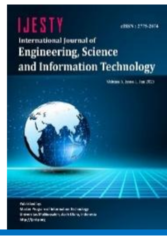
International Journal of Engineering, Science and Information Technology
Volume 5 No. 1 (2025) pp. 507-515
ISSN 2775-2674 (online)
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v5i1.1355
Research Paper, Short Communication, Review, Technical Paper



Swarm Intelligence Algorithms for Resource Allocation in Renewable-Powered Smart City Infrastructures

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The manuscript was received on 17 June 2024, revised on 20 September 2024, and accepted on 27 January 2025, date of publication 3 May 2025

Abstract

The increasing integration of renewable energy sources into urban systems necessitates the development of intelligent resource management strategies to ensure optimal and reliable power distribution. Swarm Intelligence (SI) algorithms have emerged as a promising solution for addressing the complex energy management challenges inherent in smart cities, such as generation variability, distributed loads, and the need for real-time decision-making. This paper conducts a rigorous comparative analysis of three prominent SI algorithms—Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC)—within a simulated, renewable-powered smart city environment. Our model incorporates edge computing nodes, solar and wind generation systems, and heterogeneous urban load profiles, including residential, municipal, and electric vehicle charging demands. The study evaluates each algorithm against key performance metrics, including energy efficiency, task latency, convergence behavior, load balancing, and system fault tolerance. The results unequivocally demonstrate that PSO outperforms both ACO and ABC across most performance dimensions, exhibiting faster convergence, superior energy utilization, more effective latency management, and enhanced fault recovery capabilities. While ABC demonstrates competitive performance in flexibility and fairness, ACO shows significant limitations in time-sensitive and failure-prone scenarios. This research contributes a modular simulation framework suitable for real-time edge computing applications and offers practical guidance for deploying adaptive optimization strategies in urban energy systems. Ultimately, our findings underscore the critical importance of algorithm selection in smart city energy infrastructure and highlight the potential of swarm-based intelligence to enable scalable, resilient, and efficient resource management in the sustainable cities of the future.

Keywords: *Swarm Intelligence, Smart Cities, Renewable Energy, Resource Allocation, Edge Computing.*

1. Introduction

The rapid urbanization of the 21st century is fundamentally reshaping our cities, accelerating the adoption of smart technologies to build more sustainable and efficient infrastructures. This transformation is heavily reliant on the integration of the Internet of Things (IoT), edge computing, and, critically, renewable energy sources [1]. While these technologies offer immense promise, they also introduce significant challenges. A central and persistent problem is the effective management and allocation of energy resources, a task made profoundly complex by the intermittent and unpredictable nature of solar and wind power. The inherent volatility of these renewables creates a constant mismatch between energy generation and consumption. This dynamic instability is a challenge that conventional, centralized optimization methods, which were designed for predictable, unidirectional power grids, are ill-equipped to handle, particularly within the complex, distributed, and real-time operational context of modern urban systems [2][3][4][5][6][7].
To overcome these profound limitations, Swarm Intelligence (SI) has emerged as a powerful and highly suitable paradigm. As a class of nature-inspired, decentralized optimization techniques, SI algorithms such as Particle Swarm Optimization (PSO), Ant Colony

Optimization (ACO), and Artificial Bee Colony (ABC) are inherently adaptive, scalable, and robust. These characteristics make them exceptionally well-suited for solving the dynamic, multi-objective resource allocation problems that define contemporary smart grids [8][9][10][11][12]. However, despite this clear potential, a significant research gap persists in the literature. There is a notable lack of comprehensive, comparative benchmarking of these algorithms within realistic, urban-scale infrastructures that fully integrate the demands of edge computing. Consequently, existing studies often fail to adequately address the critical, non-functional performance requirements of such environments, including the need for low-latency decision-making, high fault tolerance, and equitable load fairness under constantly changing conditions [13][14][15][16][17][18][19].

