Journal of Power and Energy Engineering, 2026, 14(9), 18-31
https://www.scirp.org/journal/jpee
ISSN Online: 2327-5901
ISSN Print: 2327-588X

A Resiliency Assessment of Predictive Power Outage Integration in Energy-Transactive Networked Microgrids Architectures

Mohamed Abaas, Pritpal Singh, Ross A. Lee

College of Engineering, Villanova University, Villanova, PA, USA
Email: ma197505@alum.villanova.edu

How to cite this paper: Abaas, M., Singh, P. and Lee, R.A. (2026) A Resiliency Assessment of Predictive Power Outage Integration in Energy-Transactive Networked Microgrids Architectures. *Journal of Power and Energy Engineering*, **14**, 18-31.
https://doi.org/10.4236/jpee.2026.149002

Received: August 11, 2026
Accepted: September 12, 2026
Published: September 15, 2026

Abstract

The reliability of the U.S. electric system underpins virtually every sector of the modern U.S. economy. Reliable electricity access is essential for daily activities, and disruptions can critically affect facilities, potentially leading to life-threatening situations. For example, Hurricane Maria in 2017 caused a prolonged outage in Puerto Rico, underscoring the need to strengthen grid resilience. The centralized architecture of the current power grid presents vulnerabilities that can be mitigated through decentralized approaches, such as networked microgrids. Significant progress has been achieved in the development of networked microgrid systems. This paper presents a patented framework that integrates power outage prediction with blockchain-based trading to enhance system resilience. The predictive model increases the demand offered for trading when a power outage is predicted. This research evaluates the impact of a machine-learning-based outage prediction model on the resilience of a secure transactive platform for networked microgrids. Preliminary results show a 36% increase in resiliency compared with similar systems that operate without such a prediction model.

Keywords

Machine Learning, Networked Microgrids, Resiliency, Energy Trading, Blockchain

1. Introduction

The present-day U.S. power grid, while highly centralized and generally reliable, remains vulnerable to severe weather events and malicious cyberattacks. A number of historical incidents underscore the need to restructure the grid to enhance its resilience. The 2003 Northeast blackout, for instance, disrupted power across eight northeastern states and resulted in an estimated $6 billion in economic losses [1]. Similarly, in 2017, Hurricane Maria hit Puerto Rico, causing the island to suffer a complete blackout for 14 days, and it took two years to achieve 98% power grid recovery [2]. Such events highlight the persistent resilience limitations inherent in the current power grid infrastructure.

The grid structure is designed to be centralized on both the physical and virtual/cyber levels [3]. Yet, with the accelerated adoption of renewable energy technologies, such as photovoltaic solar panels and wind turbines, microgrids have emerged as a system to decentralize the power grid architecture [4]. The development and adoption of microgrids helped advance the concept of a networked microgrid system, yet such a system is rarely applied. A networked microgrid system (NMGs) is a connected group of networked microgrids that the distributed generators provide power to local loads within a specific microgrid and loads in clustered microgrids. Networked microgrids represent a viable pathway toward enhanced grid resilience, primarily through the decentralization of power system architecture.

In the power industry, the Department of Energy (USDOE) defines resilience as the ability of the power grid system to reduce the probability of long-duration power outages over the service area of the power grid, in addition to the system's ability to rapidly restore power when an outage occurs [5]. This definition encompasses multiple resilience elements, such as preparation for High Impact Low Probability (HILF) events and the capacity for expedited system recovery. Nonetheless, Quantifying grid resilience remains challenging, however, since the scale of power loss triggered by a HILF event is difficult to forecast in advance [6].

Resilience continues to pose a major challenge for the existing power grid, and grid modernization is widely regarded as the most cost-effective means of achieving the desired resilience outcomes [7]. Grid modernization includes multiple approaches, such as advanced control systems, efficient generation, and integrating emerging technologies, such as Internet of Things (IoT), artificial intelligence (AI), and automated distributed ledgers [8]. In addition, existing approaches either focus on outage prediction or on trading mechanisms in isolation in decentralized power grid systems; this work uniquely combines both functions into a unified resilience-enhancing architecture. This paper proposes a system that improves the resilience of an emerging grid system-networked microgrids by utilizing AI, Blockchain, and smart contracts.

