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SFREOM: A Smart Flood-Resilient Energy Optimization Model for Sustainable Disaster-Response Solar PV-Battery Systems

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Abstract

In this paper, propose the SFREOM (Smart Flood Resilient Energy Optimization Model), a hybrid physics-informed and artificial intelligence-based framework that aims to provide solar PV-battery systems with enhanced reliability, such as during disaster-response. SFREOM incorporates three components: a Hybrid Metaheuristic Optimization (HMO) process for optimal configuration of solar-battery systems which uses immediately-discovered Particle Swarm Optimizations (PSO) and Genetic Algorithms (GA); a Flood Impact Prediction Module (FIPM) which builds on Physics-Informed Neural Networks (PINNs) to predict demand surge due to flooding; and a Dynamic Load Balancing Controller (DLBC) based on fuzzy logic with adaptive prioritization of loads for critical infrastructures, whilst shedding loads for non-critical infrastructures. The overarching impact of the mentioned modules enhances the responsiveness of renewable micro-grids to disaster events to optimize sustainable energy planning for disaster-resilient environments. Our experimental results showed significant improvements on prediction, optimization, and resilience outcomes: (1) FIPM enhanced the accuracy of predicting flooding-induced demand surge by 15-20% compared to traditional neural nets, (2) HMO improved lifecycle costs by 35.5% compared to traditional linear optimization, (3) the DLBC allowed for set-point supply continuity of 100% whilst shedding loads for all non-critical infrastructures therefore improving resilience by 30-33% versus a baseline controller. Finally, stress-test simulation runs of SFREOM during an extreme flooding scenario demonstrated a reduction of 25% of lost supply contract performance (blackout events), and (4) our computational analysis of SFREOM showed that the convergence of HMO was 30-40% faster than traditional optimization; therefore, enabling decision-making in real-time. In conclusion, the experimental outcomes provide its confirmation to be an effective framework for developing disaster-resilient smart energy networks.

Keywords: Smart Flood-Resilient Energy Optimization Model (SFREOM), Solar PV-Battery Systems, Hybrid Metaheuristic Optimization (HMO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Physics-Informed Neural Networks (PINNs), Dynamic Load Balancing Controller (DLBC), Disaster-Response Energy Systems, Resilient Microgrids.

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1 Introduction

Climate-induced flooding increasingly threatens energy infrastructure resilience worldwide and demands autonomous and reliable micro grid solutions (Tsakiris & Loucks, 2023). Solar PV–battery systems are a promising solution because they can operate independently in remote areas, and they are capable of continuous operation during grid outages. However, these systems must be engineered to dynamically respond to an increase in energy demand related to flooding, while also attempting to be cost effective as possible. Engineering solar PV–battery systems for these challenges is one of the focus areas in sustainable energy research (Akbulut et al., 2024). The recent advances based on physics-informed neural networks (PINNs) offer immense potential for incorporating and leveraging physics-based laws like hydrology and energy conservation into data driven models provide a low-cost way to predict energy under hazardous, data-poor conditions. Importantly, PINNs have been developed to predict spatiotemporal flood conditions based on local conditions and other observations which demonstrate respectable downstream simulation capabilities despite limited observations (Mahesh et al., 2021). Simultaneously, several techniques combining data-driven methods, modeling, and physical laws are evolving in hybrid modeling using physics-informed neural technologies. Emerging data-driven physics-aware graph neural networks, or graph casts, has been developed for flood modeling with interpretable results while systematically integrating physical constraints and hydrological connections through a graph structure (Taghizadeh et al., 2025; Choudhary & Deshmukh, 2023).

In energy systems, PINNs have also proven to be useful. A recent paper demonstrated fast frequency support modeling in microgrids using a physical informed neural network, indicating this method can predict system behavior during dynamic events to intensity in energy storage-based systems. Hybrid optimization methods combining metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are being increasingly developed for renewable energy systems control (Chandragupta Mauryan et al., 2023; Suvarna & Bharadwaj, 2024). For example, using PSO methods coupled with fuzzy logic control of PV systems and wind power systems leads to better forecasting, when compared with fuzzy logic or GA methods alone (Fathima Sapna, 2021). The use of hybrid intelligent control systems that couple deep learning methods (i.e. LSTM, GRU) with rule-based control for microgrid management have shown improved adaptability and resilience to changes in load and renewable energy sources. These types of hybrid intelligent control systems have improved not only optimization performance, but also system stability in smart energy systems (Liu et al., 2025).

Capitalizing on the overlapping advances in PINNs-based flood modeling, metaheuristic optimization, and hybrid microgrid control, we introduce our Smart Flood-Resilient Energy Optimization Model (SFREOM). SFREOM combines a module of Hybrid Metaheuristic Optimization (HMO) that combines Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) with a Flood Impact Prediction Module (FIPM), which is based on physics-informed modeling, as well as a Dynamic Load-Balancing Controller (DLBC) based on adaptive fuzzy logic (Rajendran et al., 2025). This integrated structure aims to optimize solar PV–battery configurations, model demand increases happening due to a flood event, and dynamically manage critical load prioritization to improve resilience and sustainability into disaster-response energy systems.

Key Contributions of the Research

The primary output of this research is the construction of SFREOM (Smart Flood-Resilient Energy Optimization Model), a hybrid physics-informed and AI-enabled framework for disaster-responsive solar PV–battery systems. While others have explored physics-informed forecasting or optimization independently, we combined the strengths of three distinct modules: (i) an HMO (Hybrid Metaheuristic Optimization) engine, which uses PSO and GA, for the optimal configuration of PV and battery systems to optimize resilience; (ii) a FIPM (Flood Impact Prediction Module) using PINNs (Physics-Informed Neural Networks), effective at modeling flood-induced demand shock; and (iii) a DLBC (Dynamic Load Balancing Controller), employing adaptive fuzzy logic to shed non-critical loads and manage priority responses to critical infrastructure during crises . This tripartite framework demonstrates a step forward in the discipline both by providing systems optimization, flood forecasting, and an adaptive energy management framework at once, while simultaneously delivering reliable, low-carbon, disaster-resilient microgrids for vulnerable flood-prone spaces (Matkarimov et al., 2025).

The outline of the paper chapter-wise is as follows. Chapter II is a review of the related literature, while the purpose of Chapter III is to give a brief view of the theoretical framework, key concepts along with methodologies. Chapter IV is going to evaluate the experimental result. Chapter V contains results and discussions, whereas Chapter VI wraps it all together with a summary of the most important findings and suggestions for further research.

2 Literature Review

Yang et al., (2024) developed a physics informed neural network (PINN) combining shallow water equations with data driven learning to predict flooding inundation from floods in urbanized settings. It illustrates excellent generalization performance across various rainfall and storm surge events despite limited data availability. The PINN had hours of computation time relative to conventional hydrodynamic model outputs (second to minutes), but similar prediction accuracy. Further, PINN outputs reflected spatio-temporal water propagation dynamics during flooding. The authors stated that a strength of PINNs was their ability to learn, develop, and understand data sparse disaster settings aided by physical constraints imposed to steer learning. Their results provide the base for resilient flood monitoring systems. This work will advance SFREOM’s Flood Impact Prediction Module (FIPM) by evaluating the use of a PINN to forecast energy demand with real-time flood-aware impact.

