Reducing the Vulnerability of Electric Power Infrastructure against Natural Disasters by Promoting Distributed Generation

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Abstract: Natural disasters cause significant damage to the electrical power infrastructure every year. Therefore, there is a crucial need to reduce the vulnerability of the electric power grid against natural disasters. Distributed generation (DG) represents small-scale decentralized power generation that can help reduce the vulnerability of the grid, among many other benefits. Examples of DG include small-scale photovoltaic (PV) systems. Accordingly, the goal of this paper is to investigate the benefits of DG in reducing the vulnerability of the electric power infrastructure by mitigating against the impact of natural disasters on transmission lines. This was achieved by developing a complex system-of-systems (SoS) framework using agent-based modeling (ABM) and optimal power flow (OPF). N-1 contingency analysis and optimization were performed under two approaches: The first approach determined the minimum DG needed at any single location on the electric grid to avoid blackouts. The second approach used a genetic algorithm (GA) to identify the minimum total allocation of DG distributed over the electric grid to mitigate against the failure of any transmission line. Accordingly, the model integrates ABM, OPF, and GA to optimize the allocation of DG and reduce the vulnerability of electric networks. The model was tested on a modified IEEE 6-bus system as a proof of concept. The outcomes of this research are intended to support the understanding of the benefits of DG in reducing the vulnerability of the electric power grid. The presented framework can guide future research concerning policies and incentives that can strategically influence consumer decision to install DG and reduce the vulnerability of the electric power infrastructure. **DOI: 10.1061/NHREFO.NHENG-1478.**

Introduction

Natural disasters, such as storms, hurricanes, and earthquakes, cause significant damage to the infrastructure and the built environment every year resulting in huge losses and repair costs. The National Oceanic and Atmospheric Administration (NOAA 2021) estimates that the US sustained 20 weather and climate disasters in 2021 where overall damage exceeded $1 billion. The total damage from those 20 events exceeded $141 billion. Electric power generation and transmission is a major element of the infrastructure, and the undisturbed availability of electric power is a necessity of the modern world and a critical element of the economy (Ali and El-adaway 2020). The disruption of the electric power service caused by natural disasters affects thousands of homes and can disable critical services such as hospitals. It is estimated that outages due to weather-related events and other cases cost the US $28 to $169 billion annually (ASCE 2020). As an example, extreme cold weather in Texas in February 2021 caused rolling blackouts and affected an estimated 4.5 million customers (Miller 2021). In addition, customers that had electric power were faced with substantial electric bills due to exorbitant electricity rates created by electric power market pricing mechanisms followed by the Electric Reliability Council of Texas (ERCOT). Accordingly, there is a critical need to reduce the vulnerability of the electric power infrastructure against natural disasters and severe weather events.

Distributed generation (DG) represents an emerging technology that can improve the reliability and resilience of the electric power grid (Arghandeh et al. 2014; Gupta et al. 2019; Yang et al. 2020). DG, typically associated with distributed solar generation (DSG) in the form of photo-voltaic (PV) systems, can provide electric power to complement conventional power from the grid when needed or operate in *isolated islands* completely detached from the grid. The increasing adoption of DG and DSG represents a shift from the reliance on large-scale centralized generation to small-scale distributed generation. Small-scale DSG, defined by the EIA (2015) as solar power resources with a capacity lower than 1 Megawatt, represents 33% of the total solar generation in the US. DSG is especially attractive in locations where solar energy is abundant and

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electricity rates are high. For example, California alone accounts for 40% of distributed PV capacity, while the following nine states account for 44%. The adoption of DSG is also motivated by growing environmental awareness combined with governmental incentives to install them.

There is a plethora of research that investigates the benefits of DG and microgrids in improving the reliability and resilience of the power infrastructure, both pre-and-post- disaster, from multiple perspectives such as: microgrid operation for disaster recovery (Abbey et al. 2014; Yuan et al. 2009); improving the resilience of the electric grid against weather-related events by leveraging distributed resources (Arghandeh et al. 2014); designing restructured electric power distribution networks with large numbers of DG to improve reliability (Driesen and Katiraei 2008); improving resilience by leveraging smart networked solar systems and storage (Gupta et al. 2019); among others. Nosratabadi et al. (2017) present a comprehensive literature review on the subject. However, there is a lack of research that investigates the benefits of promoting DSG on the resilience of electric power infrastructure as a complex multidisciplinary problem that includes ABM, optimal power flow (OPF), DG optimization, and reliability assessment. ABM is a powerful technique that enables simulating complex systems in a bottom-up approach by defining agents with simple rules and behavior and observing the emergent behavior of the SoS. As Siegfried (2014) points out: "*A key property of complex systems is that no single component controls the system behavior. Instead, the system behavior results from multiple and manifold interactions between the components. The term emergence refers to the fact that the system's overall behavior is not obviously derivable from the behavior of its constituting components. Interactions between the components have to be taken into account as well as effects of nonlinearity*". As such, ABM has been used in many applications to simulate complex systems, and for simulating wholesale power markets specifically, as described later in the background section. By integrating ABM with OPF, supply and demand can be dependent on (1) the adoption of DG by customers; and (2) the failure of transmission lines impacted by natural disasters. This paper focuses on transmission lines because they are prone to failure during natural disasters (Gao et al. 2017) and their failure can affect the supply of power to consumers and the prices in the wholesale power market. As such, the reasoning of this paper is that (1) natural disasters such as hurricanes can cause transmission line failures; (2) transmission line failures affect the electric power market and infrastructure; and (3) DG can alleviate demand during transmission line failure and thus decrease the vulnerability of electric power market and infrastructure against natural disasters such as hurricanes.

The layout of this paper will go through: (1) goal and objectives; (2) background; (3) methodology; (4) results and analysis; (5) discussion; and finally (6) conclusion.

GOAL, Methodological Philosophy, and Value

The goal of this paper is to investigate the benefits of DG in reducing the vulnerability of the electric power infrastructure. This research focuses on how to optimize the allocation of DG across an electric power grid to mitigate the impact of natural disasters on transmission lines. This was achieved by developing a complex SoS simulation of electrical power infrastructure and markets using agent-based modeling (ABM) integrated with DG optimization. N-1 contingency analysis and optimization were performed using two different approaches and compared. Both methods intend to ensure N-1 contingency where the system can survive the loss of one component which was imposed by the Federal Energy Regulatory Commission (FERC) (Hedman et al. 2009; Poyrazoglu and Oh 2015). The first approach is single-node optimization using an exhaustive search to mitigate against the need for targeted blackouts following a natural disaster. The purpose of the first approach is to determine the minimum DG needed at any single location on the electric grid to avoid a targeted blackout at a selected location. The second approach is entire network optimization, which is performed using GA. The purpose of the second approach is to calculate the minimum total allocation of DG distributed across the electric grid to satisfy demand at all nodes and avoid system blackouts. Comparing the results in the first and second objectives is intended to show the capabilities of integrating GA with ABM and OPF to perform global DG optimization for dynamic electric networks. ABM can grasp the economic and engineering parameters of the electric power infrastructure and market. OPF is used to calculate the power flow, generation commitment, and locational marginal prices (LMPs). LMPs represent the prices at each node on the grid and can vary depending on supply, demand, and congestion in the grid. GA can provide a near-optimum solution that reduces the vulnerability of the grid. In practice, the methods may indicate how DG may be allocated if DG allocation policies and decisions are made by a local utility versus a centralized utility such as Independent System Operators (ISO), or even at the state or federal level. The model was further tested a modified IEEE 6-bus system as a proof of concept (Tungadio et al. 2015; Khurshaid et al. 2019; Mantawy and Al-Ghamdi 2003; Sharma et al. 2012). The outcomes of this research support the understanding of the benefits of DG. Ultimately, this research presents a holistic framework using complex SoS simulation that combines ABM, OPF, reliability assessment, power market economics, and DG optimization, to reduce the vulnerability of the electrical power grid against natural disasters. The framework can guide future research and models related to policies and incentives that can strategically motivate the adoption of DG to improve the reliability of the electric power infrastructure.

