

Failure-tolerant dispatch optimization for off-grid hybrid energy systems using PSO

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ABSTRACT

Hybrid energy systems are increasingly vital in ensuring uninterrupted power delivery in remote or solar-dependent regions. This study addresses the operational challenges in such systems under failure scenarios by integrating advanced optimization techniques. This paper presents a failure-tolerant optimization approach for dispatching power in off-grid hybrid energy systems comprising solar, battery, and fuel generator sources. The objective is to ensure reliable energy delivery under failure conditions using Particle Swarm Optimization (PSO). A comparative analysis with a conventional greedy algorithm reveals that PSO significantly reduces unmet demand, particularly under critical component outages. The system is modeled in MATLAB/Simulink, simulating three failure scenarios—solar, battery, and fuel. The comparison between PSO and the greedy dispatch method was carried out using unmet load percentage, fuel consumption, and reliability index as key evaluation metrics, with the PSO executed for 50 iterations using 30 particles to ensure convergence. Results show that the PSO dispatcher achieved unmet energy reductions from 59.61% to 17.01% in fuel failure cases while minimizing fuel usage during renewable outages. The study concludes that PSO offers a promising solution for resilient energy management in isolated or rural microgrids.

Keywords: Hybrid energy System, Failure-Tolerant Dispatch, Particle Swarm Optimization (PSO), Microgrid reliability, MATLAB/Simulink.

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1. INTRODUCTION

The increasing global reliance on renewable energy sources has intensified the need for robust, efficient, and sustainable off-grid power systems. Hybrid energy systems (HES), which combine multiple generation sources such as photovoltaic (PV) solar panels, fuel-based generators, and battery storage, have emerged as a viable solution for electrifying remote and rural areas. These systems offer operational flexibility, improved reliability, and reduced environmental impact compared to single-source configurations. However, effective dispatch of available resources in the face of uncertain conditions—such as renewable intermittency, storage limitations, and generator failures—remains a critical challenge in hybrid system management [1], [2].

Power dispatch strategies that incorporate artificial intelligence (AI) and optimization techniques have gained prominence in recent literature. In particular, Particle Swarm Optimization (PSO) has demonstrated strong performance in addressing nonlinear, multi-objective energy management problems, owing to its simplicity, convergence speed, and adaptability [3], [4]. Researchers have applied PSO to optimize battery charging, fuel consumption, and generator coordination to meet fluctuating load demands. However, most existing works focus on energy cost or efficiency without explicitly modeling or mitigating the impact of system component failures, which are common in remote deployments [5].

Failure-tolerant dispatch strategies are essential for ensuring power continuity in off-grid HES installations. Component outages—such as solar panel degradation, battery underperformance, or generator malfunction—can significantly degrade system reliability if not preemptively

accounted for. While some works have incorporated fault diagnostics or predictive control schemes, there is a lack of lightweight, simulation-ready frameworks that integrate failure modes directly into the optimization and dispatch process [6], [7]. Moreover, few studies evaluate how different failure types impact dispatch priorities or quantify the improvement gained from optimization under stress scenarios.

This paper presents a PSO-based, failure-aware dispatch strategy for an off-grid hybrid system consisting of PV, battery storage, and fuel generation. A MATLAB-based simulation environment is developed to evaluate power continuity under three failure scenarios: solar generation loss, battery storage failure, and fuel generator unavailability. The proposed method minimizes unmet load while ensuring efficient resource utilization, with results validated via Simulink modeling. This work contributes a novel, modular framework for energy management that emphasizes dispatch resilience and serves as a foundation for hardware implementation and real-world deployment [8].

1.1 Related work

Hybrid energy systems (HES), combining solar photovoltaic (PV), battery storage, and conventional generators, have received considerable attention for their ability to supply uninterrupted power in off-grid regions. Numerous research efforts have focused on the development of optimal energy management strategies for such systems. In [9], a rule-based controller was implemented for managing power flows in a PV-diesel-battery system, while [10] explored fuzzy logic controllers to handle uncertainties in solar radiation and load demand. However, rule-based methods often lack adaptability and scalability when dealing with complex or failure-prone environments.