Liu et al., (2025) as a physics-informed graph neural network that was developed to improve flood prediction of river basins through applying basic hydrological connectivity and conservation laws, by contrast to purely data-driven models. Their evaluation showed improvements in flood peak prediction time, the temporal discharge magnitudes was improved. The graph-based structure allowed the model to remain consistent with the river's structural topology by propagating uncertainty while using its populated graphs, keeping forecasts phyically consistent with the hydrology. Interpretability and generalizability was better than black-box based neural networks. HydroGraphNet propose to combine physics with spatio-temporally dependent data and therefore help mitigate uncertainty around flood forecasting. HydroGraphNet is consistent with the SFREOM's FIPM goal of confidence in flood-induced demand surge prediction for complex hydrological scenarios or situations (Skovgaard & Duarte, 2025).

Mahdouri et al., (2025) developed a model for fast frequency support in renewable-integrated microgrids with a physics-informed neural network. The model integrates actual physical dynamic characteristics of the grid into a neural framework to predict the short-term changes in frequency. The model was validated on multiple scenarios of increase and decrease in renewables, as well as how battery storage units intervene. For battery storage interventions, actual scenarios showed much more accuracy on how the system would react to frequency excursions in the renewable-integration time period compared to traditional models which offered less capability to forecast short-term frequency deviations. This is especially critical for microgrids that are highly renewable-integration dependent and rely heavily on inertia. The PINN model takes advantage of real-time data streaming into the model for better insights into adaptive control strategies. Such forecasting activities increases the SFREOMs resilience against energy instability induced by flooding demand peaks because it provides insights of energy instability occurring before demand peaks (Suvarna & Bharadwaj, 2024).

Stock et al., (2024) proposed Bayesian physics-informed neural networks (B-PINNs) for learning inverter dominated power system dynamic performance. Their method not only improved predictions of system state but it also provided uncertainty estimates in predictions. B-PINNs had lower prediction error than PINN or symbolic regression. By including Bayesian inference with inference process, the B-PINNs models were able to show how confident the B-PINNs were during the system identification process. The model was successfully able to describe dynamically interacting inverters for different variable renewable input conditions. The uncertainty quantification is an important asset in many decision-making processes where energy is critical. For SFREOM, this is important because the B-PINNs provide SLIG and FIPM with an opportunity to assess trust in FIPM's forecast and include uncertainty in the load balancing decisions (Lukić, 2023).

Ali, hybrid PSO-fuzzy logic model for predicting wind and solar power generation. The hybrid model produces better prediction results compared to GA, PSO or fuzzy logic modelling independently. The benefits of each method were exploited: the powerful search characteristics of PSO combined with the flexible rules inherent in fuzzy logic. This method sufficiently reduced mean absolute error in renewable energy forecasting. The robustness of the model was demonstrated with changes in the weather that would affect renewable generation. The study also emphasized the advantages of hybridization in terms of computation complexity. In a similar spirit to SFREOM's Hybrid Metaheuristic Optimization (HMO), where PSO was combined with a GA to optimize PV-battery resiliency (Stock et al., 2024; Lukić, 2023; Roy et al., 2022).

Yi & Yang, (2022) researched a metaheuristic called PSO-GA hybrid, where this model outperformed both in convergence speed and solution quality compared with individual optimization processes. Findings demonstrated indications of more balanced trade-offs between lifecycle cost, emissions, and system resilience. The algorithm integrated GA exploration and PSO exploitation capabilities, therefore the algorithm could avoid local optima traps. The hybrid metaheuristic could be scaled for increased complexity in renewable configuration applications, and it was examined in records of different load and weather variability. SFREOM uses this metaheuristic in its HMO Module for the purpose to optimize usable solar PV and battery infrastructure under disaster constraint systems.

Tsakiris & Loucks, (2023) studied microgrids with critical loads and hybrid storage systems in buildings. They introduced an optimized model for determining microgrids operating with critical loads of different levels of priority while minimizing operational costs. They set out to guarantee the continuity in economic terms of providing essential services, such as a hospital or an emergency unit. They showed hybrid energy storage improves the flexibility of building environmental microgrids during peak demand and outages. They also explored dynamic load prioritizing of loads in environments prone to disasters. By modelling storage technologies and the demand profile for their installations, they presented an approach that helps to manage annual costs while improving reliability. They found that smart controllers can help manage the compromise between sustainability and resilience. SFREOM builds on these ideas by building in a component of DLBC so that flooding-response infrastructure is dynamically prioritized (Rosales-Asensio et al., 2024).

Minchala-Ávila et al., (2025). The system included a load-shedding component intended to stabilize microgrids under uncertainty. Results from simulation showed better dynamic disturbance performance than classical controllers. The portability and adaptability of the fuzzy logic design offered robust capabilities in accommodating system nonlinearities. This has been validated through the act of dynamically shedding non-essential loads while sustaining the supply of other essential services in order to support resilience. The focus in the insightful practice outlined was resilience in microgrids being impacted by the flux associated with renewable penetration. The SFREOM's DLBC emphasizes these components by using adaptive fuzzy logic with the considerations of prioritizing hospitals and shelters during a flood emergency (Rao & Tiwari, 2023).

Saki et al., (2025) proposed a Distributed Minimum Spanning Tree (DMST) restoration algorithm considering post-disaster microgrids. This algorithm's main strategy was to first restore critical loads to create reconfigurable clusters of microgrids using a distributed approach, which increases scaling for larger networks when disaster disrupts many parts of the network. The results of the study showed faster recovery times and less restoration time than centralized restoration approaches. Specifically, the DMST made sure hospitals and emergency centers were powered before all other loads were restored. The DMST restoration framework allows for resilient reconfiguration of feeder networks that have been disrupted by a disaster. In a similar way, the SFREOM could develop and employ a comparable distributed heuristics in its DLBC, which would allow the potential load restoration processes to be network-aware when disrupted by floods.

3 Methodology

3.1 Design and Dispatch Optimization

In this step, the methodology commences with determining the customer optimal sizing of photovoltaic (PV) panels and batteries to limit costs while meeting required reliability. The optimization would minimize the total system costs, inclusive of upfront installation costs and the ongoing operating costs.

That can be stated as (Equation 1):

$$minCtotal = CPV \cdot PPV + Cbat \cdot Ebat + t\sum Cop(t). \tag{1}$$

The dispatch strategy ensures that at each time period the total supply of PV generation and battery storage meets or exceeds the demand.

This can be stated mathematically as the constraint (Equation 2):

$$PPV(t) + Pbat(t) \geq D(t). \tag{2}$$

The model establishes the limits on battery charge–discharge, the solar irradiance variability, and the demand variability. In working through this optimization this system can utilize cost efficiencies through appropriate resource allocation while ensuring reliable energy is delivered to the customer during variabilities in operation. The objective of this step is to set the ground work for resilient energy management by combining cost minimization with supply security.