Background Information

Disaster Management for Electric Power Infrastructure

The electric power service can be disrupted by natural disasters such as earthquakes, hurricanes, storms, and tsunamis, in addition to other causes such as equipment failure, operational errors, and sabotage. Table 1 shows a summary of the frequency of blackouts

Table 1. Frequency and impact of blackouts

Cause	Frequency	Average number of customers affected	Average size of blackout in MW
Earthquake	0.8	375,900	1,408
Hurricane/tropical storm	4.2	782,695	1,309
Ice storm	5	343,448	1,152
Wind/rain	14.8	185,199	793
Other external cause	4.8	246,071	710
Other cold weather	5.5	150,255	542
Operator error	10.1	105,322	489
Fire	5.2	111,244	431
Equipment failure	29.7	57,140	379
Tornado	2.8	115,439	367
Supply shortage	5.3	138,957	341
Intentional attack	1.6	24,572	340
Lightning	11.3	70,944	270
Volunteer reduction	5.9	134,543	190
Voltage reduction	7.7	212,900	153

Sources: Data from Hines et al. (2008); Wang et al. (2016).

in the US between 1984 and 2006, and their causes (Hines et al. 2008; NERC 2020; Wang et al. 2016). A substantial number of blackouts are caused by natural causes. Among the natural causes, lightning and wind/rain have the highest occurrences; while earthquakes, hurricanes, and storms cause the largest blackouts and affect the largest numbers of customers. In addition, severe weather conditions were the predominant cause among 638 transmission outages between 2014 and 2018 (ASCE 2021). Accordingly, the continuous improvement of the reliability of the electric power infrastructure against natural disasters is of critical importance.

Due to the substantial impact of natural disasters on infrastructure and the built environment, there is a plethora of innovative research related to disaster management from various aspects and disciplines. Examples include big data analysis (Yu et al. 2018), social media analytics (Wang and Ye 2018), leveraging the use of unmanned aerial vehicles (Erdelj et al. 2017), and many other innovative research efforts. As shown in Table 1, hurricanes have a significant effect on the electric power infrastructure and affect the highest number of customers. Accordingly, several research efforts have focused on assessing the structural reliability of distribution systems such as overhead lines and poles impacted by hurricanes and windstorms (Bjarnadottir et al. 2013; Dunn et al. 2018; Salman and Li 2017). DG can be suitable for increasing reliability against service disruptions (Arghandeh et al. 2014; Gupta et al. 2019). They can maintain service availability during natural disasters by operating in an *island mode*. They can also be used as mobile sources of electric power for emergency post-disaster recovery (Abbey et al. 2014; Yang et al. 2020; Yuan et al. 2009).

Effect of Hurricanes on Transmission Systems

Components of transmission lines, such as towers and conductors, are exposed to adverse weather conditions during natural disasters such as hurricanes, typhoons, and tornadoes. Strong winds can cause the collapse of towers and conductors. The majority of weather-related transmission line failures in the US are attributed to such events. It is estimated that 800 to 1,000 tornadoes occur each and lead to extensive damage and failure of transmission structures (Zhang et al. 2020; Langlois 2006). Accordingly, many papers have focused on evaluating the impact of hurricanes on transmission systems using methods (Liu and Singh 2009; Ma et al. 2020), developing fragility curves, and improving the resilience of transmission lines against hurricanes (Liu et al. 2020; Moradi-Sepahvand et al. 2021).

Effect of Transmission Line Failure on Power Markets

Electric power markets are more complicated than other commercial markets because of the special properties of electricity (Xiao and Wang 2004). In addition to supply and demand dynamics, power markets are largely affected by transmission systems considering congestion and transmission losses. Accordingly, nodal pricing using locational marginal prices (LMPs), which are defined as the marginal cost of supplying one additional unit of power to a node, is an important aspect of power markets and allows for efficient management of generation and transmission resources (Vaskovskaya et al. 2018). Natural disasters, such as hurricanes, typhoons, and tornadoes, can damage transmission lines (Zhang et al. 2020; Langlois 2006). As such, natural disasters can affect power markets when transmission lines are affected.

Resilience and Vulnerability

Many studies related to managing natural disasters focus on the concepts of resilience and vulnerability. In simple terms, the concept of resilience focuses on how well a community or system can recover from the impact of stress (Bakkensen et al. 2017). The ASCE (2021) defined resilience in Policy statement 518 as follows: "*Resilience is the ability to plan, prepare for, mitigate, and adapt to changing conditions from hazards to enable rapid recovery of physical, social, economic, and ecological infrastructure*". Vulnerability is associated with the susceptibility, exposure, and sensitivity of a system to a threat (Bakkensen et al. 2017). Evaluation of environmental vulnerability can be divided into three areas: (1) natural resilience to hazard; (2) risk and exposure; and (3) acquired resilience from previous events (Eid and El-adaway 2017c). Accordingly, the concepts of resilience and vulnerability are related. The focus of this paper is to capitalize on DG to mitigate the impact of natural disasters. This can be considered as reducing the vulnerability of the power infrastructures predisaster. This paper does not directly quantify the resilience or the time to recovery. Rather, the model is focused on mitigating the impact.

Complex Simulation Using ABM

ABM is a technique for developing complex simulations. It follows a bottom-up approach that relies on interdependent *agents* to create an emergent behavior of a complex SoS. The agents (1) have simple rules and behavior, (2) interact and affect each other, and (3) can adapt and learn (Eid and El-adaway 2017c, 2018). Accordingly, the interaction between the interdependent agents in ABM creates a complex emergent behavior. ABM excels in creating an emergent behavior of the system as a whole from the bottom-up approach of defining multiple agents. This behavior can describe nonlinearity, is not controlled by a single element, and is not necessarily easily deducted from the single components of the system (Siegfried 2014). ABM has been used in many applications, such as simulating infrastructure systems (Batouli and Mostafavi 2014), occupant energy consumption in buildings (Abraham et al. 2018; Azar and Al Ansari 2017), construction safety (Choi and Lee 2018), bidding strategies (Ahmed et al. 2016; Elsayegh et al. 2020), and disaster management (Eid and El-adaway 2017c, 2018) among many other applications. Table 2 shows selected examples of previous research where ABM was used.

Power Market Simulation Using ABM

Agent-based computational economics (ACE), a specific example of an ABM where agents interact in a market, is an ideal method to study electrical power markets as it can simulate the complex interaction between the stakeholders in the market while combining the economic and electrical power engineering aspects (Tesfatsion 2006). Accordingly, the ABM method has been effectively used to simulate the complex behavior of wholesale electrical power markets (El-adaway et al. 2020; Sun and Tesfatsion 2007). Wholesale electric power markets involve a complex behavior emerging from several stakeholders including utilities, generators, and consumers, which can be integrated into ABM frameworks. Accordingly, ABM has been used to develop testbed applications to study competition between the agents, their learning behavior, the risk associated with uncertainty in demand, and different market regulations, among other aspects (Aliabadi et al. 2017a, b; Lopes and Coelho 2018).

DG Simulation Using ABM

The shift to decentralized, distributed generation represents a shift toward a more complex system of systems, which can be simulated using ABM (Clausen et al. 2017; Howell et al. 2017). The adoption of DG creates load fluctuations and seasonal loading.