2. Background

With respect to resilience, microgrids exhibit a diverse array of applications. In addition to maintaining local load service during power interruptions, they can be reconfigured to provide broader grid support functions, including blackout recovery assistance or power supply to the utility grid. Furthermore, microgrids present an opportunity to increase the proportion of electrical energy drawn from distributed energy resources (DERs), a shift that can be facilitated through peer-to-peer (P2P) energy-sharing and trading arrangements.

Energy sharing within a single microgrid has been shown to yield economic and environmental benefits over both conventional power grids and standalone DERs [9]. This form of sharing has become increasingly feasible and beneficial with the emergence of technologies such as blockchain, which offers a decentralized, encryption-based communication framework that is inherently resistant to cyberattacks. Blockchain's applicability within the energy sector has been examined extensively in the literature, spanning domains such as data management and cybersecurity. [10]. By design, blockchain obviates the requirement for third-party oversight in transaction verification and monitoring, which reduces the cost of transactions. In addition, an automation layer can be integrated into the blockchain with the smart contract algorithms as discussed by Musleh *et al.* [11].

Energy sharing within a microgrid increases the amount of DER-derived electricity available to meet demand, thereby strengthening resilience through expanded, decentralized, and secure electrical capacity. Yet, the potential of resilience improvement of microgrids is significant upon connecting multiple microgrids to create a series of interconnected energy hubs that mutually reinforce and sustain each other.

According to Zhang [12], a networked microgrid system is structured around three primary layers: application, control, and infrastructure. The first layer, the application layer, is known as a software-defined networking layer (SDN). This layer hosts all applications required to optimize, monitor, and manage the flow of information throughout the networked microgrid system.

Several studies have examined resilience applications in networked microgrids (NMGs) [13]; however, load criticality tends to be neglected within the design of energy trading smart contracts [14]-[16]. The notion of energy sharing among NMGs has been examined in previous research [6] [17]-[19], and researchers such as Sabounchi *et al.* have investigated the application of Blockchain in NMG systems [20]. The prevailing focus in these publications is on control schemes for energy dispatch and the economic benefits of transactive platform architectures. Nonetheless, key gaps remain, especially regarding the resiliency of the Networked Microgrids System, and how it can be improved. Additionally, the following areas have not been explored thoroughly:

- No existing outage-prediction model forecasts weather-related outages at either the microgrid or NMG level using a consumer's or prosumer's own local data.
- Current smart contracts for microgrid energy trading are designed primarily to maximize prosumer profit, without prioritizing critical loads within a fair bidding framework.
- No prior study has integrated an outage-prediction model, a blockchain platform, and an energy-trading smart contract within a single NMG trading platform, nor assessed the resulting effect on system resilience.

Thus, this paper addresses the above gaps by developing a simulation that mimics an energy trading platform for networked microgrids that incorporates a machine-learning-based outage-prediction model, deployed on a blockchain infrastructure, alongside a smart contract that facilitates energy transactions. This simulation functions as an assessment tool, enabling quantification of the resilience gains achieved through such an integrated system.

3. Methodology

The simulation included a multiplicity of software platforms. The simulation modeled energy trading across microgrids that differ in load and generation capacity. The simulation relies on Ganache, an Ethereum-based test-net blockchain emulator, to represent the blockchain layer. A prediction model achieving 98% accuracy, customized for each microgrid, had already been developed beforehand, as detailed in [21].

To evaluate the impact of the developed outage prediction model on transactive networked microgrids, a comparative simulation was conducted between two configurations: Scenario A, a networked microgrid system incorporating the outage prediction model, and Scenario B, a system without the prediction model. The comparative analysis quantifies the effect of predictive capability on system resiliency and trading performance.

The simulated networked microgrid (NMG) system consists of three microgrids, each with facilities that maintain individual accounts to track and execute test transactions on Ganache. Nine facilities located in Pittsburgh, Pennsylvania, take part in the trading exercise, organized into groups of three per microgrid. Every microgrid contains at least two prosumers with distributed generation available for sale, along with at least one critical facility, such as a hospital or police station. Each microgrid is assumed to run on its own substation line, with all three substations tied into a common utility grid. Facilities connect to a main substation bus that supplies power to both the individual facility and its microgrid, while the substations themselves are linked directly to the utility's main distribution network. **Figure 1** depicts the interconnection structure of the simulated NMGs.