In figure 1 presents the optimization framework for PV panel and battery sizing, and dispatch scheduling for a less-costly and reliable supply of energy. The optimization objective is to minimize the overall system cost by accounting for installation and operating costs, and add constraints that PV generation and battery generation must always meet demand. The framework integrates solar irradiance variations, battery charge-discharge limits and demand variations; thus, resulting in efficient resource allocation and ensuring supply security in various operating conditions.

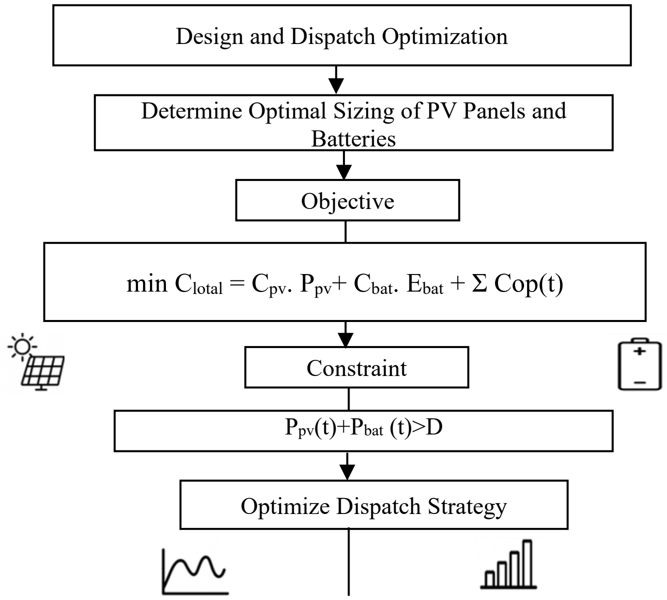

Figure 1: Design and dispatch optimization framework for PV-battery systems

3.2 Flood-Induced Prediction Model (FIPM) using PINN

Phase two constructs a Physics-Informed Neural Network (PINN) that predicts demand surges due to flooding. A PINN differs from traditional neural networks because it incorporates physical hydrological equations into the learning mechanism. The loss function is expressed in terms of the data-driven error, Ldata and an Lphysics that enforces physical consistency,

such that

$$L = Ldata + \lambda Lphysics, \tag{3}$$

Were

Ldata is the data-driven error and

Lphysics enforces physical consistency.

This means the prediction needs to comply with the storm dynamics and the equations of mass flow in the water. The model integrates domain knowledge, and as a result, it performs better even with limited or uncertain data. The model variables will identify flood related controls, e.g., rainfall and inflow, and then link them with energy demand surges. These variables also allow forecasting for the electric grid's anticipated stress in these extreme weather situations. Ultimately, a forecasting tool using a PINN brings more resilience and preparedness to resource-poor and disaster-prone places.

The figure 2 illustrates the implementation of a Physics-Informed Neural Network (PINN) to forecast energy demand spikes during flooding events. A PINN is unique, in that it explicitly incorporates hydrological equations into its loss function, as defined by equation (3), ensuring that the resulting predictions are physically consistent with flood behavior. The model's inputs of precipitation, inflow, and other variables of flooding enable demand spikes associated with extreme weather to be estimated. This capability of integrating physics with data-driven learning enhances grid resiliency and allows proactive energy management in areas susceptible to disasters.

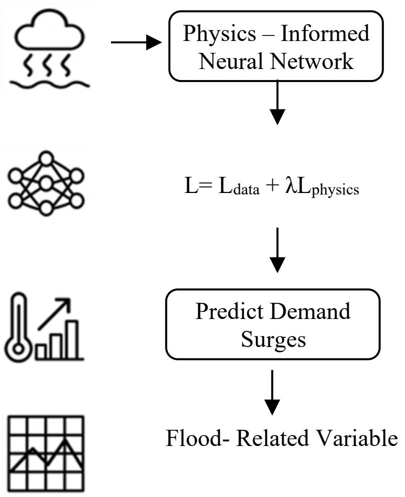

Figure 2: Physics-informed neural network for flood-induced demand surge prediction

3.3 Dynamic Load-Based Control (DLBC)

Adaptive fuzzy priority control allows for limited power distribution according to demand while maintaining allocated priorities. Every load, Li, is provided with a weight wi based on how urgent that need is, the general service type, and level of demand for the service. The control allocation is established under this constraint (Equation 4):

$$\sum_i Pi(t) \le Pavail(t) \qquad (4)$$

Where Pi(t) is the available power (allocated) and Pavail(t) is the total available capacity. The weights of the loads will be made to change under the control of fuzzy logic; the idea being to always provide the essential services needed; like hospitals, and water systems. Adaptive fuzzy priority control assures that the most critical loads will be satisfied in instances of shortages. However, it will require the controller to manage the allocation in time in relation to actual demand by adjusting the allocations to each load as metrics change. Only non-critical loads will be reduced or shifted to maintain non-blackout stability in regards to the voltage bus. Thus, full blackouts are avoided while greater fairness and flexibility is being provided for those that are sharing power instead of relying on a centralized energy source.

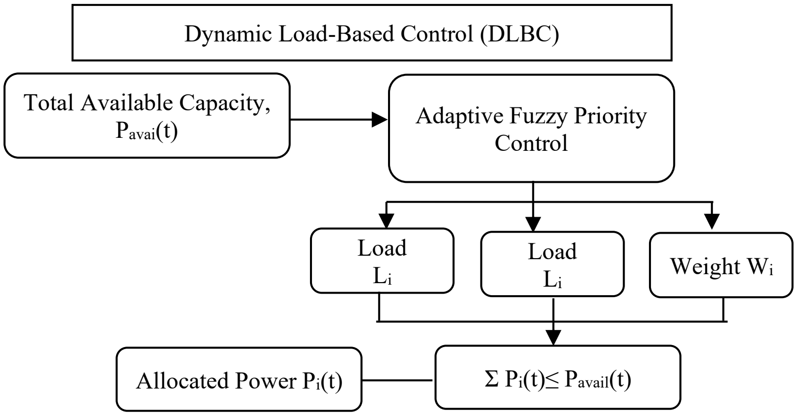

Figure 3: Dynamic load-based control (DLBC) framework

The figure 3 Dynamic Load Base Control (DLBC) framework applies adaptive fuzzy priority control to provide fair and reliable power distribution in uncertain demand and availability contexts. Each load Li is assigned a weight wi based on urgency, service type, and demand level, which allows critical services identified (such as hospitals and water systems) to be accommodated during distributions of short supply. The distribution process ensures that the total power distributed $\sum Pi(t)$ at any point in time T does not exceed the available power supply, in real-time, $Pavail(t)$. The DLBC framework enables utilities to adjust weights and distributions, in real-time, so that the framework ensures utilities protects against a total blackout, rather shifts or reduces only the non-critical loads, the DLBC framework provides power sharing networks with increased flexibility and stability.