Table 2. Examples of previous research applications using ABM

Research area	Objective	References
Infrastructure management	Simulate and assess integrated management of infrastructure networks	Batouli and Mostafavi (2014); Bernhardt and McNeil (2008); and Pereyra et al. (2016)
	Test innovative financial structures for infrastructure projects	Mostafavi et al. (2012a, b, 2014); and Mostafavi and Abraham (2010)
Energy conservation and simulation	Model occupant behavior in buildings	Abraham et al. (2018); and Azar and Menassa (2012)
	Study energy conservation in buildings	Azar and Al Ansari (2017)
	Model the interaction between occupants and appliances	Carmenate et al. (2016)
	Investigate the effect of lightning sensors on energy use	Norouziasl et al. (2019)
Transportation engineering and urban planning	Create traffic simulations	Zhang et al. (2013)
	Simulate roundtrip bus transit lines	Huang et al. (2019)
	Study the interaction between travel behavior and urban forms	Du and Wang (2011)
	Study the effect of driverless vehicles on energy use, emissions, and parking use	Harper et al. (2018)
	Assess walkability in cities	Yin (2013)
	Optimize road surface maintenance management based on travel time and maintenance costs	Yu et al. (2019)
	Simulating electric vehicles such as investigating the patterns of electric vehicle ownership and driving activity to enable strategic deployment of charging infrastructure	Sweda and Klabjan (2015)
Water management	Simulating water resources planning problems	Berglund (2015)
	Investigate the effect of various factors such as demographics, household characteristics, and social influence on the adoption of residential water conservation technology	Rasoulkhani et al. (2017, 2018)
	Assess the behavior of users for water demand management in river basins	Xiao et al. (2018)
Project scheduling, performance, and productivity analysis	Simulate compensatory management to achieve distributed coordination of schedule changes	Kim and Paulson (2003)
	Study the impact of crew composition and project schedule on knowledge sharing and task durations	Kiomjian et al. (2020)
	Simulate the interactions between construction crews for decision making and performance analysis	Kedir et al. (2020)
	Investigate the interaction of human and organizational factors to study construction performance	Du and El-Gafy (2012)
	Simulating randomness and uncertainty in crew performance and motivation	Raoufi and Fayek (2018, 2020)
	Evaluate collaboration between inter-organizational teams	Son and Rojas (2011)
	Simulate construction sites to evaluate labor efficiency	Watkins et al. (2009)
	Evaluate the uncertainty and performance of integrated project management in complex projects	Zhu and Mostafavi (2015, 2016, 2018)
Construction safety	Simulating workers' unsafe behavior to study socio-cognitive processes and their interaction with the environment in shaping safety behaviors	Choi and Lee (2018)
Bidding	Study bidding strategies, interactions between bidders, and learning capabilities	Ahmed et al. (2016); Asgari (2016); Awwad et al. (2015); and Elsayegh et al. (2020)
	Simulate negotiations in public-private partnership projects	Zhu et al. (2016)
Disaster management and evacuation of buildings	Investigate disaster recovery strategies and economic resilience	Ahmed et al. (2016); and Eid and El-adaway (2017a, b, 2018)
	Study the impact of infrastructure service losses due to disasters on households	Esmalian et al. (2019)
	Simulate the emergency response of ambulances during disasters	Koch et al. (2020)
	Analyze building evacuation	Liu et al. (2016); Pan et al. (2012); and Smith and Brokaw (2012)

The uncertainty in predicting demand due to the adoption of DG is an obstacle faced by system operators. ABM can be used to manage and control those grid disturbances with increased robustness compared to conventional centralized methods (Khan et al. 2016). ABM can create integration and cooperation between DG which results in a network that is more robust and reliable compared to conventional centralized networks that rely on large power plants solely (Phillips et al. 2006). Accordingly, this research capitalizes on the advantages of integrating ABM and DG to simulate the benefits of DG in improving the reliability of the electric power grid.

Meta-Heuristic Optimization Methods

In this paper, a genetic algorithm (GA) is used to optimize the size and location of DG to reduce the vulnerability of electric power grids against natural disasters. GA is classified as a meta-heuristic optimization method. In general, meta-heuristic optimization methods are widely used for optimizing complex problems in many fields. Most meta-heuristic optimization methods are inspired by nature, involve stochastic behavior, do not require gradients, and have adjustable parameters (Boussaïd et al. 2013). There are many meta-heuristic methods such as genetic algorithms, simulated annealing (SA), Tabu search (TS), particle swarm optimization (PSO), ant colony optimization (ACO), harmony search (HS), artificial bee colony (ABC), cuckoo search algorithm (CSA), shuffled frog leaping algorithm (SFLA), shuffled bat algorithm (SBA), plant growth simulation algorithm (PGSA), biogeography based optimization (BBO), firefly algorithm (FA), and imperialist competitive algorithm (ICA), among other techniques and variations (Abdmouleh et al. 2017).

The GA is a heuristic optimization technique that is inspired by evolution and survival of the fittest. GAs have been used in countless applications and research such as water resources planning (Nicklow et al. 2010), construction planning and resource allocation (Hegazy 1999), disaster management (Eid and El-adaway 2017a), optimizing the maintenance cost of bridges (Ghodoosi et al. 2018), among many others. It was also used in many papers to optimize DG allocation problems under different considerations (Abdmouleh et al. 2017; Ganguly and Samajpati, 2015; Pisica et al. 2009). While GA is considered the most applied optimization technique in solving problems related to DG placing and sizing, many other optimization methods such as simulated annealing and particle swarm were applied to grid optimization and DG optimization (Abdmouleh et al. 2017). However, there is limited research that combines hybrid heuristic and OPF optimization to perform two-step optimization of DG allocation. Few papers presented hybrid GA and OPF methods to investigate the capacity of distributed systems for new DG systems (Harrison et al. 2007, 2008), and to minimize the cost of active and reactive power using DG (Mardaneh and Gharehpetian 2004). In this paper, GA is used because (1) it is a robust method that has been used in many applications; (2) it has been previously used as a hybrid method with OPF; and (3) there is a technical proximity between ABM and GA because solutions in GA are represented as chromosomes which can be easily linked to the parameters of the agents. This allows seamless integration and cross-validation between them (Eid and El-adaway 2021). Still, there is a need for future research comparing hybrid meta-heuristic techniques as related to the problem presented in this paper.

Methodology

This paper follows an interconnected multistep methodology as follows: (1) development of the ABM where the agents are defined according to the entities in wholesale power markets and the relationships between them; (2) development of a DC-optimal power flow (DC-OPF) optimization solver; (3) reliability analysis and optimization are performed using: (3.1) single-node optimization, and (3.2) global optimization using GA; (4) defining a proof of concept to verify and test the behavior of the model; and (5) development of the demand parameters used in the proof of concept. The following subsections present each step.

Development of the ABM

The development of an ABM is a bottom-up process that begins by defining agents with simple rules and behavior. The agents are interconnected and can interact within their defined relationships. The collective behavior of the agents creates an emergent behavior of SoS. The design of the SoS framework is outlined in Fig. 1. The framework follows the structure of wholesale power markets (Sun and Tesfatsion 2007). There are two main types of agents in the developed ABM: (1) LSEs, which represent utilities that are located at nodes, buy power from generators, and sell it to their customers; and (2) generators, which generate and sell power to the LSEs. These agents interact in a wholesale power market which includes (3) nodes, which are locations in the electrical power grid such as cities or towns; and (4) transmission lines, which connect the nodes and transfer power between them.

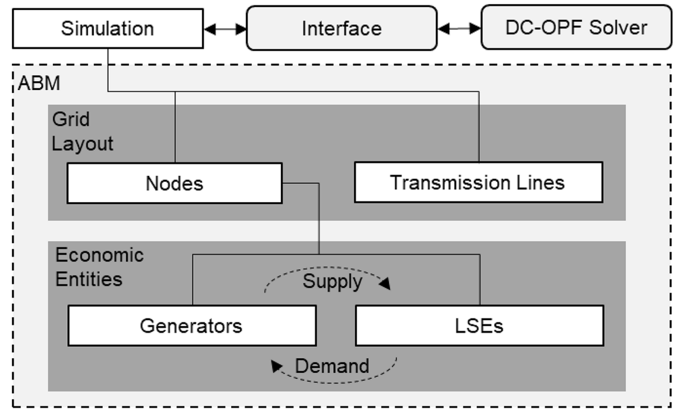

Fig. 1. Outline of the ABM framework.

The LSEs have an initial number of customers that do not have DG. Consumers at an LSE can install DG and activate it in an *isolated island* mode when needed. Accordingly, when a natural disaster strikes and the supply of electric power is limited, consumers who have DG can rely on their DG in an isolated mode that is completely detached from the electric grid. Accordingly, the objective of the framework is to determine the allocation of DG to an LSE needed to mitigate the impact of natural disasters on a transmission line and maintain electric power service availability. To calculate the flow of power in the network, the simulation is connected to an OPF solver through an interface which translates the data in the simulation to the OPF solver and feeds the results back into the simulation. The interaction between the agents in the simulation results from the collective effect of the economic relationships between them, the calculation of the OPF in the network, and the allocation of DG. The framework offers a flexible and dynamic testbed to investigate different strategies that capitalize on DG to reduce the vulnerability of electric power grids against natural disasters.

DC-OPF

A DC-OPF approach is used to calculate the optimal power flow in the network (Sun and Tesfatsion 2007). The following two subsections clarify: (1) Why a DC-OPF problem is used, and (2) the formulation for the problem.

