calculated by using kWh per unit for a 24 h period. It is assumed that the event considered in this research should be recovered

within 24 h. If it takes more than 24 h, it will not affect this system modelling and there will be a need to consider another 24 h for further action. Another important consideration for this research is system losses and system environmental emissions calculated for 24 h [21]. Critical loads based on load priorities are also selected with a fixed position in the load buses that already exist in the multi-MGs distribution system. During extreme events, mobile storage will be considered, delivering their power based on the load priority. Since there are uncertainties in the load generation states because of renewable generators and load variations, in this research, their corresponding uncertain behaviors are also considered to obtain more closed accurate results. Figure 3 shows the system under study with a multi-MG-based power distribution system with multiple distributed generators located inside the microgrids.
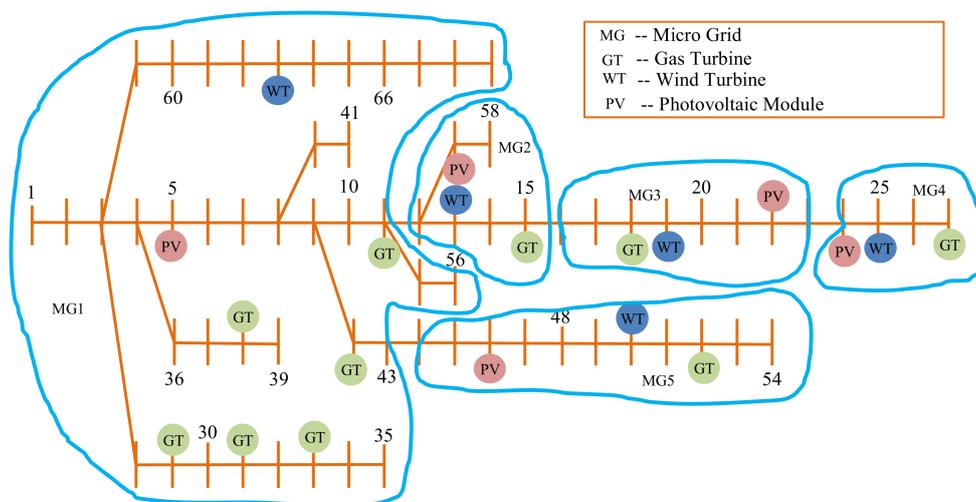
Figure 3. Multi-microgrid power distribution system.

7. Verification Results and Discussion

In this section, optimal locations and capacities of mobile storages have been identified within the multi-MGs before the event start. Basically, these two actions, finding locations, and capacities happen in the planning stage described in Section 2. The objective of finding these two parameters is to enhance the system resiliency, and that is basically to reduce the system losses during those periods. Since system resiliency events are based on assumption and there is no exact definition for that, in this research, four different time slots have been considered for the simulations. The planning and avoidance stage is considered for 8 h before the event starts. Operational and recovery stages are considered for 16 h. The last stage, the post-recovery stage, is considered for 8 h for the simulation. Even, the event time periods may not be the same based on real event situations, and it would not affect the system modeling and formulations. Two different capacities of mobile energy storage have been considered for this research and their corresponding energy management operations have been performed to find the system operational performance in terms of system operational costs, losses, emissions, and total system operational costs.

7.1. Mobile Storage Optimal Locations and Capacities inside Multi-MGs

In this case, 150 kW of mobile energy storage have been included in multi-MGs system. Dispatchable gas turbine, non-dispatchable PV solar, and wind turbine are in different buses within multi-MGs, and their corresponding capacities, 250 kW, 150 kW, and 150 kW are also given in Table 1. Moreover, the most interesting points for this research are the critical loads, which should be the priority from the existing generations, especially during the extreme events and the operational and recovery stages. The critical load is selected in the bus numbers 8, 14, 21, 26, and 48, and their corresponding capacities are 100 kW each.

When the multi-MGs have these resources, the optimal locations and capacities of mobile energy storages have been found out in different bus numbers shown in Table 1.

Table 1. Optimal locations and capacities of mobile energy storage in multi-MGs for 150 kW of mobile energy storages.