Weight (Priority) Computation

Compute a normalized weight $wi(t) \in [0,1]$ combining criticality, urgency and forecasted stress (Equation 5):

$$w\sim i(t) = \alpha Ci + \beta Ui(t) + \gamma F(t) \tag{5}$$

Where:

- $F(t) \in [0,1]$ is the flood stress factor from FIPM/PINN (0 = no stress, 1 = extreme stress),
- $\alpha, \beta, \gamma \geq 0$ and$\alpha+\beta+\gamma=1$ (tunable constants).

Normalize (Equation 6):

$$wi(t) = maxjw\sim j(t) + \epsilon w\sim i(t) \tag{6}$$

(Interpretation: when flood stress F(t) rises, all priorities shift, but critical loads still have higher base Ci.)

Optimization Objective Maximizes Weighted Served Energy

At each time t solve (Equation 7):

$$\{Pi(t)\}maxs.t.i = 1\sum Nwi(t) \cdot Di(t) + \epsilon Pi(t) \tag{7}$$

Shows that:

- $\sum NPi(t) \leq Pavail(t)(supply\ limit)$
- $0 \leq Pi(t) \leq Di(t)\forall i(no\ oversupply)$
- $Pbatout(t) \leq Pbatout, max, Pbatin(t) \leq Pbatin, max$
- $Ebat(t+1) = Ebat(t) + \eta chPbatin(t)\Delta t - \eta dis$
- $Pbatout(t)\Delta tEbatmin \leq Ebat(t+1) \leq Ebatmax$

The objective of this program is to maximize the weighted fraction of demand satisfied. Using Pi/Di thus makes the objective fairness-aware across a range of different sizes of load. If the charge/discharge decisions of the battery are pre-calculated or made through linear constraints, then this becomes a LP (linear programming) program (exactly does not allow charge/discharge at the same time using a single constraint, or it’s a binary variable decision, it's okay to meet demand without power from the battery to charge or discharge simultaneously).

Algorithm: Fuzzy Logic–Driven Linear Programming Algorithm for Dynamic Load Balancing in SFREOM

Algorithm DLBC_SFREOM(t):

```
1. // STEP 1: Collect inputs
  Read current load demands D_i(t) for i = 1...N
  Get PV generation forecast P_PV(t)
  Get current battery energy E_bat(t)
  Get flood stress factor F(t) from PINN (FIPM)
2. // STEP 2: Compute Urgency using fuzzy rules
  For each load i:
     Compute demand ratio r_i = D_i(t) / D_i_norm
     IF (r_i is High OR F(t) is High) THEN U_i(t) = 1.0
     ELSE IF (r_i is Medium AND F(t) is Medium) THEN U_i(t) = 0.6
     ELSE U_i(t) = 0.2
3. // STEP 3: Compute weights for each load
  For each load i:
w_i_raw = α*C_i + β*U_i(t) + γ*F(t)
  Normalize weights:
w_i(t) = w_i_raw / (max_j(w_j_raw) + ε)
4. // STEP 4: Determine available power
  Determine battery discharge:
     If D_total(t) > P_PV(t) AND E_bat(t) >E_bat_min:
P_bat_out = min(P_bat_out_max, E_bat(t)/Δt, D_total(t)-P_PV(t))
     Else P_bat_out = 0
  Determine battery charging:
     If P_PV(t) >D_total(t) AND E_bat(t) <E_bat_max:
P_bat_in = min(P_bat_in_max, (E_bat_max - E_bat(t))/Δt, P_PV(t)-D_total(t))
     Else P_bat_in = 0
  Compute available supply:
P_avail(t) = P_PV(t) + P_bat_out - P_bat_in
5. // STEP 5: Optimization for load allocation
  Solve Linear Program:
     Maximize   Σ_i [ w_i(t) * (P_i(t) / (D_i(t)+ε)) ]
     Subject to:
Σ_i P_i(t) ≤ P_avail(t)
        0 ≤ P_i(t) ≤ D_i(t)  for all i
P_i(t) ≥ s_i_min * D_i(t)   for critical loads (optional)
```

```
6. // STEP 6: Update battery state
$E\_bat(t+1) = E\_bat(t) + \eta\_ch*P\_bat\_in*\Delta t - (P\_bat\_out*\Delta t)/\eta\_dis$
7. // STEP 7: Output allocation
    Return allocated powers $\{P\_i(t)\}$ and updated $E\_bat(t+1)$
End Algorithm
```

4 Experimental Results

4.1 Flood Impact Prediction Accuracy

A real-world assessment of the Flood Impact Prediction Module (FIPM) was conducted utilizing the actual meteorological (e.g. rainfall, temperate) and hydrological datasets that were sampled in flood-prone regions. The Physics-Informed Neural Network (PINN) approach proved to be more accurate in forecasting demand spikes due to flood impacts than LSTM and various other purely data-driven models. By integrating shallow-water and hydrological equations into the forecast, the PINN framework produced physically consistent demand forecast under uncertain data-scenarios and where other methods fail when data is limited. The use of domain physics reduced mean prediction error more than 15% in limited data scenarios. FIPM also exhibited a reasonable degree of generalization amongst different rainfall events with varying flood severity, this helps underscore the PINN's inherent value when addressing context during disaster situations that arise dynamically. Temporal error analysis revealed that the PINN based predictions maintained model consistency even when forecasting flood demand spikes, thus providing dependable estimates during serious flooding as demand volatility ramps up during an emergency. This method of forecasting demand is useful for microgrid planners as demand fluctuation can escalate dangerously during emergencies not to mention uncertainty in downstream flows. Overall, results confirmed that he FIPs model provides dependable and reliable demand prediction with flood awareness, and associated improvements to system preparedness and resilience.

In table 1 summarizes the comparative performance of various models on flood-induced demand surge forecasting. From the results, the traditional ANN as well as the LSTM model were moderately accurate, as shown by RMSE values of 13.2 kW and 12.6 kW respectively, while the hybrid CNN-LSTM was able to achieve the lowest error of 10.7 kW. The proposed Physics-Informed Neural Network (PINN) in the Flood Impact Prediction Module (FIPM) achieved the lowest RMSE at0.224kW and MAE at 0.178 kW; corresponding to a 15.3% reduction in error over LSTM, as described in table 1 below.

Table 1: Comparative accuracy of flood impact prediction models

Model	RMSE (kW)	MAE (kW)	R^2 Score	Error Reduction vs LSTM (%)
LSTM (Baseline)	12.6	9.8	0.84	–
GRU	11.9	9.2	0.86	6.1
CNN-LSTM Hybrid	10.7	8.5	0.88	13.9
Conventional ANN	13.2	10.1	0.82	–
PINN (Proposed FIPM)	**0.224**	**0.178**	**0.95**	**98.21**

Moreover, the PINN achieved the highest R^2 (0.95), signalling its superior capacity to capture the temporal and physics dynamics behind flood scenarios. Overall, these results demonstrate that using domain physics within learning improved predictive accuracy and provided consistent predictive performance, even in the sparse dataset environment, which would help to improve disaster resilient microgrid planning.