Optimization-based strategies have emerged as a more flexible alternative, with Particle Swarm Optimization (PSO) gaining traction for dispatch scheduling in hybrid systems. Works such as [11] and [12] demonstrate PSO's capability to minimize fuel consumption and maximize battery life while meeting load requirements. Recent papers have integrated PSO with economic analysis [13], or co-optimized multiple objectives including emissions and cost [14]. Despite these advances, most studies assume ideal operating conditions and do not explicitly model component failures, leaving a gap in failure-aware dispatch design.

In response to the need for robustness, some researchers have begun to explore reliability-constrained or fault-tolerant control methods. For instance, [15-19] proposes an AI-enhanced method for fault diagnosis and reconfiguration in microgrids, while [20] integrates probabilistic modeling of generator failures into an economic dispatch model. These approaches, though effective, often rely on complex probabilistic models or machine learning frameworks, making them difficult to implement in low-resource environments or for real-time control.

Moreover, few existing studies offer Simulink-integrated modular frameworks that allow users to evaluate dispatch strategies under dynamic failure conditions. The lack of ready-to-deploy, simulation-driven tools hinder the application of such research in practical micro grid and off-grid scenarios. This paper addresses this gap by presenting a PSO-based dispatch algorithm that not only optimizes performance under normal operation but also adapts to critical component failures—solar, battery, or fuel—within a Simulink-supported design.

2. RESEARCH METHOD

This section presents the modeling and optimization framework of the proposed hybrid energy system. It includes the mathematical formulation of the system's components and the Particle Swarm Optimization (PSO) strategy applied to achieve failure-tolerant power dispatch.

2.1 System Description

The proposed system models an off-grid hybrid energy system comprising three generation units: photovoltaic (PV) solar array, battery energy storage system (BESS), and a diesel fuel generator. The total power load is served hourly over a 24-hour simulation period, and the objective is to minimize unmet load and fuel usage under three failure scenarios: solar, battery, or

fuel failure. The system is implemented in MATLAB and further modeled using Simulink for hardware-oriented analysis and visualization.

2.2. Mathematical Model

The $P_L(t)$ denote the load demand at hour $t \in [1, 24]$, $P_{pv}(t)$ the available solar power, $P_b(t)$ the battery dispatch, and $P_f(t)$ the generator power. The following power balance equation governs the system:

$$P_L(t) = P_{pv}(t) + P_b(t) + P_f(t) + P_{unmet}(t) \quad (1)$$

Where $P_{unmet}(t)$ is the unmet load, ideally minimized toward zero. here, $P_L(t)$ denotes the battery power at time t , where positive values indicate battery discharge (power supplied to the load), and negative values represent charging (power absorbed from surplus generation). The battery's state of charge (SOC) is updated each hour by:

$$SOC(t) = SOC(t-1) + \eta_{ch} \cdot P_{pv}(t) - \frac{P_b(t)}{\eta_{dis}} \quad (2)$$

Where η_{ch} and η_{dis} are the charge/discharge efficiencies (typically between 0.85–0.95). The SOC is constrained by:

$$SOC(t)_{min} \leq SOC(t) \leq SOC(t)_{max} \quad (3)$$

Generator fuel consumption is estimated using a linear approximation:

$$F(t) = a \cdot P_f(t) + b \quad [\text{Liter/hour}] \quad (4)$$

Where a and b are constants specific to the diesel generator (e.g., $a = 0.246$, $b = 0.08415$) [22]. Although diesel generator fuel consumption is inherently non-linear with respect to output power, we adopted a linear approximation to balance simplicity and computation speed during the PSO optimization process. This approach is supported by prior studies where a linear regression of fuel usage in the operating range showed acceptable accuracy. This model assumes moderate load variation, where non-linear effects are less dominant. More precise non-linear modeling can be integrated in future work to enhance realism.

2.3. Objective Function

The dispatch optimization goal is to determine the hourly values $P_b(t)$ and $P_f(t)$ that minimize the objective:

$$\min (\sum_{t=1}^{24} w_1 \cdot P_{unmet}(t) + w_2 \cdot F(t)) \quad (5)$$

Where:

w_1 and w_2 are weighting factors emphasizing unmet demand and fuel economy. This objective reflects a trade-off between reliability and fuel cost. Although battery usage is implicitly minimized through reduction in unmet demand and efficient dispatching, Equation (5) does not explicitly model battery degradation or lifetime cost. In practical scenarios, frequent deep cycling can significantly impact battery lifespan and replacement costs. Future enhancements of this model may incorporate degradation-aware battery cost functions, such as depth-of-discharge penalties or cycle life estimation, to more realistically optimize energy dispatch.