Reason for DC-OPF

Planning and managing electric power grid resources requires determining the optimum allocation of resources, a topic that is covered by a plethora of research (Frank and Rebennack 2016; Padhy 2004; Sheblé 1999). One of the simplest approaches can be formulated as an economic dispatch (ED) problem, which determines the optimum allocation of generators considering their generation cost while minimizing overall network costs. However, there may be a need to consider many additional constraints depending on the planning horizon and the required level of complexity. For example, there may be a need to consider when to start and shut down generators considering the associated minimum uptime/downtime time and startup costs, which extends to a unit commitment (UC) problem. There are also additional generation constraints that can be considered such as ramp rates which define the maximum change of generation output per unit time. There is also a need to consider transmission properties and constraints. At the least, there may be a need to consider the maximum operational capacity of transmission lines. There is also a need to consider transmission losses which, in broad terms, energy consumed during the process of moving power from generation to load (Wong 2011). Such requirements for more detailed analysis develop into OPF problems which also have many variations in formulations (Wong 2011). In this paper, a DC-OPF formulation adopted by Sun and Tesfatsion (2006) is used because it fits the requirements of the developed model for the following reasons: (1) it determines the optimum allocation of generators considering their cost parameters and maximum capacities; (2) it calculates the power flow in transmission lines considering their maximum capacities and reactance which is important to study the effect of transmission line failure during natural disasters; (3) it minimizes losses using a penalty function; (4) there is no need to consider time-dependent constraints such as ramp rates; and (5) it is computationally fast enough considering that large numbers of iterations are required for the DG optimization performed in this paper.

Design and Formulation

It calculates the commitment of each generator and power flow in each transmission line based on the cost for each generator, demand at each LSE based on the number of customers, and transmission parameters by minimizing the total network cost and losses. As shown in Fig. 1, the ABM is connected to an interface that translates the parameters of the ABM to a DC-OPF problem and feeds the results back into the model. The supply is defined by the generation parameters, a_g and b_g, for each generator g, as shown in Eq. (1), where P_g is the active power, in megawatts (MW), supplied by generator g. The generation parameters and constraints depend on the type of the generator such as coal, nuclear, or natural gas plants, and the maximum capacity of the generators, as will be shown in a later subsection of the methodology. The demand is determined at the LSE level according to the number of customers and the average demand per customer at each node, which are also explained in a later subsection. The objective function of the DC-OPF optimization is shown in Eq. (1), where δ refers to the phase angles at the nodes and π refers to a penalty constant to minimize the phase angles between the nodes considering the reactance of the transmission lines, i.e., minimize the reactive power losses. Accordingly, the constraints of the problem are: (1) node balance such that the sum of the generation, demand, and power flowing in or out of each node is equal to zero, as shown in Eq. (2); (2) generation capacity constraints for each generator as shown in Eq. (3); and (3) transmission line constraints as shown in Eq. (4)

$$\text{Minimize: } \mathrm{a_g} + \mathrm{b_g P_g} + \pi \sum_{\mathrm{km}} [\delta_{\mathrm{k}} - \delta_{\mathrm{m}}] \tag{1}$$

Subject To:

- Node balance constraints for each node (k):

$$\sum_{\mathrm{j \in J_k}} \mathrm{P_j} - \sum_{\mathrm{g \in G_k}} \mathrm{P_g} + \sum \mathrm{P_{km}} = 0 \tag{2}$$

- Generation constraints for each generator (g):

$$\mathrm{P_{g,min}} \leq \mathrm{P_g} \leq \mathrm{P_{g,max}} \tag{3}$$

- Transmission line constraints for each transmission line (km):

$$|\mathrm{P_{km}}| \leq \mathrm{P_{km,max}} \tag{4}$$

where $\mathrm{a_g}[\$/\mathrm{MW.h}]$ & $\mathrm{b_g}[\$/\mathrm{MW^2.h}]$ = generator parameters such that $\mathrm{Cost_g} = \mathrm{a_g P_g} + \mathrm{b_g P_g^2}$; $\mathbf{P_g}$ = generator commitment for generator (**g**); $\mathrm{P_j}$ = demand for LSE (j); π = penalty constant; δ_{k} = phase angle at node (k); $\mathrm{P_{km}}$ = power flow in transmission line from node (k) to node (m).

The DC-OPF problem is solved using dual stage optimization (Goldfarb and Idnani 1983). The results of the optimization problem are the commitment of each generator (P_g), the power flow in each transmission line, and the LMP at each node. The results are then fed back into the agents in the ABM. The model is recalculated every hour in simulation time. Overall, by defining the ABM and solving the DC-OPF which includes the economics of the electrical power market, the SoS results in a dynamic behavior that allows it to be used as a testbed to perform a holistic assessment using dynamic grid parameters and configurations.

DC-OPF Optimization Method

The DC-OPF formulation is solved using a dual stage optimization method proposed by Goldfarb and Idnani (1983). It is suitable to solve the DC-OPF optimization problem as supported by previous literature (Sun and Tesfatsion 2007). The problem is a positive definite quadratic problem subject to linear equality and inequality constraints. The dual-stage method is efficient and numerically stable. It relies on the unconstrained minimum of the objective function as the starting point and utilizes Cholesky and QR factorizations to update the minimum of the objective function.

Optimizing for Disaster Management

The optimization approach in this research intends to determine the location and number of DG. It is assumed that any transmission line can be damaged during natural disasters and therefore limit the power flow in the grid. When the grid is unable to meet the total demand, system operators may need to strategically reduce power to parts of the system instead of risking a complete blackout of the entire grid, which is a measure referred to as load *shedding*, or *rolling blackout*, or *brownout*, depending on the procedure (Agarwal and Khandeparkar 2021; Liu et al. 2015; Tofis et al. 2017). The method presented in this research proposes and compares two perspectives to allocate DG at one node or several to mitigate the disruption caused by the failure of transmission lines.

Method 1: Optimizing at a Single Node

The purpose of the optimization approach in the first method of to calculate the minimum number of DG to place at one node to (1) mitigate the effect of a damaged transmission line; and (2) avoid a complete system blackout or the need for a targeted blackout at the problematic node. The outline of the algorithm for Method 1 is shown in Fig. 2.

The algorithm assumes that each transmission line is susceptible to failure in separate scenarios per line. In each scenario, a transmission line is considered completely damaged, and the electric network is recalculated to determine its feasibility, i.e., whether the demand from the LSEs can be satisfied. If the demand cannot be satisfied, the algorithm iterates each LSE to find which one would make the network feasible again if power to the determined LSE would be cut off to avoid a complete grid blackout instead. The algorithm then proceeds to search for the minimum number of DG to allocate to the determined node in the previous step,

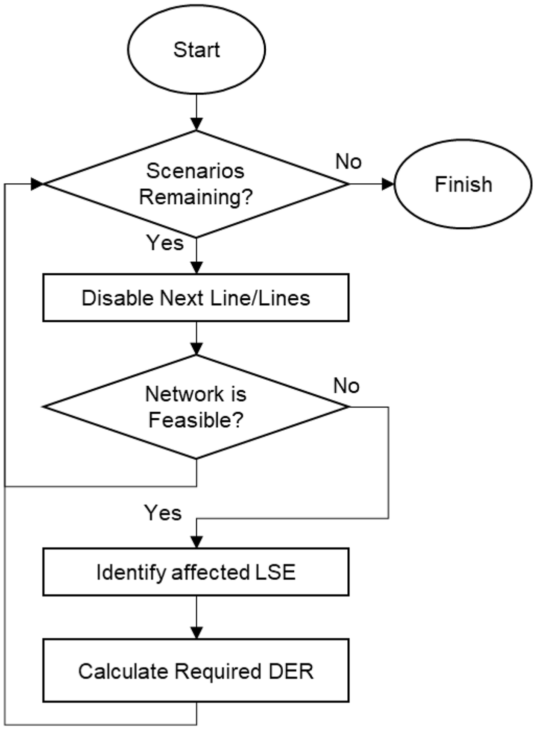

Fig. 2. Outline of the algorithm for method 1.

which would satisfy the feasibility of the electric grid. The algorithm then proceeds to iterate over each transmission line to determine the required DG to mitigate against the failure of the targeted line. Ultimately, the outputs of the scenarios are cross-referenced to determine the number of DG at each node needed to avoid the failure of any transmission line at any time. It should be noted that the algorithm is integrated into the ABM model, which means that the allocation of DG would affect the electric power market economics of the entire grid including the supply of all the generators, the demands from all LSEs, and the LMPs across the nodes.