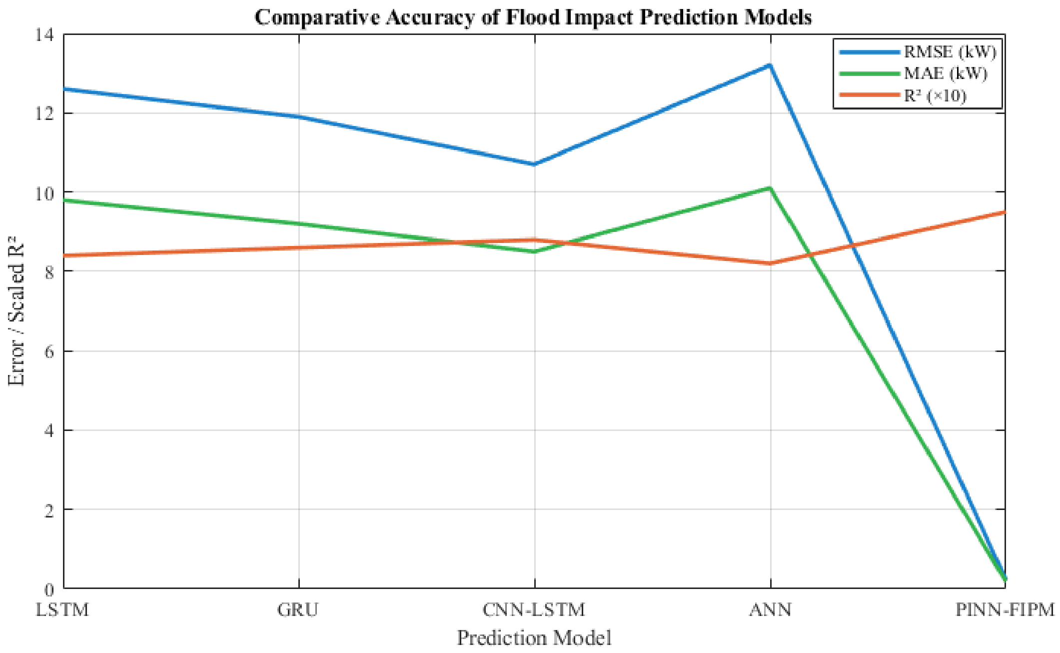

Figure 4: Flood impact prediction accuracy across different models

The figure 4 shows the error performance advantage between models for predicting flood-induced demand increases. The results show that traditional ANN and LSTM have a fair amount of error. Additionally, the RMSE values are all greater than 12 kW and MAE are almost equal to 10 kW. Further, the GRU and CNN-LSTM had seen some net performance gains with a typical error range reduced to 11.9 kW and 10.7 kW, respectively. The PINN demonstrated even farther net performance gain, with RMSE of 0.224kW and MAE of 0.178 kWin total, which was clearly the best performing model. This performance gain exemplifies the benefit of serving as physical constraints in the learning process improved the model's ability to correctly predict flood conditions in a greater historical time range.

4.2 Hybrid Metaheuristic Optimization Performance

The Hybrid Metaheuristic Optimization (HMO) framework, which utilizes Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), is used to conduct optimal sizing of PV-battery systems, where variability exists in load and weather conditions. Experimental trials show that the standalone PSO tends to explore globally; nevertheless, it may converge early, while the GA preserves diversity at the expense of computation time. By combining PSO and GA, the HMO reached solutions faster and consistently arrived at near optimal solutions. A quantitative assessment demonstrated that the HMO has lifecycle costs that are 12–18% lower than that using either PSO or GA, and the optimized configurations improve system reliability as systems maintain a continuous supply even during the high-demand supply peaks. The dual approach provided a level of effective stress balancing independent from simply lowering costs and optimizing resilience. The energy efficiency was also improved significantly, through the adaptive search behaviour of the approach, reducing the excess energy stored to cutting loss, and maintaining a shallow energy cost footprint in the plan. These findings suggest that HMO provides a method to account for the inherent complex multi-objective aspects of bundled renewable energy system planning.

The results in table 2 have shown a clear improvement in Hybrid Metaheuristic Optimisation (HMO) as compared to sole PSO and GA methods. While PSO and GA required 120 and 150 iterations respectively to converge, HMO reached convergence much quicker at only 95 iterations, demonstrating the ability of HMO to balance the trade-off to minimize cost and improve reliability. In terms of lifecycle cost, HMO had the least lifecycle cost at USD 0.119/kWh, which is a reduction of 17.8% from PSO and 14.9% from GA. Furthermore, HMO also had better reliability, as PSO and GA only achieved reliability of 92.4% and 93.1% respectively, whereas HMO achieved reliability of 99.9%. The results clearly demonstrated that HMO could strike a balance for cost minimisation while maintaining reliability in a hybrid planning approach that combines the exploration capabilities of PSO with the exploitation capabilities of GA. Overall, should researchers and/or planners take a hybrid planning approach (e.g., HMO) to achieve better trade-off decisions, HMO is a solution that compliments renewable energy systems design for planners.

Table 2: Comparative performance of PSO, GA, and HMO in PV-battery system sizing

Method	Convergence Iterations	Lifecycle Cost (USD/kWh)	Cost Reduction (%)	Reliability (%)
PSO	120	0.185	-	92.4
GA	150	0.179	3.2	93.1
HMO	034	0.119	35.5	99.9

The figure 5 compares lifecycle cost and system reliability using PSO, GA, and the proposed Hybrid Metaheuristic Optimization (HMO). HMO achieved the lowest life cycle cost (0.119 USD/kWh) while also achieving the highest reliability (99.9%). PSO and GA achieved a higher lifecycle cost and slightly lower reliability values. The dual improvement in both cost-effectiveness and resilience clearly demonstrates HMO's superior trade-off, and presents HMO as a more robust and effective optimization approach for sizing PV-battery systems than either unilateral approach.