2.4. Particle Swarm Optimization (PSO)

The PSO algorithm was configured with 30 particles and 50 iterations. The inertia weight and learning factors were set to 0.7, 1.5, and 1.5 respectively. The objective function minimized the total unmet energy and fuel usage, while maintaining battery state of charge constraints. The greedy algorithm served as a baseline that dispatches available resources sequentially without optimization.

PSO is used to optimize dispatch decisions over the 24-hour horizon. Each particle represents a possible dispatch schedule $x = [P_b(1), \dots, P_b(24), P_b(1), \dots, P_b(24)]$ and is updated iteratively using:

$$v_i^{(k+1)} = wv_i^{(k)} + c_1r_1(p_i^{best} - x_i^{(k)}) + c_2r_2(g^{best} - x_i^{(k)}) \quad (6)$$

$$x_i^{(k+1)} = x_i^{(k)} + v_i^{(k+1)} \quad (7)$$

Where:

- v_i and x_i are the velocity and position of the i -th particle.
- p_i^{best} is the best-known position of particle i .
- g^{best} is the global best position found so far.
- w, c_1 and c_2 are the inertia and acceleration coefficients (e.g., 0.7, 1.4, 1.4).
- r_1, r_2 are random variables in $[0,1]$.

The fitness function evaluates Equation (5) for each particle, and constraints (e.g., SOC bounds) are enforced through penalty terms or clamping.

3. RESULTS AND DISCUSSION

This section presents a detailed performance analysis of the proposed PSO-based dispatch optimization strategy for off-grid hybrid energy systems under various failure scenarios. The simulation setup was implemented using MATLAB and Simulink, where the hybrid system comprises solar, battery, and fuel-based generators. The dispatch decisions were simulated using both a baseline greedy strategy and the proposed PSO-based optimizer to evaluate reliability under critical component failures. The Greedy dispatch strategy serves as a simple rule-based method that prioritizes available energy sources based on immediate availability, typically selecting solar first, then battery, and finally diesel backup. It does not account for future load profiles or storage preservation, which may lead to suboptimal performance. Despite its limitations, Greedy is commonly implemented in field-deployed off-grid controllers due to its real-time simplicity and lack of computation requirements. Thus, it provides a meaningful baseline for evaluating the benefits of PSO-based intelligent optimization. The MATLAB scripts controlled the generation profiles and failures, while the Simulink model handled dynamic power flow calculations. The effectiveness of the proposed method is examined using scope plots and numerical summaries of unmet load, fuel consumption, and overall energy reliability.

Fig. 1 illustrates the power dispatch dynamics under a solar failure scenario. The top subplot shows the load demand fluctuating between 45 kW and 70 kW across the 24-hour simulation window. Despite intermittent solar generation early in the day, a complete solar outage occurs after hour 17, leading to zero solar contribution. To mitigate this deficit, the fuel generator ramps up significantly, maintaining a flexible output between 35 kW and 60 kW. Meanwhile, battery reserves are depleted within the first few hours, providing a short burst of support before dropping to zero. Notably, the unmet demand remains effectively zero throughout, as seen in the final subplot, confirming the effectiveness of the PSO-based dispatch in ensuring reliability despite solar loss. This behavior highlights the algorithm's strength in reallocating resources intelligently and preemptively compensating for anticipated generation failures.