DG Name	Total Capcacity	Locations (Bus)	Capacities (Bus)
Gas Turbine	250 kW	11, 15, 18, 27, 29, 31, 33, 38, 42, 52,	20, 30, 30, 30, 20, 20, 30, 20, 20, 30
PV	150 kW	5, 22, 24, 46, 57	30, 30, 30, 30, 30
Wind Turbine	150 kW	13, 19, 25, 50, 63	30, 30, 30, 30, 30
Critical Load	500 kW	8, 14, 21, 26, 48	100, 100, 100, 100, 100
Mobile Storages	150 kW	20, 21, 26, 45, 53	35, 30, 20, 25, 40

As can be seen from Table 1, the maximum capacity of mobile energy storage is in bus number 53 and the capacity is 40 kW. This is mainly for the energy management process during extreme event to make the system more resilient. This could happen due to the capacities of existing dispatchable and non-dispatchable distributed generators, and the position and capacities of critical loads. The minimum capacities of the energy storage position are shown in bus 26. It should be noted that if the existing capacities of distributed generators and critical loads change, the storage position may also change and can be performed in a similar way.

When the mobile energy storage capacities increase to 300 kW from 150 kW, it is seen from Table 2 that the maximum capacity of mobile energy storage is in bus 53 and 21, and their corresponding capacity is 60 kW each. This is also mainly for the energy management process during extreme events to make the system more resilient. One noticeable change from the previous case of 150 kW that the locations increase to six positions compared to five positions before, and again, those are for the mutual contributions of dispatchable and non-dispatchable distributed generators.

Table 2. Optimal locations and capacities of mobile energy storage in multi-MGs for 300 kW of mobile energy storages.

DG Name	Total Capacity	Locations (Bus)	Capacities (Bus)
Gas Turbine	250 kW	11, 15, 18, 27, 29, 31, 33, 38, 42, 52,	20, 30, 30, 30, 20, 20, 30, 20, 20, 30
PV	150 kW	5, 22, 24, 46, 57	30, 30, 30, 30, 30
Wind Turbine	150 kW	13, 19, 25, 50, 63	30, 30, 30, 30, 30
Critical Load	500 kW	8, 14, 21, 26, 48	100, 100, 100, 100, 100
Mobile Storages	300 kW	14, 20, 21, 26, 45, 53	50, 45, 60, 35, 50, 60

7.2. Multi-MGs Power Distribution System Operational Performance

This stage investigates the operational performance of multi-MGs distribution system in terms of system operational costs, emissions, system loss, and finally total system operational costs, which is the summation of operational costs, emissions, system loss cost together in dollar values. When 150 kW of mobile energy storage is included in the system for supporting the critical load along with the existing distributed generators, the total cost needed to operate the system is USD 3569.30. The system losses and emissions are USD 138.40 and USD 252.20, respectively, shown in Table 3.

When the system has more energy storage than before, in this case 300 kW, it is noticeable that the total system cost has fallen to USD 3448.50 compared to USD 3569.30 from the previous case for 150 kW. This is mainly due to cheap energy from energy storages and less uses of gas turbines during those periods. Since energy storage as well as other non-dispatchable distributed generators such as PV and wind are pure energy sources, having no emissions, it is expected to reduce the environmental emissions for 300 kW

of storage integration compared to the 150 kW case. Therefore, for this case, the system environmental costs have reduced to USD 243.30 compared to USD 252.20 for the case of 300 kW of energy storage support.

Table 3. Multi-MGs system operational performances for mobile storage operations.

Mobile Storages Capacities	Operational Costs	Emissions	System Losses	Total System Operational Costs
150 kW	3178.7	252.2	138.4	3569.30
300 kW	3070.1	243.3	135.1	3448.50

8. Impact of IoT and Uncertainties

This section considers the IoT impacts for multi-MG operations. Additionally, the demand and price uncertainty for the extreme event is discussed in this section.

8.1. IoT Impact on Multi-MG Operation

In this research, IoT plays a crucial role in the real-time operation and is controlled for multi-MGs. This study shows the impacts of IoT for multi-MGs, and the results are shown in Table 4.

Table 4. Multi-MGs system operational performances for mobile storage operations without considering the IoT.