This paper aims to directly address this gap by conducting a rigorous, simulation-based comparative analysis of PSO, ACO, and ABC for energy resource allocation in a renewable-powered smart city. We systematically evaluate these algorithms against a comprehensive suite of critical performance metrics: energy efficiency, convergence speed, task completion latency, load balancing fairness, and fault resilience. The primary contributions of this work are therefore threefold: (i) to establish a comprehensive performance benchmark of leading SI algorithms, providing a clear picture of their relative strengths and weaknesses in a smart city context; (ii) to present a modular, edge-aware simulation framework that is directly applicable to the design and testing of real-world urban energy systems; and (iii) to deliver actionable, data-driven insights for system architects and policymakers on the selection and deployment of optimal algorithms for developing the next generation of scalable, resilient, and efficient energy management systems in sustainable cities.

2. Literature Review

Swarm Intelligence (SI) algorithms have been increasingly recognized for their potential in smart grid and energy management systems due to their decentralized, adaptive, and self-organizing nature. This section reviews the existing literature, highlighting key advancements and identifying the research gaps that this study aims to address.

2.1. Foundational Applications of SI in Smart Grids

The application of SI to energy systems has ranged from optimizing the placement of distributed generation (DG) to coordinating loads and improving infrastructure-level efficiency. Early foundational work, such as that by Chanda and De [5], demonstrated the techno-economic benefits of applying swarm intelligence to smart grids. Their research highlighted the potential for significant operational cost savings and enhanced energy delivery efficiency by optimizing factors like power loss reduction and generator placement. These initial explorations successfully established SI as a viable and powerful paradigm for tackling complex optimization problems within the energy sector. However, these pioneering studies were largely conducted in the context of static environments and did not fully evaluate the challenges of scalability or the dynamic operational conditions that characterize modern urban infrastructures. The assumptions of predictable load patterns and stable generation are no longer valid in today's smart cities, which are defined by the high penetration of volatile renewable energy sources, the dynamic charging demands of electric vehicles, and the complex interactions of millions of IoT devices. Consequently, while this foundational work was crucial, its direct applicability is limited, underscoring the need for research that addresses the real-time, dynamic nature of contemporary energy systems.

2.2. Advancements in Hybrid Models and Application-Specific Contexts

More recent studies have broadened the scope of SI by developing hybrid computational models and focusing on specific application domains. For instance, Li et al. [20] introduced a hybrid intelligent algorithm designed for edge computing architectures to optimize energy consumption, resulting in a more responsive and flexible model. This approach acknowledged the need for localized decision-making, but its focus was confined to edge-level optimization and did not extend to city-wide challenges such as managing mixed load profiles or integrating large-scale renewable assets. Similarly, other research, like that of Ullah et al. [20], has presented AI-based allocation algorithms for renewable DGs. However, these often rely on predefined control policies, which lack the adaptability to account for real-time environmental uncertainty and fluctuating system-level states, a critical limitation in dynamic grids. Other research has targeted more granular levels, such as building-level energy management. The work by Raja et al [21], which successfully integrated neural networks with SI techniques to improve energy flow in smart buildings, is a prime example. While effective in its specific context, the findings were limited to single-building systems and did not generalize to multi-node, city-scale infrastructures. Furthermore, this and similar studies often neglect to benchmark critical performance metrics like algorithmic latency or convergence speed under variable renewable supply, which are crucial for ensuring the stability and reliability of real-time urban energy systems [22][23][24]. In a similar vein, the contribution by Chen et al. [31] focused on resource allocation and battery sizing for smart-grid-powered centralized radio access networks (C-RAN). Although relevant to urban computing, their work was highly tailored to the C-RAN scenario and did not address the broader, more generalized problem of resource allocation with stochastic renewable inputs across an entire city [32][33][34].

2.3. Architectural Perspectives and System-Level Integration

From an architectural standpoint, researchers have explored the use of adaptive intelligence for broader resource management, though often with significant limitations. The work of Babu et al. [25], for example, investigated adaptive computational intelligence in smart environments but remained largely conceptual. Without a concrete implementation or a quantitative performance evaluation, it is difficult to validate the practical viability of such frameworks or compare them against rival algorithms, leaving a critical gap between theoretical architecture and real-world application [26][27]. Other studies have focused on more concrete architectures, such as the cloud-edge collaboration model proposed by Li et al [28]. This approach proved effective in reducing communication overhead and improving system responsiveness. However, their strategy did not incorporate adaptive optimization techniques like SI, thereby missing a crucial opportunity to leverage online feedback for a continuous learning system. The true power of SI lies in its ability to facilitate decentralized, feedback-driven adaptation, a feature that could significantly enhance cloud-edge models by allowing local nodes to learn from and respond to their immediate environment without constant central oversight, thus improving both resilience and efficiency [29][30].