Method 2: Network Optimization Using Genetic Algorithm

The purpose of Method 2 is in the same direction as Method 1 concerning that it intends to mitigate against the failure of transmission lines subjected to natural disasters and avoid blackouts. However, in Method 2 the number of DG is optimized across the entire grid as opposed to a single node at-a-time. This can help achieve a lower number of DG at the cost of spreading them across many locations. To achieve that objective, an ad-hoc solver was developed using GA and integrated into the ABM model. A metaheuristic optimization layer using GA is integrated on top of the ABM and OPF. GA is a preferred method because there is a technical proximity between ABM and GA that allows seamless integration between them (Eid and El-adaway 2021). Specifically, the parameters of the agents in the ABM can be easily integrated in a GA as chromosomes and optimized in an iterative evolutionary process. Collectively, ABM, OPF, and GA can be integrated in a multilayer DG optimization approach that fulfills the need for simulating and optimizing dynamic electrical networks as opposed to a conventional static grid model (Abdmouleh et al. 2017). As shown in Fig. 3, the general steps of a GA are as follows: (1) initialization: An initial population of solutions is generated using *chromosomes* where each *gene* is a variable in a feasible solution of DG allocation of Node i; (2) selection: The best solutions in the population are kept and the rest of the solutions are omitted to mimic survival of the fittest; (3) cross-over: The *genes* of the selected solutions are mixed in a *cross-over* to create new solutions with mixed genes from the best solutions similar to the inheritance of genes from parent to offspring; and (4) mutation: The variables in a few solutions are randomized to create new solutions outside of the search area of the current population of solutions to escape possible local minima and attain a global minimum. The mutation step is not performed on every iteration of the GA; it is performed according to a preset probability that is usually low and tweaked according to the problem. The loop is then repeated until a stopping criterion is reached, which can be a maximum number of epochs.

The GA and ABM are integrated seamlessly at the agent level. The list of numbers of DG for the LSEs in a grid represents a solution or a *chromosome* in the GA, as shown in Fig. 3. GA optimization is performed for each transmission line in the electric

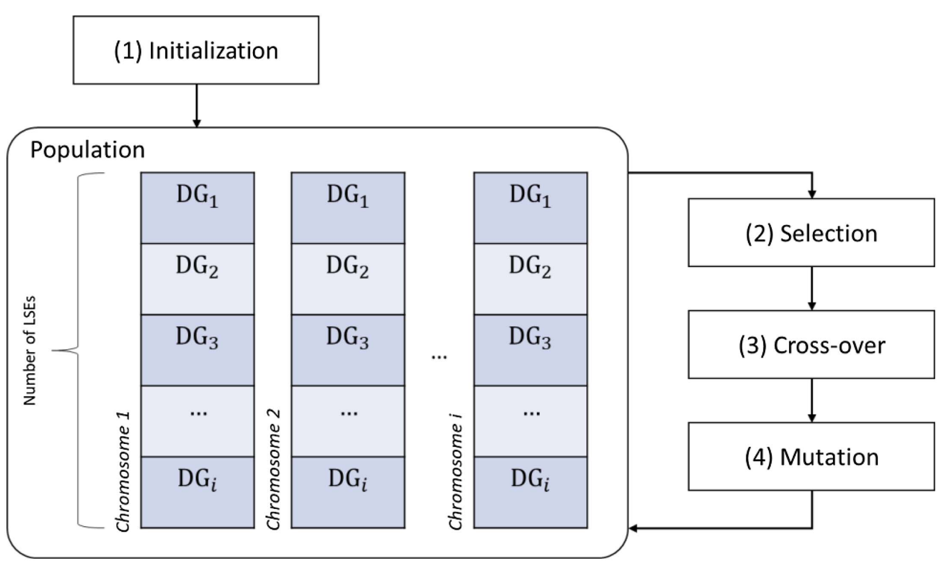

Fig. 3. Outline of evolutionary algorithm.

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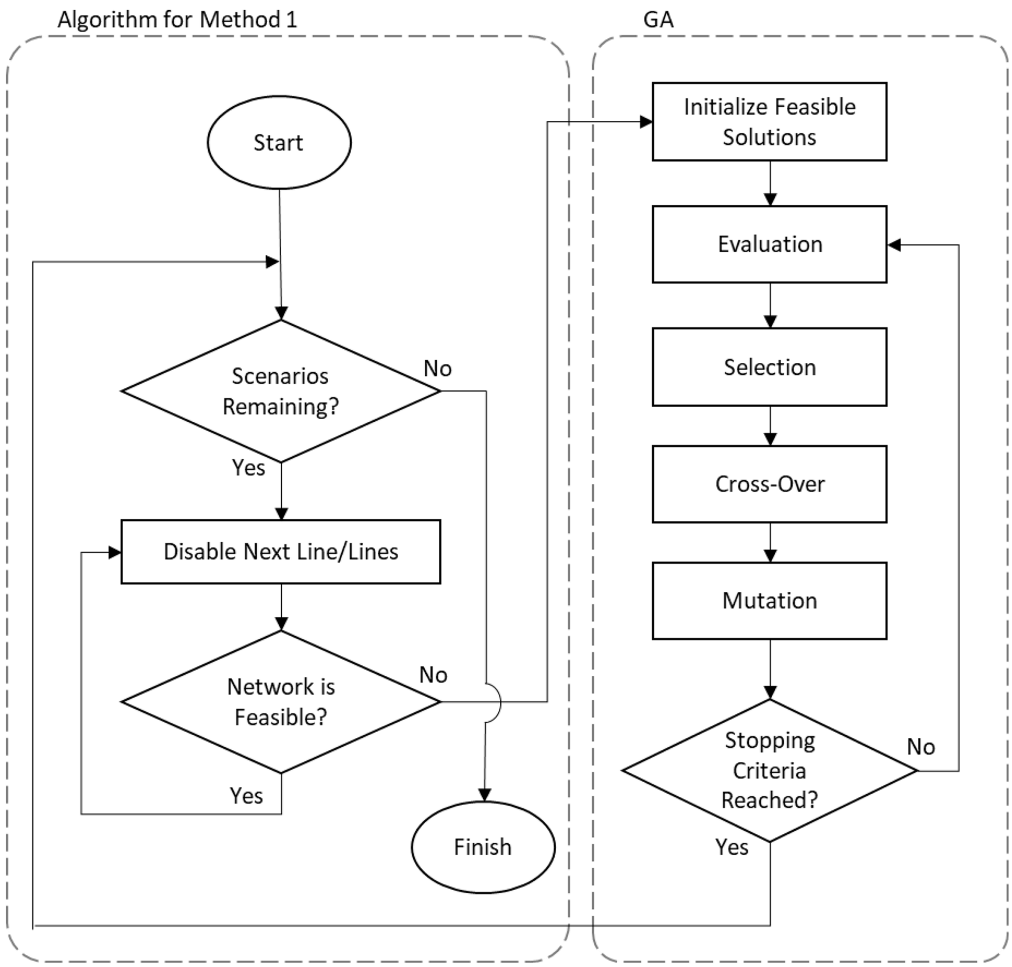

Fig. 4. Outline of the algorithm in method 2.

grid as shown in Fig. 4. Each transmission line is considered nonoperational in a separate scenario similar to method 1. If disconnecting a line renders the network infeasible, then the optimization is performed to determine the number and location of DG to make it operational again. The optimization goes through all the steps of a GA as previously described and illustrated in Fig. 3. The algorithm loops through all the scenarios and returns an optimized allocation of DG_i, for every node (i), that can effectively mitigate the failure of any transmission line

$$Minimize: \sum_i DG_i \tag{5}$$

where:

$$0 \leq DG_i \leq Customers_i$$

Proof of Concept

The developed model is applied on a modified IEEE 6-bus system as proof of concept to verify its behavior and functionality and to test the optimization model. Many previous papers used 6-bus systems to test their proposed models, such as optimizing reactive power in power grids (Mantawy and Al-Ghamdi 2003; Sharma et al. 2012) for example among many others. Research related to DG also tested their models using 6-bus systems. For example, Leeton et al. (2010) presented a solution of reactive power flow optimization for electric power distribution systems integrating with distributed generating and tested it on a 6-bus system. Nazari-Heris (2020) proposed a robust energy management framework of integrated power infrastructure and gas networks considering the effect of renewable energy sources and gas/nongas fired power generation plants and applied it to a 6-bus system. More specifically on the topic of this paper, several papers tested models studying the resilience and vulnerability of the power infrastructure using 6-bus systems. Panteli and Mancarella (2015) used an IEEE 6-bus system to model the resilience of critical electrical power infrastructure to extreme weather events using a sequential Monte-Carlo-based time-series simulation. Yang et al. (2018) proposed a quantitative resilience assessment framework for power transmission systems operated under typhoon weather and tested it on a modified IEEE 6-bus system. Kiel and Kjølle (2019) presented a method to model transmission line failure rates, considering both protection system reliability and extreme weather exposure, and applied it to an IEEE 6-bus system. Yu et al. (2021) proposed an optimal restoration strategy, considering the resilience index of power transmission systems in restoration processes, and applied it to a 6-bus system. As such, a 6-bus system is a feasible test bed for this paper based on previous literature. Still, the model is easily scalable to larger networks by adding more nodes, transmission lines, LSEs, and generators. However, a 6-bus system avoids unwarranted complexity and allows streamlined dissemination and easier understanding of the results.