Without IoT	Mobile Storages Capacities	Operational Costs	Emissions	System Losses	Total System Operational Costs
	150 kW	3264.14	259.13	146.8	3670
	300 kW	3152.18	249.96	143.3	3545.4

Table 4 shows that the total operating costs increase to USD 3670 from the typical operating expenses of USD 3569.3 with the same capacities of mobile energy generation operation capacities in multi-MGs without considering the IoT. Similar increment patterns are shown for the system loss and emissions as well. Thus, it is essential to consider the IoT for system performance to operate and control the multi-MGs. The details in multi-MG system performance comparison with and without the IoT for 150 kW and 300 kW of mobile storage operations are shown in Figures 4 and 5, respectively.
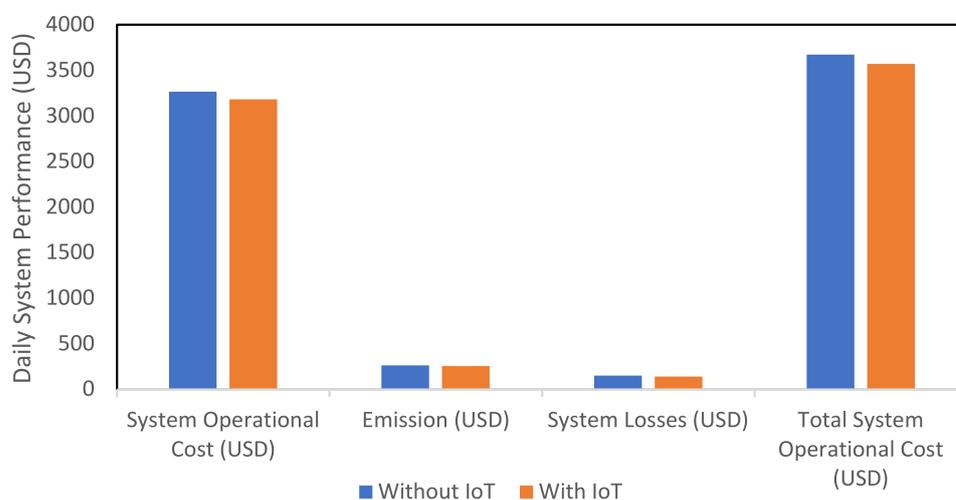
Figure 4. Multi-microgrid system performance for 150 kW of mobile storage operation with and without IoT.
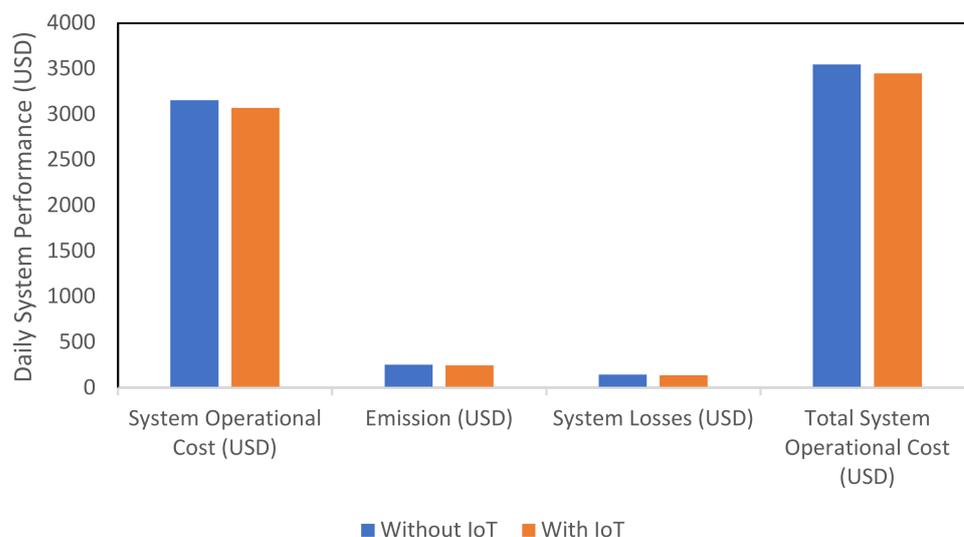
Figure 5. Multi-microgrid system performance for 300 kW of mobile storage operation with and without IoT.

8.2. Demand Uncertainty

In this stage, the demand uncertainty is calculated by considering the demand increase and decrease. It is expected that the demand may rise or drop, especially in the planning and avoidance stage and post-recovery stage. When there is forecast data for any power system extreme event, customers will use more energy to make them ready for that event or reduce energy usage based on the situation. It will typically happen before and after the event. From this perspective, this research considers two cases of demand uncertainty for 10 percent and 20 percent increment and decrement and observes the impacts on the system performance indices.