In **Figure 1**, the substations use manual and automatic reclosers to isolate each microgrid from the utility grid and to enable power transfer within and between microgrids. The single microgrids contain two privately owned PV systems supplying two prosumers, with critical facilities each relying on its own privately owned diesel generator for backup.

A central assumption of the simulation is that a resilient communication network, hosted via external secure servers in secure data centers, is already in place. As a result, communication capabilities remain functional even during a power outage.

In order to examine how energy storage influences networked-microgrid resilience, the simulation included an additional configuration in which each facility operates a privately owned battery system.

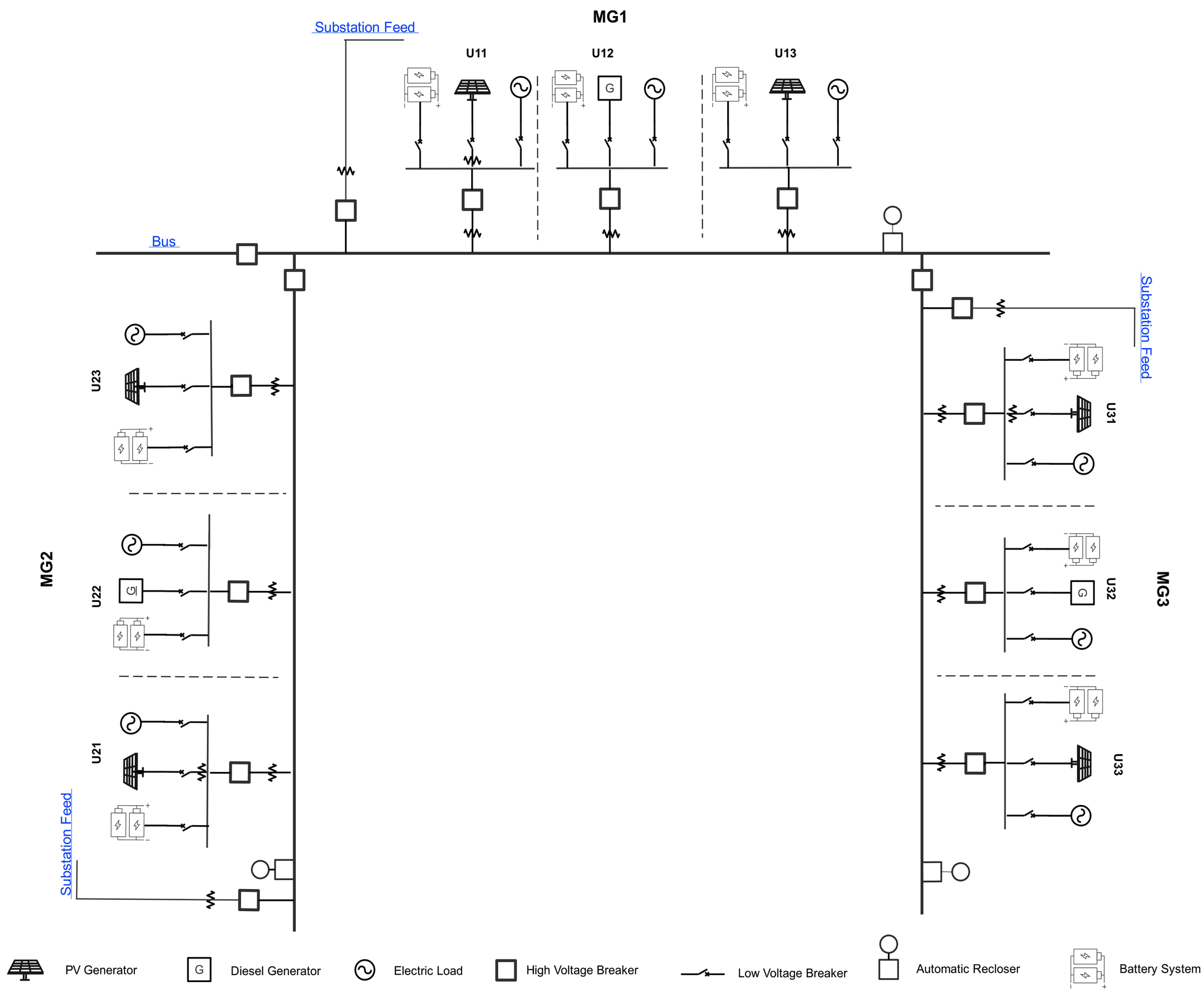

Figure 1. One-liner diagram of the networked microgrids.