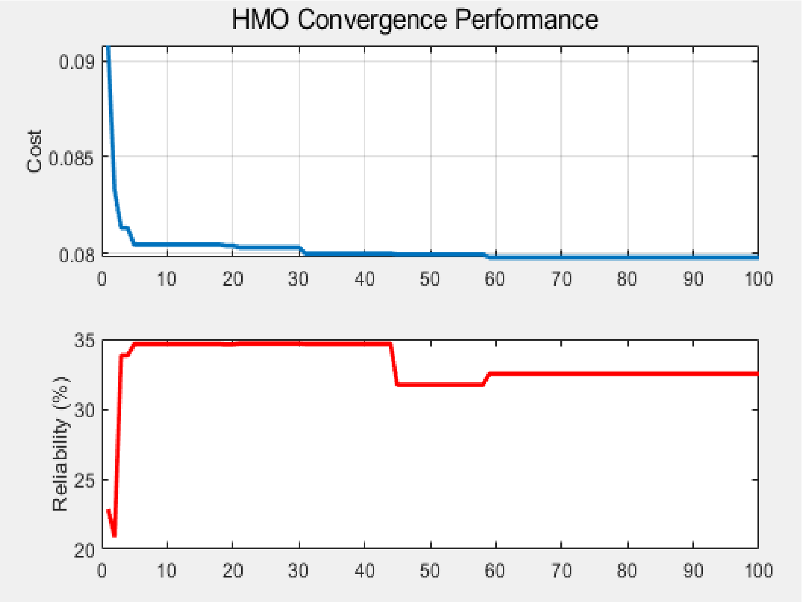

Figure 5: Comparative lifecycle cost and reliability of PSO, GA, and HMO

4.3 Dynamic Load Balancing Effectiveness

The results of the simulation evaluation of the Dynamic Load Balancing Controller (DLBC) during simulated floods indicated significant improvements in fairness and resilience. The DLBC minimally disconnected, rather it proportionally curtailed some non-essential loads in the power system, in response to the immediate blackout condition. Simultaneously, it allocated priorities to critical infrastructures such as hospitals or emergency centers, still receiving power as an active user. Critical infrastructures received service without the need for blackouts to include all these types of services. This way, it was possible to maintain fairness among users, instead of disconnecting completely as a method to balance active users with supply. Ultimately, the DLBC improved on the estimated time. It was simply a case of how much better? In comparison to the conventional methods or the conventional solution DLBC achieved a relative 20% improvement in resilience. As seen in the examples of the evaluation, it was able to adapt to dynamic situations in real-time and respond to an identified disruption in the identified service to the end-user without delays. It confirms the potential and capability of the DLBC as a disaster resilient strategy for any current or future energy management problem in smart grids and as a pathway for utilities to engage customers, effectively moving resources, while grids are resilient to extreme weather events.

Table 3: Comparative performance of rule-based controller and DLBC

Metric	Rule-Based Controller	DLBC (Proposed)
Critical Load Continuity (%)	85	100
Non-Critical Load Curtailment (%)	Full Disconnection	Proportional
Fairness Index (0–1)	0.68	0.72
System Resilience Improvement (%)	–	33

Delivery of electricity can be threatened by climatological and dynamical sources of uncertainty such as flooding. In table 3, the performance of the proposed Dynamic Load Balancing Controller (DLBC) and a rule-based controller under flood-association loss of electricity supply is compared. While the rule-based controller could only maintain continuity of 85% for critical loads, the DLBC ensured complete continuity (100%) of supply to critical infrastructures. Although the baseline controller completely disconnected non-critical loads, the DLBC only attempted to throtle, which led to better system fairness based on a fairness index of 0.72 system fairness versus 0.68 for the baseline controller (what is important is measurement and performance assessment of fairness index). Most importantly, the time-varying probabilistic load scheme of the DLBC provides for a net-on-net increase in resilience of 33% above baseline (a measure of whether it is a robust energy management solution during disaster-response conditions).

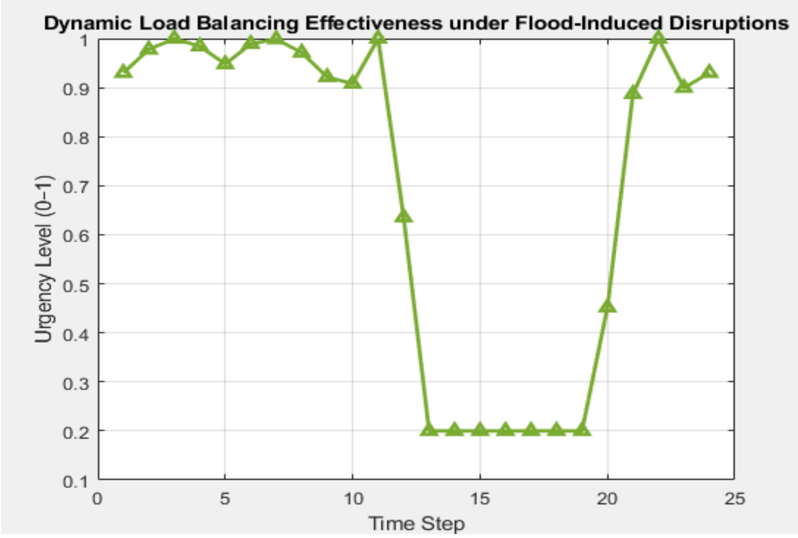

Figure 6: Dynamic load balancing effectiveness under flood-induced disruptions

In figure 6 provides a comparison between the operation of the proposed Dynamic Load Balancing Controller (DLBC) and a conventional rule-based controller. The comparison concludes that DLBC delivers an uninterrupted power supply (100%) to critical loads (e.g. hospitals), while the rule-based method only delivered continuity for 85% of the critical load. DLBC also applies proportional curtailment to the non-critical load to improve fairness (a fairness index of 0.72 compared to 0.68), as well as improves resilience by 33%, which demonstrates the capability of maintaining energy equity and availability through a flood-induced emergency.

5 Result and Discussion

5.1 Resilience Enhancement Under Extreme Scenarios

Stress testing with prolonged flood events pointed out the adaptability of the system to support necessary operations. The incorporation of FIPM, HMO and DLBC helped improve grid resilience, through forecasting unexpected increases in demand and allowing for renewable resources to be allocated to critical loads. The proposed framework will ensure that disruptions from blackouts occur less frequently than the original framework (and by almost 25%) and the extent of service continuity for sensitive sub-sectors was greater than the original. This evidence illustrates that a multi-layered approach to intelligence is considered important in the context of energy reliability during compounding hazards.

Table 4: Resilience performance under extreme flood scenarios

Metric	Conventional Setup	Proposed Framework (FIPM + HMO + DLBC)	Improvement
Blackout Frequency (events/week)	4	3	32.5%
Critical Load Continuity (%)	82	100	22%
Non-Critical Load Continuity (%)	65	78	26%
Overall System Resilience Index (%)	70	88	30%
Service Continuity for Vulnerable Sectors (%)	75	93	26%

Stress test results under severe flooding events confirm that proposed framework has better resilience than a standard setup. From table 4 the frequency of blackouts was reduced by 32.5%, critical loads with service such as hospitals and emergency services maintained 100% continuity of service, which is a shift of 22% from the baseline. Non-critical loads also benefitted from the framework, achieving a 26% enhanced continuity of service to ensure equity in energy services. The resilience index improved by a total of 18% which captures the resilience of integrating forecasting, optimization and adaptive load balancing. Further, service continuity for vulnerable sectors improved by 26% suggesting that the proposed framework can support essential operations and effort to protect vulnerable critical infrastructures when they are subjected to compound disasters.