The parameters of the proof of concept rely on actual data acquired from several sources. The parameters of the case concerning

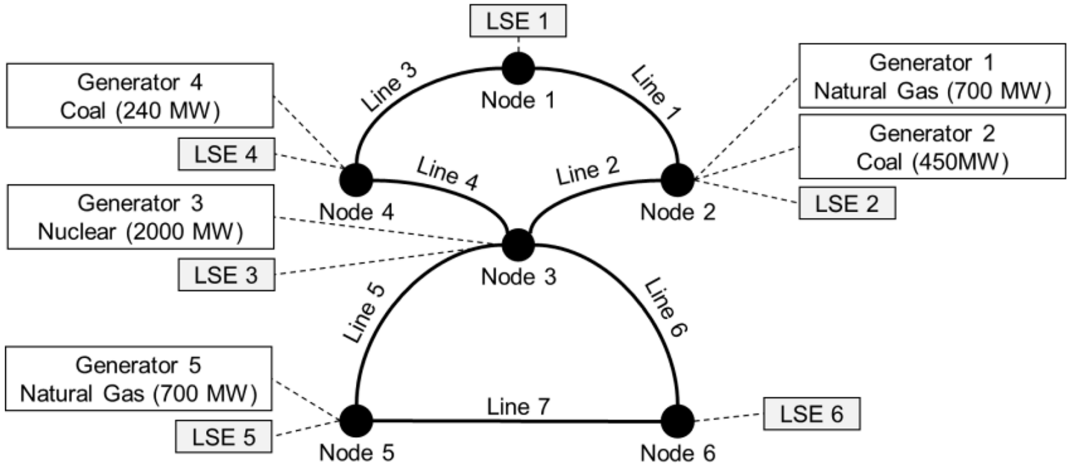

Fig. 5. Grid layout for the case study.

Table 3. Generator parameters

Generator	Type	$a\left(\frac{\$}{\text{MW.h}}\right)$	$b\left(\frac{\$}{\text{MW}^2\text{.h}}\right)$	Max capacity (MW)
1	Natural gas	29.77	0.0009674	700
2	Coal	13.71	0.0011989	450
3	Nuclear	3.75	0.0000958	2,000
4	Coal	13.71	0.0011989	240
5	Natural gas	29.77	0.0009674	700

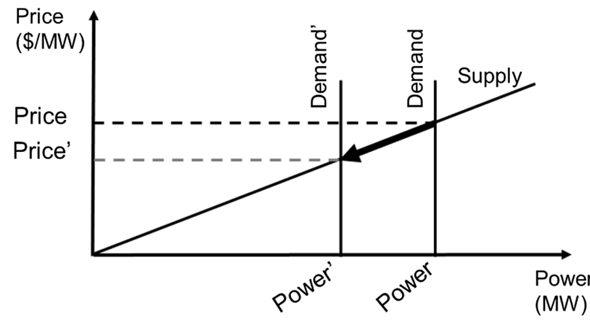

Fig. 6. Equilibrium of supply and demand showing a shift in demand.

electric demand and pricing parameters rely on real data published by the EIA (2020). The parameters for the generators are based on data acquired from the Tennessee Valley Authority (TVA). The parameters are representative of the average supply and demand in the US. However, they can be easily modified for specific locations and markets. A representation of the grid is shown in Fig. 5. It includes six nodes, five generators, six LSEs, and seven transmission lines. Table 3 shows the parameters of the generators, which include their type, the supply parameters a_g and b_g, and the maximum generation capacity. Each LSE is configured to have an initial 400,000 customers each. It should be noted that the number of customers is dynamic as customers will detach if they install DG and activate them in an isolated mode. When an LSE is affected by the failure of a transmission line, DG will be used in isolation from the grid, and therefore the number of customers connected to their LSEs will be lower. The demands for each LSE are then calculated during the execution of the simulation based on the updated number of customers. The transmission lines were set to have a max capacity of 400 MW and a reactance of 35 Ω. Reactance represents the opposition of a transmission line to flow which is affected by its material and length. Both the reactance and the capacity affect the flow of power in the grid between the nodes.

Equilibrium of Supply and Demand

The supply and demand parameters for the generators and LSEs, respectively, are included in the formulation of the ABM and the DC-OPF problem. The equilibrium between the supply and demand determines the amounts of electric power and their prices through the DC-OPF problem, as shown in Fig. 6. The generation parameters a_g and b_g, which define the supply curve for each generator, are based on the type of the generator, i.e., coal, natural gas, or nuclear. They are estimated based on data acquired from the Tennessee Valley Authority (TVA), as shown in Table 3. On the other hand, the demand at each LSE is determined by the number of customers connected to the LSE and who do not have DG, and the average hourly demand per customer. When the customers who have DG activate them, they are considered detached from their LSEs, which creates a shift in demand, as shown in Fig. 6. The assumption that customers have a fixed demand in this simulation follows the logic that electric power is very price-insensitive in the short term as proven by previous research (Burke and Abayasekara 2018; Lijesen 2007). In addition, it would not be expected that customers would reduce their electric power demands in response to a natural disaster immediately without intervention, especially for unavoidable load requirements. For example, when Texas was faced with unexpected cold weather and power outages in early 2021, electrical power was critical for heating (Miller 2021).

Demand Parameters

The average hourly demand per customer was calculated from the electrical power sales data published by the US Energy Information Administration (EIA 2020). The data includes monthly electricity demand quantities, electricity rates, and the number of customers. A histogram of the residential hourly sales per customer is shown in Fig. 7(a). The data available for the residential sector for all states was used to calculate the mean demand per customer, which was found to be 1.283 kWh/Hour/Customer. This translates to a monthly average of approximately 923 kWh/Month/Customer, which is a reasonable monthly usage. This calculated average

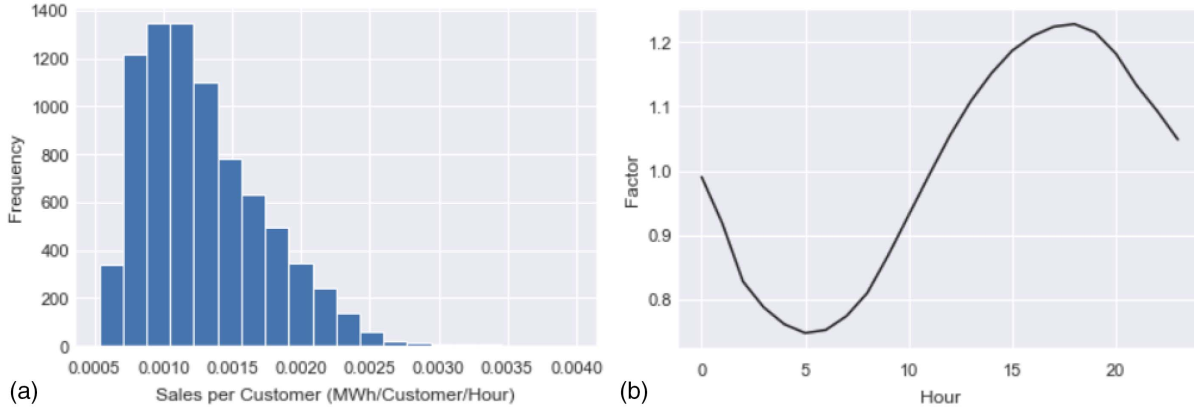

Fig. 7. (a) Histogram of hourly sales per customer; and (b) variation in hourly demand.

Table 4. Tools and software used

Name	Description	Reference
Python	Programming language	Millman and Aivazis (2011); and Oliphant (2007)
Numpy	Numerical methods	Oliphant (2006); and Van Der Walt et al. (2011)
Matplotlib and Seaborn	Visualization	Hunter (2007); and Waskom et al. (2018)
Pandas	Data manipulation	McKinney (2011)
Statsmodels and Linearmodels	Statistical analysis	Seabold and Perktold (2010); and Sheppard (2017)
SciPy	Scientific computing	Virtanen et al. (2020)
Networkx	Network analysis and visualization	Hagberg et al. (2008)
VSCode and Jupyter Notebooks	Code editing/development	—

demand does not account for the variation in demand during the day. A typical hourly variation is shown in Fig. 7(b) (EIA 2020). Accordingly, a factor of 1.2 was used to scale up the data to simulate maximum congestion during the day.