Each microgrid is instantiated as a virtual machine and assigned three Ethereum accounts, each corresponding to a different prosumer. A smart contract governs and initiates energy transactions based on AI-generated inputs received from prosumers and consumers. Based on the AI inputs, the smart contract controls mainly the following parameters:

1) The prices at which energy is bought and sold.

2) The quantity of energy exchanged (dispatched or received).

Three core algorithms work together within the simulation to establish benchmark thresholds for energy dispatch and receipt. 1) A machine-learning model that analyzes load, weather, and renewable generation and storage data to determine the energy quotient to be dispatched or needed. 2) A smart contract that collects energy offers and demands from users and facilitates trading on a first-come, first-served basis. 3) An algorithm that integrates the machine-learning model with the blockchain emulator, transferring energy data to individual users based on the smart contract's trading results.

3.1. Outage Prediction Model

The outage-prediction model is built on a Long Short-Term Memory (LSTM) neural network, a machine-learning approach that analyzes historical data on weather, load, generation, and outages, if available, applied to each prosumer or consumer on an hourly basis to estimate the probability of a weather-induced outage [21]. As a recurrent neural network, the LSTM incorporates a forget gate, whose role is to reduce the likelihood of the model becoming trapped in a local minimum during training. The model used in the simulation achieved a low root-mean-square error (RMSE) and was validated against grid reliability data, reaching 98% agreement with recorded grid reliability [21]. In the adopted model, outages are inferred continuously from abrupt drops in predicted demand tied to outage-inducing weather conditions, such as wind speeds above 8 m/s [21], rather than via binary classification due to the lack of outage data at a facility level. When an outage is inferred for a facility, its demand offered for trading increases from 50% to 100%, giving that facility a trading advantage during forecasted outages.

3.2. Smart Contract

The smart contract operates through a ten-step process carried out via user wallets and facility smart meters. Steps 1 and 2: Local meter data analyzes demand and supply data with AI, resulting in an output of a trading signal. Steps 3 - 5: The smart contract receives trading offers, checks for balances, registers traders, and executes trading. Steps 6 - 10: the smart contract sends fund and energy trading results orders to traders to finalize the trading process in a trading event.

3.3. Simulation Resilience Measurement Parameters

The analysis draws on standard reliability and resilience metrics, consistent with the IEEE 1366 criteria governing power uptime [22]. The first measure, System Average Interruption Duration Index (SAIDI), serves as a grid reliability measure used to calculate system uptime. The second measure, Customer Average Interruption Duration Index (CAIDI), captures resilience by measuring the interruption time experienced per customer during a service disruption or power downtime. The third measure, System Average Interruption Frequency Index (SAIFI), reflects how frequently interruptions occur, and can be represented as the ratio of SAIDI to CAIDI. Equations (1) - (3) present the formulas for SAIDI, CAIDI, and SAIFI, where r_i denotes restoration time in seconds, N_i represents the number of customers affected by downtime, and N_T indicates the total number of customers served by the grid. The recovery time r_i is expressed in seconds by dividing the remainder demand ($D_{\text{remainder}}$) from a trading event by 3600 seconds, as shown in Equation (4).

$$\text{SAIDI} = \frac{\sum(r_i * N_i)}{N_T}. \tag{1}$$

$$\text{CAIDI} = \frac{\sum(r_i * N_i)}{\sum(N_i)}. \tag{2}$$

$$\mathrm{SAIFI} = \frac{\mathrm{SAIDI}}{\mathrm{CAIDI}}. \tag{3}$$

$$r_i = \frac{D_{\mathrm{remainder}}}{3600}. \tag{4}$$

Buyers and suppliers are paired by the smart contract on a first-come, first-served basis. Prices are set by the suppliers themselves and remain uniform across all suppliers during standard, non-outage operation. This pricing structure is anchored to Pennsylvania's PV sell-back rate of \$0.04/kWh [23]. When the supplier's substation experiences an outage, trading prices rise to \$0.08/kWh, incentivizing suppliers to sell their energy.