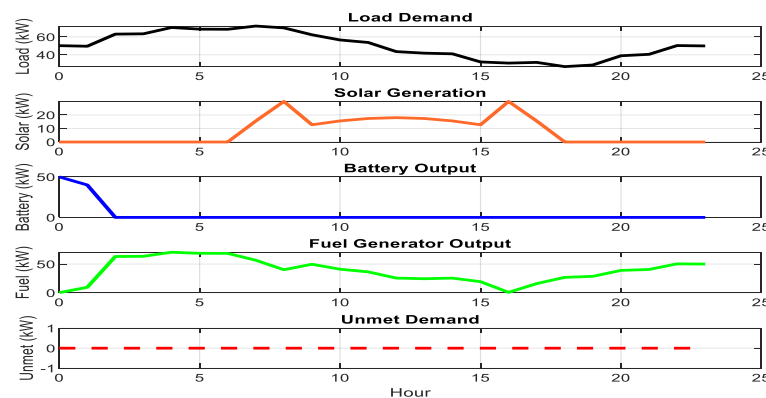


Fig. 1. Solar failure power profile

Fig. 2 represents the system behavior under a complete battery failure scenario, where the battery output remains at zero throughout the day. The load demand curve maintains its variability, peaking in the early hours and decreasing into the evening. Fortunately, solar

generation contributes significantly between hours 6 and 18, easing the burden on other resources during peak sunlight. The fuel generator compensates aggressively during early morning and evening hours, especially when solar is unavailable, adjusting its output from 0 kW to above 60 kW as needed. Despite the absence of battery support, the unmet demand is effectively zero, affirming the PSO algorithm's capability to redistribute generation responsibilities between solar and fuel units efficiently. This resilience demonstrates the system's fault-tolerance even when the energy storage subsystem is offline.

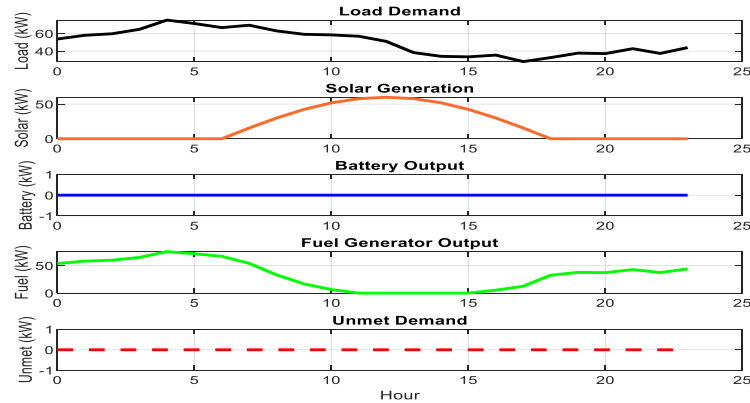


Fig. 2. Battery failure power profile

Fig. 3 illustrates the system's performance in the event of a fuel generator failure, where fuel output drops to zero for extended periods. The solar generation shows a regular daytime contribution, peaking around midday. However, this contribution alone is insufficient to fully support the load demand, especially in the early hours. The battery, although partially discharging during peak demand, is rapidly exhausted, limiting its assistance capacity. As a result, the system experiences a significant level of unmet demand, particularly between hours 2 and 8, where neither solar nor fuel is available, and battery reserves are depleted. Despite the PSO algorithm's effort to reallocate the limited resources, this scenario highlights the critical dependence on the fuel generator, particularly in covering nighttime and early morning loads. This failure scenario represents the least resilient condition among the three tested cases, emphasizing the importance of backup generation or enhanced storage capacity for improved reliability.