Tools and Software Used

The model was developed entirely using the programming language Python, which is a popular and well-established environment for scientific and engineering applications. Development relied on free and open-source development environments such as Microsoft's Visual Studio Code and Jupyter Notebooks (Kluyver et al. 2016). A summary of the tools and software used is shown in Table 4. The model relies entirely on open-source packages that are freely available. The ABM, OPF, and GA were developed from scratch ad-hoc using Python.

Results and Analysis

Single-Node Optimization

The results of the proof of concept for the percentage allocation of DG, demands, and generator commitments are shown in Tables 5–7, respectively. As shown in Table 5, the results show that scenario 2 did not affect the stability of the grid. However, the remaining scenarios affected the grid, and the DG was needed to mitigate against the failure of transmission lines. Each scenario was found to have singular solutions, whereas two scenarios were found to have two possible solutions each: Scenario 4 can be solved by allocating 62% DG at LSE 1 or LSE 4, and Scenario 5 can be solved by allocating 22% at LSE 5 or LSE 6. In total, the entire grid may be optimized against the failure of any line by allocating a total of 640,000 units. It is assumed in Tables 6 and 7 that DG is allocated at LSE 4 and LSE 6 to mitigate scenarios 4 and 5. By referring again to the configuration of the grid, the allocation DG at the determined LSEs is expected. For example, it is expected that a failure in the transmission lines of scenarios 1 and 3 would affect LSE 1, which was found to limit the maximum demand at 62% and 36% respectively. Similarly, LSE 6 was affected in

Table 5. DG allocation

Scenario	LSE 1	LSE 2	LSE 3	LSE 4	LSE 5	LSE 6
Line 1	62%	0%	0%	0%	0%	0%
Line 2[a]	0%	0%	0%	0%	0%	0%
Line 3	36%	0%	0%	0%	0%	0%
Line 4[b]	62%	0%	0%	62%	0%	0%
Line 5[b]	0%	0%	0%	0%	22%	22%
Line 6	0%	0%	0%	0%	0%	36%
Line 7	0%	0%	0%	0%	0%	36%
Maximum	62%	0%	0%	62%	0%	36%

[a]Scenario does not require DG.
[b]Scenario has two possible solutions.

Table 6. Total demand at LSEs in MW

Scenario	LSE 1	LSE 2	LSE 3	LSE 4	LSE 5	LSE 6
Line 1	234.02	615.84	615.84	615.84	615.84	615.84
Line 2	615.84	615.84	615.84	615.84	615.84	615.84
Line 3	394.14	615.84	615.84	615.84	615.84	615.84
Line 4	615.84	615.84	615.84	234.02	615.84	615.84
Line 5	615.84	615.84	615.84	615.84	615.84	480.36
Line 6	615.84	615.84	615.84	615.84	615.84	394.14
Line 7	615.84	615.84	615.84	615.84	615.84	394.14

Table 7. Generator commitments

Scenario	Generator 1	Generator 2	Generator 3	Generator 4	Generator 5
Line 1	0	215.84	2,000	449.86	647.52
Line 2	547.52	450	1,600	450	647.52
Line 3	159.98	450	2,000	215.84	647.52
Line 4	165.7	450	1,600	450	647.52
Line 5	295.04	450	1,668.32	450	696.2
Line 6	295.04	450	1,668.32	450	609.98
Line 7	295.04	450	2,000	450	278.3

scenarios 6 and 7, where the maximum demand needed to be reduced to 36% for each. By allocating the cumulative maximum over all scenarios, the entire grid can survive the impact of natural disasters on any line. Table 6 shows the results for the demands at the LSEs. The resulting changes in demands are consistent with the allocation of DG shown in Table 5, such as LSE 1 in Scenarios 1 and 3, and LSE 6 in Scenarios 6 and 7. The generators were affected by the disruptions as shown by their commitments in Table 7. The results show a change in the commitment of each generator according to the flow of power when a line is affected. A notable example is the commitment of Generator 1 is highest when Line 2 is disconnected. This may be due to the fact that Node 2 is no longer receiving power from Node 3 when Line 2 is disconnected. This may also be confirmed by the reduced commitment of Generator 3. Several similar observations can be made by observing the results, which show the complex dynamics of the power infrastructure and market. Also, it shows that relieving the demand using DG, combined with the dynamics of the wholesale power market, can reduce vulnerability to natural disasters.

Network Optimization Using GA

The optimization approach using a GA enabled the optimization of the entire network to determine the minimum DG allocation over all LSEs that would mitigate the loss of any transmission line. Compared to the previous method, the GA algorithm was designed to find feasible solutions that mitigate the failure of any transmission by optimizing over all the nodes. The population size was set to 100 and the stopping criteria for the GA was set to 50 Epochs. This configuration was found to be suitable to achieve a near-optimum solution is achieved. The convergence of the optimization is shown in Fig. 8. The evolutionary behavior of the GA can be seen in the convergence of the population as the best solutions are kept and the nonsuitable solutions are removed in every epoch. The best solution was achieved quickly at Epoch 22 with a total DG requirement of 395,873 units.

Table 8 shows the optimized DG allocation size and percentage for each LSE. The optimization algorithm found an allocation of DG that is better distributed and lower than the allocation resulting from the one-node-at-a-time optimization in the previous method. By strategically allocating DG across the grid, the effect of natural disasters on transmission lines was mitigated with fewer resources: The total number was 395,873 using the genetic optimization versus 640,000 using the previous method of optimizing single nodes. Further, as shown in Table 9, the distribution of the generator commitment is close to the average results from the previous method. Also, the average total generation in the previous method was 3,499 MW and in the GA method it was found to be 3,085 MW. Although the total demands from both methods are therefore close, the GA achieved a better distribution of DG. It can be seen the optimized solution allocated most DG at LSE 1, LSE 4, and LSE 6, which are the same LSEs identified in the single-node

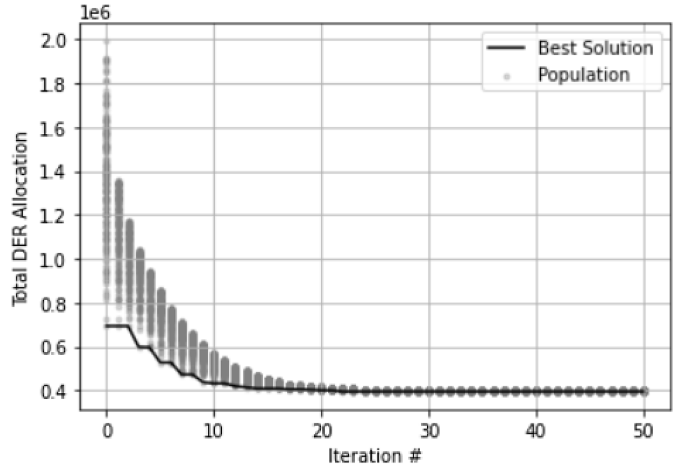

Fig. 8. Convergence of the GA.

Table 8. Optimized allocation of DG

LSE #	Allocation percentage
LSE 1	42.43%
LSE 2	0.11%
LSE 3	0.45%
LSE 4	19.60%
LSE 5	1.11%
LSE 6	35.27%

Table 9. Generator commitments

Scenario	Generator 1	Generator 2	Generator 3	Generator 4	Generator 5
Line 1	0	427.24	2,000	450	208.31
Line 3	119.72	450	2,000	307.52	208.31
Line 4	164.84	450	1,812.41	450	208.31
Line 5	0	392.44	1,813.09	272.39	607.63
Line 6	0	392.44	1,813.09	272.39	607.63
Line 7	0	450	2,000	426.56	208.99

optimization approach. Overall, the results show that optimizing the entire network, combined with the capabilities of ABM, has resulted in less DG needed to mitigate the effect of natural disasters on transmission lines.