Half of any facility's existing demand is made available for trading, with the remaining 50% supplied by the utility company or centralized grid. Should the available supply fall short of covering that 50% share, the grid steps in to meet the shortfall, provided no outage is underway. During downtime, critical facilities are assumed to operate a diesel generator capable of running for at least 96 hours, in line with Federal Emergency Management Agency (FEMA) requirements. This generator supplies 70% of the critical load, while the remaining 30% is offered for trading [24] [25]. On the supply side, every prosumer is assumed to list their surplus energy for trading. This holds true in both Scenario A and Scenario B, with surplus energy made available for trading whenever a prosumer's net demand reaches 0 kWh.

4. Data, Analysis, and Results

The data used in the simulation is publicly available, such as utility companies, U.S. Department of Energy [26], National Renewable Energy Lab (NREL) ReOpt PV simulator [27], and others [28]-[31]. The data features used in the simulation are weather data for the 2021 period in the Penelec power utility zone in western Pennsylvania. Demand data, renewable energy supply data, and battery capacity and state-of-charge data were simulated via NREL ReOpt and PVWatts for the same zone. Also, NREL ReOpt and PVWATTS have been adopted to size the PV system, diesel generator, and battery sizes for each facility. The outage-prediction model employed in this study is grounded in the LSTM architecture and is designed to produce hourly power outage forecasts. The Hourly supply and demand data from the NREL ReOpt feed into hourly-triggered energy trading, which reduces recorded demand upon a successful transaction. This demand reduction is evaluated using the SAIDI, CAIDI, and SAIFI metrics (Equations (1) - (4)).

Ganache serves as the blockchain platform for this simulation, constituting a locally deployed instance built atop an Ethereum test network. Its consensus mechanism is proof-of-authority, implemented with a limited gas fee. Within this structure, the three microgrids correspond to three blockchain nodes responsible for transaction verification, with each user assigned a distinct account ID or public key, detailed in **Table 1**.

Table 1. Blockchain users accounts.

MG1	Public Key
U11	0xd050C61e63C5F53af6b022F748C934D9C6F1Eeab
U12	0x842BdBbE826141905A3b5f27516aBdC21B51fd99
U13	0x49EF37E8Bc9a81315b4819071Cfcb8D6F4f38324
MG2	Public Key
U21	0x980f9bf21cE36835576AE93E3C1Ea3f2216BC4B5
U22	0x7195E4c5d8250336Fc884E16B5036Acc531BFd22
U23	0x43eD8D248E6C45445e499CC64163652c3C90df09
MG3	Public Key
U31	0xFE94aa6A6A2B76aEb8764681d9B00B8221279De3
U32	0xDf47213508B9a178Dd171C7E7D45c83c8d0788b3
U33	0xEc7E31B1A842439FFb752701B041eBBa61D4BA77

The networked microgrid system comprises nine facilities that vary in load, criticality, generator type, and generation capacity—six classified as non-critical and three as critical. This diversity in facility activity and type is intended to reflect a realistic deployment scenario for networked microgrids within an urban or sub-urban community. Table 2 and Table 3 detail the configuration of each simulated facility.

Table 2. NMG facility configuration details.

Id	MG.	Facility Type	Demand (kWh)	Criticality
U11	MG1	Hospital	7561340.50	Critical
U12	MG1	Residential House	233321.1	Non-Critical
U13	MG1	Residential House	233321.1	Non-Critical
U21	MG2	Small Market/Retail store	452529.9	Non-Critical
U22	MG2	High School	2284917.9	Non-Critical
U23	MG2	University Police Department	1554393.7	Critical
U31	MG3	Hospital	7561340.50	Critical
U32	MG3	Coffee shop	166825.9	Non-Critical
U33	MG3	Hotel	670152.6	Non-Critical

Table 3. Networked microgrids on-site generator sizes.