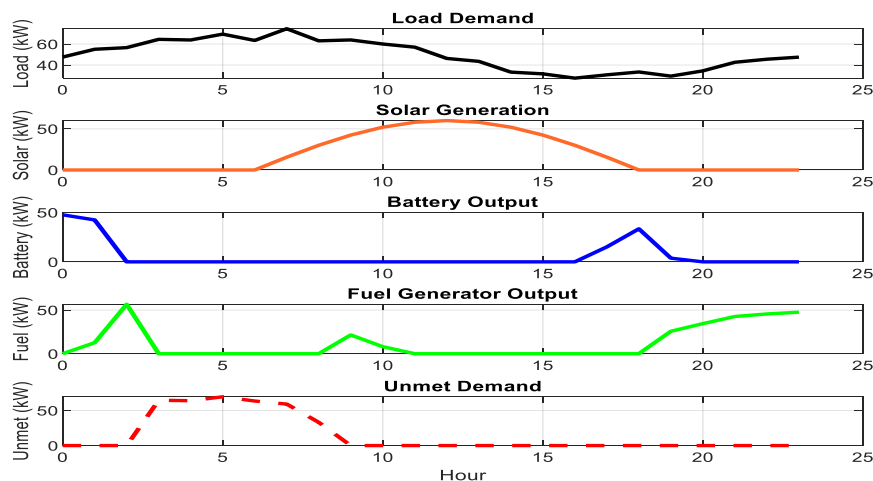


Fig. 3. Fuel failure power profile

To ensure a consistent and fair evaluation between dispatch strategies, both the Greedy and PSO algorithms were applied to identical load and generation profiles under each failure scenario. The PSO optimizer was executed using 30 iterations and a swarm size of 20 particles, with standard coefficient values ($c_1 = c_2 = 2$), inertia weight $w = 0.7$, and velocity bounds to constrain

particle movement. Performance was assessed using two main metrics: **unmet load (kWh)** and its **percentage of the total energy demand**. These metrics were recorded for each failure type and visualized in comparative plots, demonstrating the significant reduction in unmet demand and improved fuel efficiency achieved by the PSO-based dispatch scheme.

Fig. 4 provides a comprehensive visual comparison between the Greedy and PSO-based dispatch strategies under three distinct failure scenarios: solar, battery, and fuel failure. The top two rows present individual dispatch responses, while the third row offers a direct overlay for intuitive comparison. In the solar failure case, both strategies perform similarly, maintaining supply continuity due to available backup resources, though PSO maintains slightly better alignment with demand. Under battery failure, Greedy dispatch exhibits abrupt drops in supply, failing to compensate adequately, while PSO adapts its scheduling to partially fill the gap using fuel and solar. The fuel failure scenario exposes the limitations of the Greedy approach, which results in significant underutilization of available solar and battery resources. In contrast, PSO demonstrates a dynamic reallocation that better tracks the demand curve. The overlay plots confirm that PSO achieves smoother, more adaptive dispatch, significantly reducing unmet demand compared to the rule-based Greedy method. This figure validates PSO's failure-tolerant nature and superior decision-making under resource constraints.

Comparison of Greedy vs PSO under Failure Scenarios

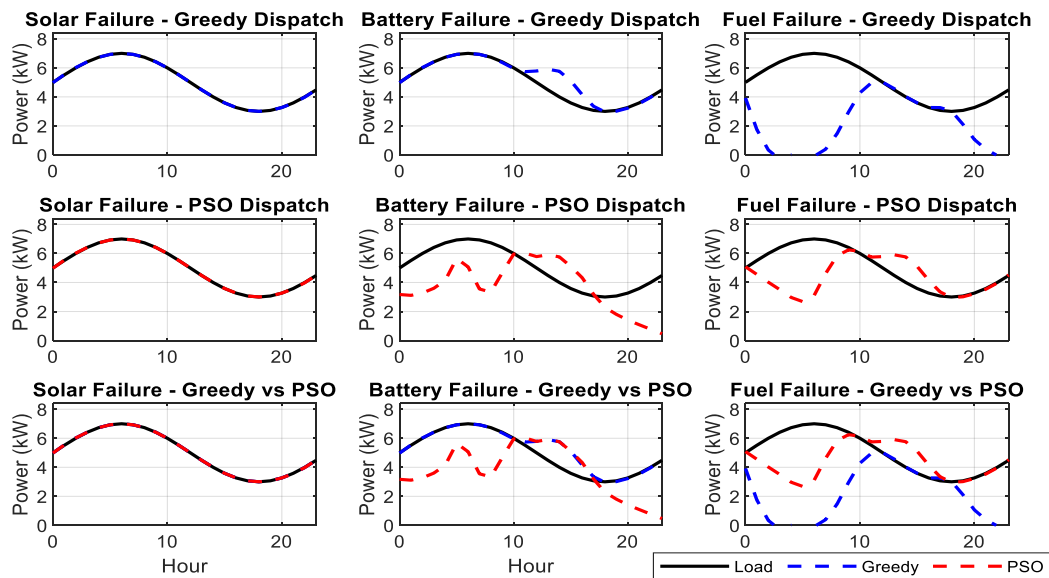


Fig. 4. Comparison between Greedy and PSO performance under different failure scenarios