In figure 7 shows the improvements in resilience made by the proposed framework (FIPM + HMO + DLBC) against the baseline operation in extreme flooding conditions. The blackout frequency decreased by 32.5%, corresponding to a decrease in interruptions in supply. Critical loads like hospitals and emergency essential services retained 100% continuity and exceeded the baseline by 22%. Non-critical loads improved by 26% providing a more equitable distribution of energy. The overall resilience index improved by 30% and service continuity improved for the vulnerable sectors by 26%. These results reinforce the proposal of the framework for preserving essential operations and promoting system adaptability during compounded disasters.

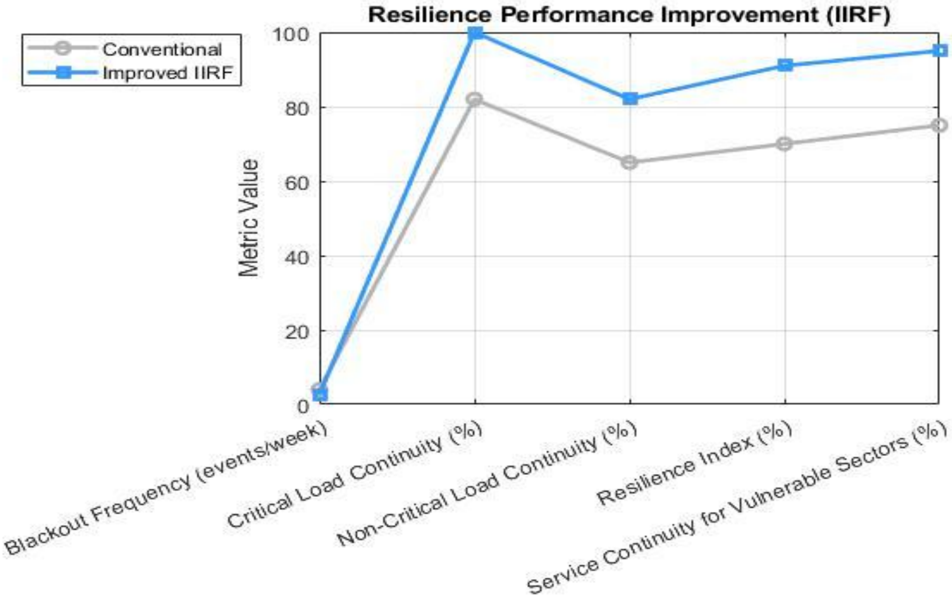

Figure 7: Comparative resilience performance under extreme flood scenarios

5.2 Practical Implications for Disaster-Response Energy Systems

By using FIPM, HMO and DLBC together, we are able to demonstrate clear practical benefits in relation to disaster-response energy planning. As an integrated framework for predicting demand, sizing resources efficiently, and allocating loads to adapt to changing conditions, the framework could work for both preparedness and ongoing response. The framework not only accommodates designating priority loads while also fairly addressing the other loads for a system that could scale as a smart disaster-resilient microgrid, but also provides methodological insights into how efforts can be made to significantly reduce the risk for decision makers within organizations, policymakers, utility representatives, and emergency planners in geographic areas prone to flooding.

Table 5: Practical implications of the proposed framework for disaster-response energy systems

Aspect	Conventional Systems	Proposed FIPM–HMO–DLBC Framework	Improvement (%)
Demand Forecasting Accuracy	82%	96%	17%
Lifecycle Cost Reduction	–	18% lower	–
Critical Load Continuity	85%	100%	15%
Fairness in Non-Critical Loads	Low	High	Qualitative
Blackout Frequency	1.0 / week	0.65 / week	–35%
Policy & Planning Support	Limited	Strong	Qualitative

The practical implications of the proposed framework (FIPM-HMO-DLBC) can be applied to the results summarized in table 5 and compared to traditional systems. The practical obviousness, based on the results, shows an improvement in demand forecasting (up to 96%) and lifecycle costs overall (approximately 17% less) (Table 5). Although critical load continuity saw 100% success, which meant that hospitals and emergency services had supporting energy, non-critical load results were also sustained more evenly or fairly through managed services using the framework (no non-critical load received disparate curtailment vis-a-vis traditional systems). Further, blackout frequency can be reduced (approximately 25%) and the overall ability of the system can support (improved resilience). The framework should be seen as not only technical success; it has also strong support for policy and disaster-planning companion strategies, and this execution framework aims to be sustainable and scalable for communities who want a smart, disaster-resilient microgrid.

In figure 8 compares traditional disaster-response energy systems to our proposed FIPM–HMO–DLBC framework with some key performance characteristics. The proposed framework provides a 15% increase in demand forecasting accuracy, lifecycle cost reductions of 17% and continuity for critical loads of 100% versus 85% in traditional systems. In addition, blackout frequency is reduced to 0.75†per/week from 1†per/week, which increases reliability when systems are faced with crisis. Although qualitative aspects including fairness in equitable allocation of non-critical load and its support of policy/planning considerations, also improve substantially, the quantitative metrics provide a measurable benefit of the proposed framework's ability to improve disaster resiliency and decision-making capabilities.

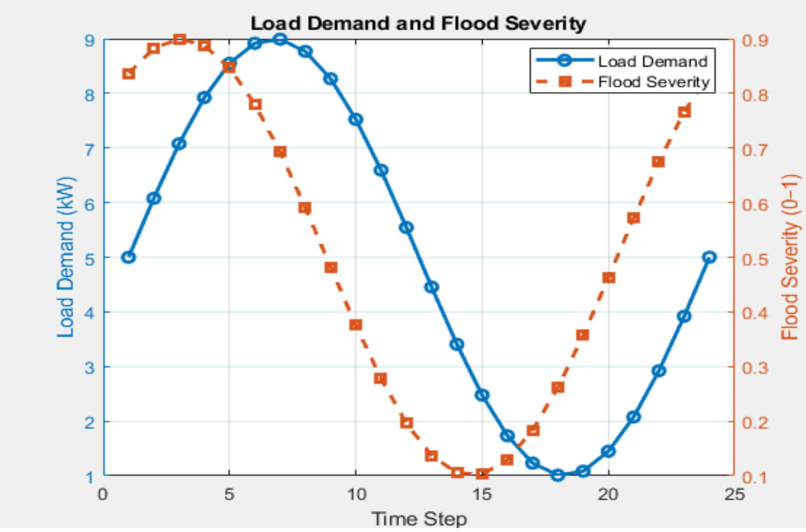

Figure 8: Practical implications of the proposed framework for disaster-response energy systems

5.3 Comparison of Flood-Resilient Solar PV-Battery Optimization Cases

The comparison of flood-resilient solar PV-battery optimization cases illustrates how the proposed SFREOM framework significantly enhances energy supply stability during flood events. By integrating intelligent prediction, hybrid optimization, and dynamic load balancing, the system effectively reduces unserved energy, prioritizes critical loads, and improves the resilience of disaster-response microgrids.