User Id	PV System Size (KWdc)	Diesel Generator Size (KW)	Battery System Size (kW)
U11	NA	281	643

Continued

U12	26	NA	16
U13	21	NA	16
U21	23	NA	54
U22	300	NA	74
U23	NA	90	52
U31	NA	281	643
U32	162	NA	42
U33	185	NA	252

4.1. Simulation Scenarios

The outage-prediction model changes how much demand is made available for trading. The NMG is assumed to be grid-tied, with the capability to island itself during an outage. To keep utility and prosumer supply balanced, 50% of total demand is offered for prosumer trading, while the utility grid supplies the other half. This split is intended to ensure fair market participation for both sides. Based on this 50% market allocation, the simulation compares Scenarios A and B:

1) Scenario A: The machine-learning model is active in this case, letting PV-equipped prosumers trade surplus energy in both outage and non-outage states. Facilities shift all of their demand to prosumers once an outage is predicted, logging any shortfall as lost power. In the case of no predicted outage, prosumers handle just 50% of demand while the utility supplies the balance. Also, the utility fills any prosumer shortfall automatically, maintaining reliability.

2) Scenario B: In this scenario, no machine-learning model is used; PV-equipped prosumers trade surplus energy under a fixed 50/50 allocation rule that applies in both outage and non-outage periods. When an outage hits, affected users lose at least 50% of their demand as utility supply is cut off, with the rest dependent on prosumer trading to be met.

Scenarios A and B are further replicated by integrating battery storage, with prosumers equipped with PV and battery systems. This configuration enables resilience assessment of battery storage when deployed in the energy transactive platform. In total, eight simulation iterations were conducted: four for scenarios A and B with PV-only networked microgrids, and four for scenarios A and B with PV + battery networked microgrids.

4.2. Simulation Results and Interpretation

At the individual user level, prosumers with more capacity to produce energy (e.g., U32 and U33) showed a greater tendency to sell surplus energy during outage periods, while high-demand users (e.g., U11 and U31) tended to purchase energy. For these high-demand facilities, trading did not impact SAIDI values; however, U23, a critical facility that has lower demand, exhibited a 9% SAIDI improvement as shown in Table 4. Comparing iterations of PV-only and PV + Battery networked microgrids, prosumers achieved greater SAIDI improvements, whereas critical facilities experienced marginal declines, which were mitigated in the PV + battery case. This indicates that PV + battery systems enhance resilience for prosumers or low-demand loads. The observed decline in SAIDI for some users results from the opportunistic trading mechanism, which lacks purchase caps and fair-share allocation, allowing certain users to acquire more energy during outages and limiting access for others.

Table 4. Single load SAIDI analysis.

	PV			PV + Battery		
Order of Users in Trading: 11-23-31-33-32-22-21-12-13						
	SAIDI in Minutes			SAIDI in Minutes		
User	A	B	%	A	B	%
U11	6777.82	6723.64	−0.81%	6426.77	6408.02	−0.29%
U12	6960.00	6960.00	0.00%	5116.49	6600.00	22.48%
U13	6960.00	6960.00	0.00%	5647.92	6900.00	14.43%
U21	5640.00	5640.00	0.00%	5175.05	5880.00	11.99%
U22	5880.00	5880.00	0.00%	5820.11	5880.00	1.02%
U23	4849.38	5339.64	9.18%	5880.00	5670.24	−3.70%
U31	7259.61	7259.61	0.00%	6900.00	6900.00	0.00%
U32	5220.00	5220.00	0.00%	4620.00	4620.00	0.00%
U33	6480.00	6480.00	0.00%	6060.00	6060.00	0.00%

At the microgrid level, higher generation-capacity microgrids performed better on SAIDI and CAIDI under Scenario A, with CAIDI showing marked improvement in the PV + battery configuration. As Table 5 indicates, both CAIDI and SAIDI are elevated in this configuration. This improvement in SAIDI and CAIDI is attributable to batteries' capacity to supply power for more hours each day.

Table 5. Microgrids' resilience parameters analysis.

PV only			
Users Order in Trading: 11-23-31-33-32-22-21-12-13			
Scenario	CAIDI	SAIDI	SAIFI
A	7817.46	6225.20	37.22
B	8071.39	6273.65	37.22
A/B	**3.15%**	**0.8%**	**0%**

Continued

PV + Battery			
Scenario	CAIDI	SAIDI	SAIFI
A	7354.17	5738.48	37.22
B	11556.03	6102.03	37.22
A/B	36.36%	6%	0%

Overall, the power outage prediction model proved to improve the overall system's CAIDI if compared to an energy trading platform that lacks the outage prediction feature. In other words, scenario A shows better results than scenario B. This is due to the preparedness of the system for forthcoming power outages and the ability to trigger energy transactions that can shorten the power outage period. Figure 2 shows an overall cumulative monthly SAIDI and CAIDI comparison between scenario A and scenario B for the PV + Battery system.