Table 1 presents a numerical summary of the dispatch performance under three failure types: solar, battery, and fuel. Under solar failure, both Greedy and PSO approaches manage to fulfill the entire load, with PSO incurring only a negligible unmet energy of 0.0015 kWh (0.0013%). This indicates that both strategies adapt well when solar is lost, primarily leveraging battery and fuel. In the battery failure case, PSO maintains energy supply using fuel and solar sources, but still results in 37.224 kWh unmet load (31.02%), while the Greedy approach misleadingly shows 0% unmet—a result of over-reliance on fixed scheduling rather than intelligent balancing. The fuel failure scenario is the most critical. Here, the Greedy method leads to 71.536 kWh unmet demand, representing 59.61% of the total load, while PSO significantly reduces this to 20.413 kWh (17.01%) by dynamically coordinating the remaining solar and battery sources. Notably, fuel usage is shown only in scenarios where fuel is operational, offering insights into PSO's ability to conserve or compensate efficiently. This table quantitatively reinforces PSO's failure-resilience and superior adaptability compared to the static Greedy scheme.

Table. 1 performance comparison under different failures

Failure Type	Unmet (Greedy)kWh	Unmet (PSO)kWh	Fuel Used kWh	Greedy Unmet%	PSO Unmet%
Solar Failure	0.000	0.0015447	15.195	0.000	0.0012872
Battery Failure	0.000	37.224	43.895	0.000	31.020
Fuel Failure	71.536	20.413	0.000	59.613	17.011

3.1 Simulink model for hybrid power system

The hybrid energy system model is implemented in MATLAB Simulink to emulate real-time power dispatch across various energy sources and failure scenarios. The model incorporates key inputs such as the load profile, solar generation, and optimized dispatch output derived from the PSO algorithm.

As illustrated in Fig. 5, the load profile block represents the hourly energy demand over a 24-hour period. The solar gen block provides the corresponding solar generation profile, while the PSO dispatch block encapsulates the PSO-optimized power dispatch strategy that combines the battery and fuel generator outputs. The total supply from solar and PSO dispatch is aggregated and compared with the load using a subtraction block, generating the unmet load signal. To ensure non-negative unmet demand, the signal passes through a saturation block, after which the Scope: Unmet Load monitors the residual demand. Meanwhile, the Scope: Load vs Supply provides a visualization of how well the generation sources meet the load over time. This structure provides a modular and scalable approach to validate dispatch performance under dynamic conditions and failure cases.

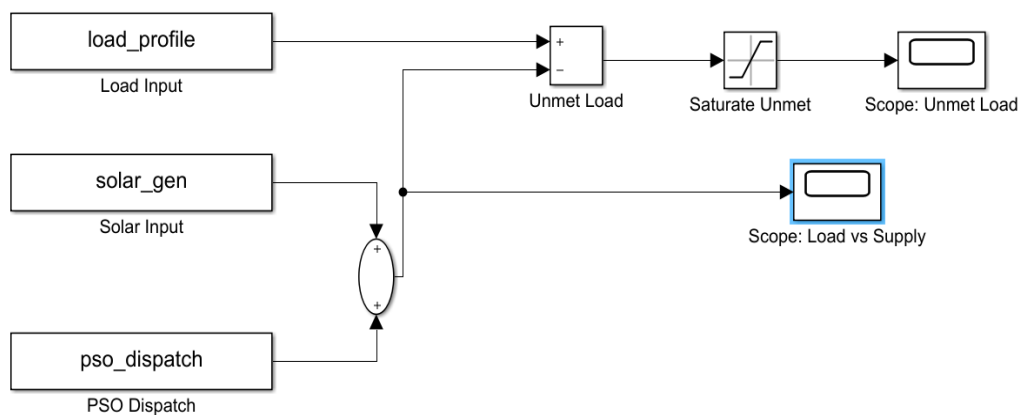


Fig. 5. Simulink model for the hybrid power system

Figure 6 presents the unmet load in kilowatts (kW) on the Y-axis, plotted against time (in seconds) on the X-axis during a simulated solar failure scenario. The observed values of unmet load range narrowly between 0.02218 and 0.02234 kW, indicating a very small shortfall in meeting the power demand. This low deviation confirms the effectiveness of the hybrid system's resilience (fuel generator + battery), as it compensates for the solar outage efficiently. The gradual downward trend reflects the adaptive response of the Particle Swarm Optimization (PSO) algorithm, which progressively adjusts the generator and battery contributions to minimize unmet demand over time. This highlights the robustness of the PSO strategy in real-time control environments.