As can be seen in Table 5, when the demand increases by 10 percent, the total system operational costs increase to USD 3905.10 from the initial value of USD 3569.30. This costs even more for a 20 percent demand increment due to the increase in the generation from gas turbines. Therefore, the emission cost also rises to USD 275.30 and USD 298.70 for the two cases. One way to reduce those impacts is to increase the energy storages capacities; therefore, the total system operational costs drop to USD 3771.60 and USD 4101.20, and the system environmental emissions fall to USD 265.50 and USD 287.90, as shown in Table 5. On the contrary, when the demand falls by 10 percent and 20 percent, the total system operational costs reduce to USD 3238.60 and USD 2897.60, respectively, compared to USD 3569.30. Therefore, the emissions also dropped to USD 227.90 and USD 206.90 for the two cases due to lower gas turbine generation.

Table 5. Demand uncertainty impacts on multi-MGs system operational performances for mobile storage operations.

Demand Uncertainty	Mobile Storages Capacities	Operational Costs	Emissions	System Losses	Total System Operational Costs
−10%	150 kW	2898.2	227.9	112.6	3238.6
	300 kW	2801.6	223.8	108.7	3134.1
10%	150 kW	3463.5	275.3	166.4	3905.1
	300 kW	3343.7	265.5	162.4	3771.6
−20%	150 kW	2609.4	206.9	81.3	2897.6
	300 kW	2523.8	200.3	79.5	2803.6
20%	150 kW	3751.4	298.7	197.5	4247.5
	300 kW	3620.4	287.9	192.9	4101.2

8.3. Price Uncertainty

It is also expected that the fuel price rises or falls for different reasons. Thus, this research also considers two cases of price uncertainty for 5 percent and 10 percent increments and decrements and observes the impact on the system performance.

It is seen from Table 6 that when the price increases by 5 percent and 10 percent for 150 kW of energy storages operation, the total system operational costs increase to USD 3727.30 and USD 3885.30. When there is 300 kW of energy generation support, the total system operational costs drop to USD 3600.80 and USD 3753.20 compared to USD 3727.30 and USD 3885.30 for 150 kW of energy storage support. Due to higher energy prices in the multi-MGs, the cost of system loss increases from USD 145.30 to USD 152.20 for 150 kW of storage. Opposite scenarios happen for the price decrements. When the price drops by 5 percent and 10 percent for 150 kW of energy storage, the total operational costs drop to USD 3612.70 and USD 3454.70, respectively, compared to USD 3569.30. These drops will be more for 300 kW of storage integration.

Table 6. Price uncertainty impacts on multi-MGs system operational performances for mobile storage operations.

Price Uncertainty	Mobile Storages Capacities	Operational Costs	Emissions	System Losses	Total System Operational Costs
−5%	150 kW	3198.6	266.06	148.3	3612.7
	300 kW	2924.5	243.3	128.3	3296.1
5%	150 kW	3329.7	252.2	145.3	3727.3
	300 kW	3215.7	243.3	141.9	3600.8
−10%	150 kW	3047.5	266.1	141.4	3454.7
	300 kW	2778.9	243.3	121.6	3143.8
10%	150 kW	3480.8	252.2	152.2	3885.3
	300 kW	3361.3	243.3	148.6	3753.2

9. Conclusions

This research formulates and develops algorithms for the problem of finding the optimal location and operation of MES in a multi-MG power distribution system during an extreme event. The algorithm allows variously dispatchable and non-dispatchable distributed energy resources on the multi-MG system for energy sharing while needed and simultaneously improves the multi-MG operational performances. Moreover, a multi-stage event-based system resiliency index is defined and the impacts of IoT application and the demand and price uncertainty for multi-MG operational performances is investigated. A new hybrid PSO-TS optimization algorithm is developed and utilized for the PG & E 69-bus multi-MG power distribution network simulation. Due to the uncertain characteristics of PVs and wind turbines, a probabilistic approach is applied to obtain more realistic results. The simulation case studies show how the distributed energy resources along with storage units help to improve the distribution system's resiliency and operational performance during an extreme event.

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