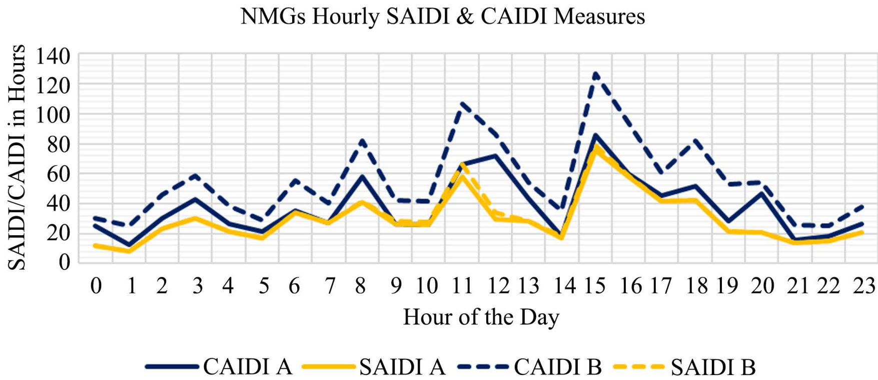

Figure 2. NMGs monthly SAIDI & CAIDI pattern for scenarios A & B.

The economic analysis revealed little overall difference in net electricity cost between the two scenarios. That said, U12, U13, and U21 recorded savings of 4%, 3%, and 6% over Scenario B (Table 6). This result is driven by 1) their trading order and 2) the timing of their non-outage-priced purchases from other prosumers.

Table 6. NMGs economic analysis.

Users Trading Order: 11-23-31-33-32-22-21-12-13			
Net Energy Price ($/yr)			
User	**A**	**B**	**%**
U11	822903.69	822902.29	0%
U12	16391.77	17066.20	4%
U13	16938.48	17515.73	3%
U21	40572.71	43001.22	6%

Continued

U22	212911.27	213916.63	0%
U23	168257.56	167647.95	0%
U31	827185.46	827153.69	0%
U32	5301.90	5301.90	0%
U33	51788.84	51787.23	0%

5. Conclusions

The occurrence of recent natural disasters and severe weather phenomena has confirmed that resilience constitutes a significant challenge within the existing power grid system. In response, a variety of solutions have been developed, among which decentralized power grid architectures, specifically networked microgrids, represent one of the most widely recognized. By adopting a networked microgrids architecture, grid resilience is enhanced and outage recovery periods are correspondingly reduced. Nevertheless, preparedness for outages continues to represent a notable gap within the current body of networked microgrids research. This paper, therefore, presents a novel system that leverages machine learning to forecast weather-related outages, integrated within a networked microgrid energy trading platform. The impact is assessed by simulating an energy trading platform integrating a power outage prediction model against another platform without a machine learning model for the same networked microgrid system. The machine learning model determines predicted power outages and determines the demand offered for trading for each prosumer and consumer.

Incorporating outage prediction into the energy trading platform was shown to deliver greater resilience benefits for prosumers and consumers with lower load profiles, particularly those equipped with PV + Battery systems. The simulation showed 36% CAIDI improvement over systems that have PV + Storage, yet without a power outage prediction feature. Economically, the power outage prediction showed a marginally better electricity price for prosumers and consumers. Moreover, this innovative approach of incorporating machine learning for outage prediction in networked microgrids has been patented by the USA patent office [32].

Overall, the NMG trading platform yielded positive outcomes. Building on this, future work will aim to replicate the simulation across different facility numbers and types, in order to confirm the system's positive effect on NMG resiliency. Future research will also focus on developing an optimizer that incorporates facility proximity, demand, supply, and outage timing to enable more granular optimization within the trading system. Additionally, since trader social behavior can meaningfully influence trading patterns, later iterations of this work will incorporate varying social dynamics to better capture how energy trading unfolds across different communities.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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