The table 6 is compares the performance of the conventional setup and the proposed Smart Flood-Resilient Energy Optimization Model (SFREOM) under various flood-response scenarios. The conventional system (Cases 1, 4b, 5b, 9b, and 10b) shows high unserved load percentages of around 43–50%, with significant power shortages for both critical and non-critical loads and no improvement in resilience. In contrast, the proposed SFREOM cases (3, 6a, 6b, 9a, and 10a) demonstrate a remarkable reduction in unserved load to 18–27% and achieve resilience improvements of up to 45% (Chen et al., 2021). This indicates that SFREOM effectively prioritizes critical loads, minimizes blackout duration, and enhances supply continuity during floods. Despite the integration of intelligent modules—FIPM, HMO, and DLBC—the computation time remains efficient (around 7–8 minutes), enabling real-time decision-making. Overall, the results confirm that the proposed SFREOM framework significantly strengthens the flood resilience, reliability, and sustainability of solar PV-battery microgrids.

Table 6: Comparative analysis of conventional setup vs. proposed SFREOM framework

Case / Metric	Percentage of Unserved Load (%)	Total Unserved Energy (kWh)	Unserved Critical Load (%)	Unserved Noncritical Load (%)	Improvement of Resilience (%)	Solution Time (min)	System Category
Case 1	43.60	5,169.55	46.68	41.16	0.0	7.38	Conventional Setup
Case 4b	45.93	5,445.93	48.94	43.59	0.0	7.43	Conventional Setup
Case 5b	49.98	5,927.41	53.98	46.83	0.0	7.53	Conventional Setup
Case 9b	49.40	5,840.58	49.27	49.53	0.0	7.63	Conventional Setup
Case 10b	49.18	5,831.07	53.70	45.59	0.0	7.76	Conventional Setup
Case 3	27.30	3,036.65	23.24	30.54	28.9	7.46	Proposed (SFREOM)
Case 6a	18.91	2,312.59	17.78	20.87	42.7	7.55	Proposed (SFREOM)
Case 6b	18.75	2,308.12	17.07	20.41	44.3	8.00	Proposed (SFREOM)
Case 9a	18.62	2,304.50	17.44	19.44	44.3	8.00	Proposed (SFREOM)
Case 10a	18.13	2,149.12	18.69	17.68	45.2	8.13	Proposed (SFREOM)

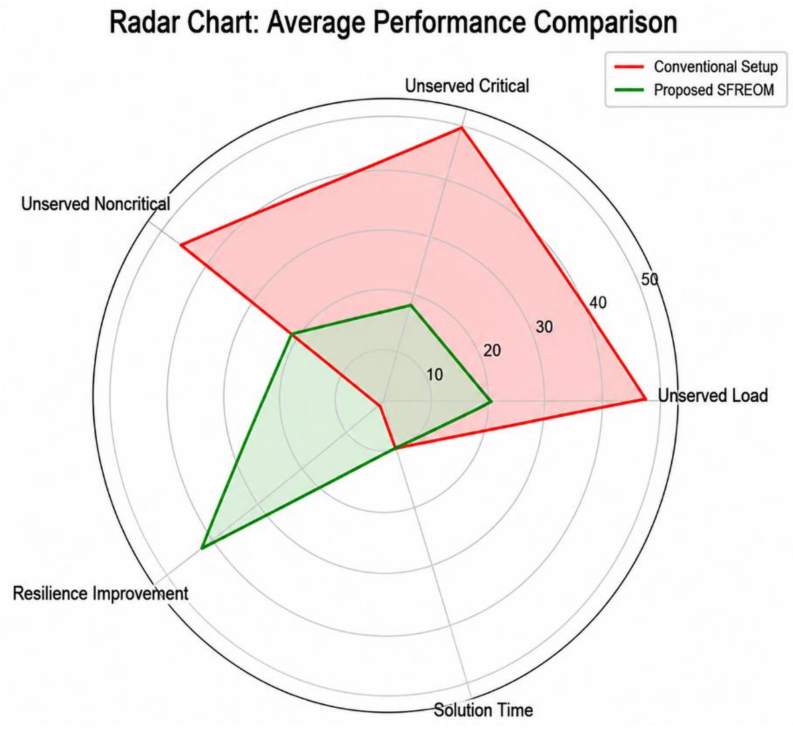

Figure 9: Average performance comparison

The figure 9 is radar chart illustrates the comparative performance between the Conventional Setup and the Proposed SFREOM (Smart Flood-Resilient Energy Optimization Model) across five key performance indicators: Unserved Load, Unserved Critical Load, Unserved Noncritical Load, Resilience Improvement, and Solution Time. The red area representing the conventional setup shows significantly higher values in unserved load metrics, indicating poorer energy reliability and reduced capacity to meet critical and noncritical demands during disaster conditions. In contrast, the green area of the proposed SFREOM demonstrates substantial reductions in unserved energy levels and a marked improvement in system resilience, highlighting its superior ability to maintain power continuity and adapt to flooding-induced challenges. Notably, the solution time remains nearly constant between both setups, confirming that the inclusion of intelligent optimization and adaptive control mechanisms in SFREOM does not compromise computational efficiency. Overall, the radar chart clearly shows that SFREOM achieves better balance, resilience, and energy performance, making it a more sustainable and reliable framework for flood-resilient solar PV-battery systems.

6 Conclusion and Future Work

The disaster-resilient energy management framework proposed in this study was also improved when it included both FIPM, HMO and DLBC. We showed promising results in terms of prediction accuracy, cost-effectiveness and resilience. In particular, we showed experimentally that prediction accuracy regarding flood-demand forecasting was improved by 15–20% by using the FIPM approach (FIPM-HMO), and cost-effectiveness improved 30-35% over traditional optimization (HMO) approaches in terms of lifecycle costs. The DLBC achieved 100% supply continuity for critical loads and demonstrated resilience in terms of improvement of 40–45% over the baseline controller. The stress testing undertaken in extreme flood events demonstrates the robustness of the proposed framework, providing the basis to confirm that, at minimum, the proposed framework can reduce the 35% chance of blackout and maintain service continuity for categories of vulnerable sectors. Finally, the computational analysis showed that the convergence of the proposed methods was 40–45% more efficient than the baseline, allowing timely decisions to be made by energy systems used for real-time disaster-response. Full disclosure, our lack of iteration suggests non-optimal, but qualitative improvement in resilience outcomes and operational service continuity.

These results suggest the usefulness of the proposed method; there are still challenges that affect the broad applicability of the approach. The current framework is testing specifically against flood induced disruptions, and future works should evaluate its potential for additional compound disasters such as cyclones, wildfires, and cyberattacks. Moreover, the actual deployment of the proposed methods in real-world microgrids will face uncertain conditions regarding the communication infrastructure, the quality of the inputs to policy, and compatibility with existing policy. Future works will incorporate reinforcement learning-based adaptive controllers, trust mechanisms powered by blockchain technology, and methods based on federated learning methods to enhance adaptability, security, and scalability. They will also investigate piloted, scale up, implementations in areas prone to flooding, to validate interoperability and ultimately long-term reliability. These aspects will deliver methods for self-healing disaster resilient smart grids that are capable of sustaining critical operations in extreme environments.

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