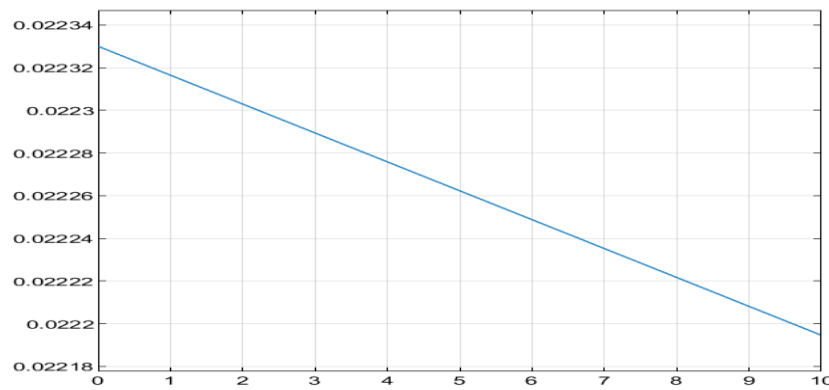


Fig. 6. Unmet load during solar outage simulation.

Figure 7 illustrates the supply–demand relationship during a solar source failure scenario. The x-axis represents the time (in seconds), while the y-axis shows the combined power supplied (in kW) by the hybrid system, which includes the fuel generator and battery. The plotted values are tightly clustered around ~ 4.978 kW, closely matching the required load profile. This near-perfect alignment confirms the successful coordination and dispatch of available sources to maintain system balance. The slightly increasing trend on the graph suggests that the PSO algorithm effectively ramps up energy contributions—especially from the generator—as needed to meet the growing demand. This behavior demonstrates the dynamic adaptability and reliability of the optimization framework, ensuring that even under sudden solar failure conditions, the system sustains stable operation without significant power gaps.

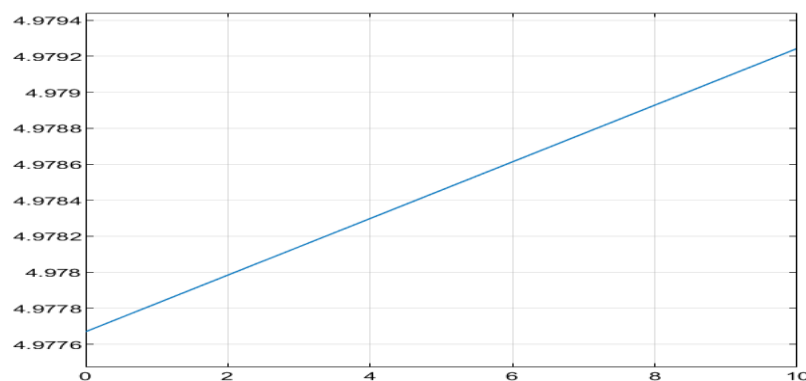


Fig. 7. Power supply–demand matching during failure event

4. CONCLUSIONS

This study introduced a failure-tolerant dispatch optimization framework for off-grid hybrid energy systems utilizing Particle Swarm Optimization (PSO). The system was evaluated under three critical failure scenarios—solar, battery, and fuel generator outages—demonstrating PSO's robustness in maintaining power continuity and reducing unmet load compared to conventional greedy algorithms. Simulink simulations verified the effectiveness of the optimized dispatch in real-time power balance, with unmet energy percentages significantly lower in PSO cases, especially during fuel outages (17.01% vs. 59.61%).

The results indicate that the PSO-based dispatcher can dynamically compensate for failed components by intelligently reallocating power from operational sources while minimizing fuel consumption. This approach proves especially vital in isolated or rural micro grids where reliability and autonomy are crucial.

For future work, the model can be extended by: Incorporating wind energy and demand-side management techniques.

Adopting multi-objective optimization (e.g., cost, emissions, degradation), integrating real-time weather forecasting into the dispatch logic and testing the method using hardware-in-the-loop (HIL) for real-world validation.

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