Although the GA reached a minimum allocation of DG, the issue of the LMPs requires a deeper analysis. Fig. 9 shows separate plots for the average LMP and variation in the LMP as the difference between the highest and lower LMPs, for each of the critical transmission lines. It can be seen that although the GA achieved a near-optimum DG allocation minima, the best solution is associated with the highest LMP, and in some cases high variations in LMPs between the nodes in the network. In some cases, such as line 3 for example, a lower average LMP may be achieved with minimal addition of DG beyond the optimum solution. The cost of installing DG at different locations could be taken into consideration to develop multiobjective optimization that considers minimizing the variations in LMPs in conjunction with the cost of installing DG, which is beyond the scope of this paper. However, even considering that limitation, the effect of LMPs should be taken into consideration to mitigate against natural disasters while

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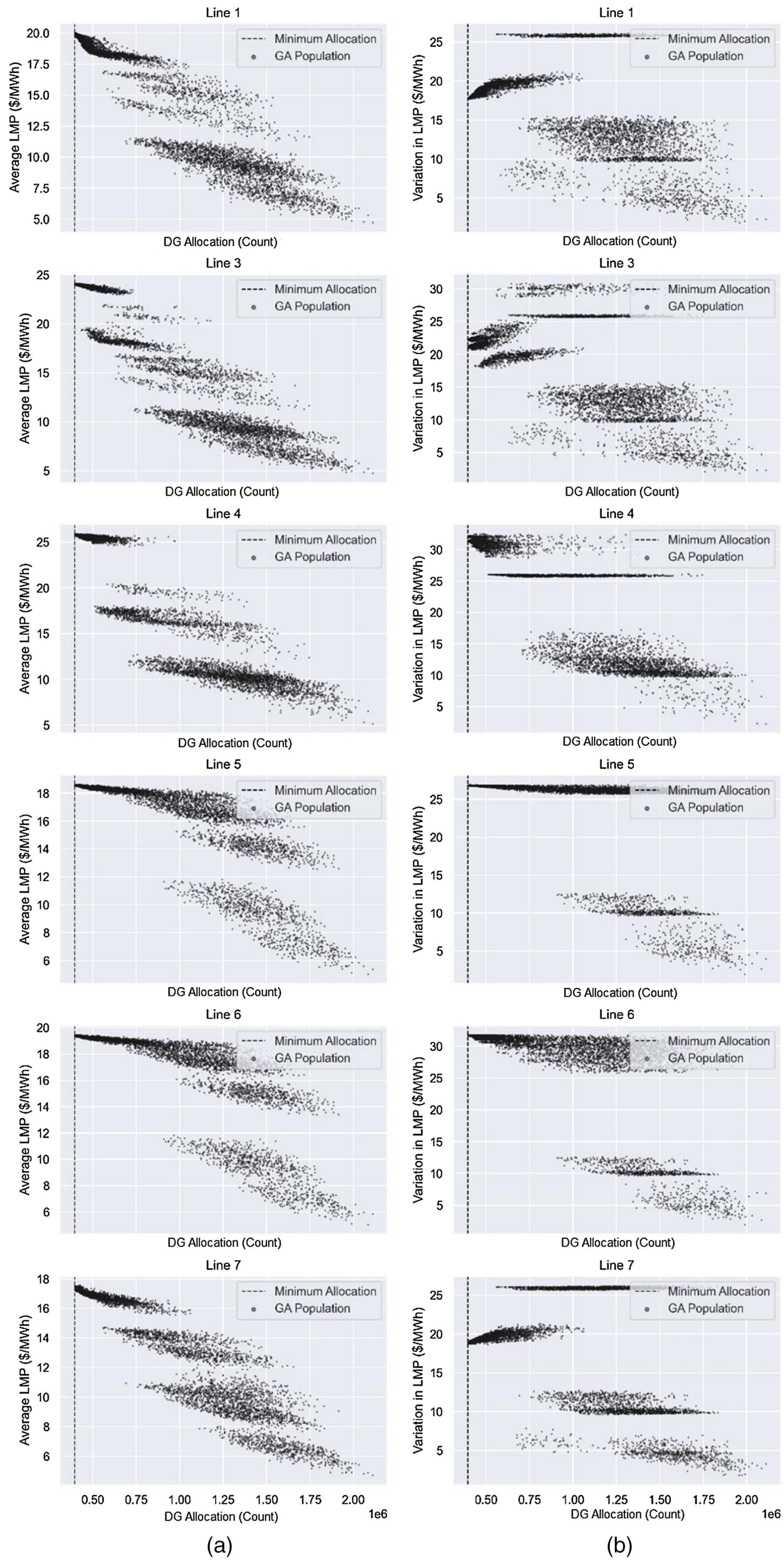

Fig. 9. GA population by transmission line failure: (a) average LMP versus DG allocation; and (b) variation in LMP versus DG allocation.

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avoiding exuberant electricity rates for customers. The results of the GA show that this can be achieved by strategically motivating the best allocation of DG that results in reasonable real-time electricity rates for customers.

Discussion

The framework developed in this model combined ABM, economic of supply and demand in wholesale power markets, OPF optimization, and reliability assessment to create a complex SoS and investigate the requirements for DG to mitigate the impact of natural disasters. The results show that the developed approach can capitalize on the benefits of DG to reduce the vulnerability of the electric power grid. Two optimization methods were used in this research to optimize the use of DG and mitigate the impact of natural disasters on transmission lines. The first method involved the allocation of a minimum number of DG at one location on the grid such as to avoid a targeted blackout following the failure of a transmission line. In practical application, the calculated number of DG may be deployed post-disaster to the determined location on the grid to meet demand and recover the stability of the electric grid. The results of this method also show that a few selected locations can be assigned an optimized number of DG pre-disaster to mitigate the loss of any transmission line to natural disasters. The second method improves on the first method by optimizing the entire grid for any transmission line failure using a GA. The optimization resulted in a lower number of DG that can be strategically distributed across the electric power grid predisaster to mitigate against the failure of any transmission line. Further analysis of the results shows that, although there are many feasible allocations of DG that can mitigate against the failure of transmission lines, the shifts in demand and electricity rates should be taken into consideration. If left unchecked, the locational prices at some locations on the grid may reach unreasonably high electrical power prices, which is a known problem that may occur due to electric power congestion when the electric grid is disrupted.

Conclusion

Every year, natural disasters, such as storms, hurricanes, or earthquakes, cause significant damage to the electrical power infrastructure and result in significant losses and necessary repair costs. DG are small-scale decentralized power resources that can improve the reliability of the electric power grid against such disasters. Accordingly, the goal of this paper was to investigate reducing the vulnerability of the electric power infrastructure against natural disasters by leveraging DG. This was achieved by developing an ABM model as a complex SoS simulation of the electrical power infrastructure and market to enable reliability analysis and planning. DG optimization was performed using two different approaches: (1) single-node optimization, and (2) entire network optimization using GA. The model was further tested on a modified IEEE 6-bus system using realistic parameters of supply, demand, and cost of PV systems. The results show that GA combined with ABM is an effective approach to test strategic allocations of DG that mitigate the effect of natural disasters. Further analysis of the results shows that LMPs should be taken into consideration to further mitigate unreasonable electricity rates, which is a problem that can occur in wholesale power markets impacted by natural disasters. Ultimately, this research intends to benefit future researchers in capitalizing on using ABM and heuristic optimization to develop and optimize complex SoS of electric power infrastructure and markets and reduce their vulnerability against natural disasters. Although the parameters in the proof of concept are representative of average supply and demand in the US, the parameters and layout of simulated networks can be easily modified. The developed framework integrates ABM, OPF, and GA in a multilayer DG optimization approach that fulfills the need for simulating and optimizing dynamic electrical networks as opposed to a conventional static grid model. The limitations of this research, which are also suggested for future work, are (1) to account for the cost of installing DG systems at different locations on the grid, which can lead to the development of a multiobjective optimization problem that investigates the trade-off between vulnerability and the cost of expansion; (2) design a multiobjective optimization that also considers the LMPs; (3) extend the current model to also include distribution networks considering rooftop PV systems; (4) test and compare other optimization algorithms in addition to GA such as simulated annealing, particle swarm optimization, and others; (5) perform a probabilistic analysis considering a daily variation in demand for each LSE; and (6) verify the model using a large-scale case study with a realistic natural hazard scale of impact, geographic system footprint, and market conditions. Overall, the framework and methods presented in this research are intended to support the understanding of the benefits of DG in reducing the vulnerability of the electric power grid against natural disasters, which can be achieved pre-or-post-disaster. The vulnerability of the grid may be improved by adjusting market regulations and policy incentives such as tax incentives to strategically promote the adoption of DG such as PV systems at targeted locations on the electric grid. DG can also be strategically allocated for emergency post-disaster relief.

Data Availability Statement

All data and models generated or analyzed during the study are included in the published paper.

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