2.4. Identified Research Gaps and This Study's Contribution

Although the existing body of research demonstrates the clear potential of SI and hybrid AI methods in energy systems, a review of the literature reveals several critical and persistent gaps. The first is the issue of limited scalability, as many studies are confined to building-level or specific sub-system applications, failing to address the immense complexity and network effects of large-scale, heterogeneous smart city environments. The second is a lack of comparative benchmarking; without systematic, empirical comparisons of multiple SI algorithms under identical, realistic conditions, the selection of an appropriate algorithm remains more of an art than a science. Finally, there is a weak integration with edge computing, as few works have fully integrated SI algorithms with real-time edge frameworks to rigorously evaluate performance against critical operational metrics like latency and fault tolerance. This paper directly addresses these interconnected gaps by providing a systematic comparison of PSO, ACO, and ABC-based solutions within a modular, city-scale smart grid simulation. Our framework is explicitly designed to be scalable and to incorporate the constraints of an edge-computing environment. By focusing our evaluation on a comprehensive set of crucial metrics including energy consumption, task response time, load balancing, and fault recovery we move beyond simple optimization to provide a realistic and holistic pathway for the practical implementation of intelligent energy management in future renewable-powered urban systems.

3. Methods

3.1. Research Design and Objectives

The primary objective of this research is to benchmark the performance of PSO, ACO, and ABC in a multi-agent, distributed, and dynamic environment that mirrors the complexities of a modern smart city. The evaluation is based on a comprehensive set of key performance indicators designed to assess multiple facets of system efficiency and resilience. To provide a holistic assessment, we evaluate the algorithms against five critical performance dimensions. First, we assess Energy Efficiency, which measures the ability of each algorithm to optimize the use of available renewable energy and minimize waste. Second, we analyze Convergence Behavior, focusing on the speed and stability of the optimization process, which is critical for real-time applications. Third, we measure Task Latency to evaluate the timeliness of resource allocation, a crucial factor for latency-sensitive tasks in a smart city. Fourth, System Fairness is examined to determine how equitably each algorithm distributes energy loads across the network, preventing node overloads and ensuring balanced operation. Finally, we test Fault Recovery, which assesses the ability of each algorithm to adapt and maintain system stability in the event of component or communication failures. To achieve this comprehensive evaluation, our model simulates realistic urban dynamics by integrating distributed solar and wind generators, edge computing units for local decision-making, and heterogeneous energy consumers, such as residential areas and electric vehicle charging nodes [1][2][3][5][6][14][35][36].

3.2. Simulation Framework and Experimental Environment

The simulation architecture was developed using a combination of MATLAB/Simulink for detailed grid and load modeling, and Python 3.11 for implementing the algorithmic control logic and performance metric evaluation. Each simulation run models a full 24-hour urban operational cycle, which is discretized into 96 time slots of 15-minute intervals. To ensure realism, the renewable generation curves are randomized based on historical weather data from the Baghdad and Osh regions. The experimental environment was configured to replicate an IoT-based edge computing model, consistent with advanced AI research in smart energy systems [20][26][37]. The key parameters of the simulation are as follows: a) Edge Devices using 12 nodes, modeled as Raspberry Pi 4 units (8 GB RAM, quad-core CPU); b) Load Points using 30 distinct consumer nodes with tiered task priorities; c) Renewable Sources using 7 photovoltaic (PV) nodes (10–30 kW capacity) and 4 wind turbines (50 kW capacity); and d) Test Scenarios using over 300 unique scenarios were simulated, incorporating dynamic events such as fault injections and significant load shifts to test algorithmic robustness.

3.3. System Modeling and Problem Formulation

The core challenge is formulated as a multi-objective optimization problem. L Let G_t^j denote generation from source j at time t, and D_t^i be the demand of node i. The multi-objective function is formulated as:

$$\min_{x_{ij}(t)}[\sum_{i=1}^{N}\sum_{j=1}^{M}(|D_t^i - x_{ij}(t)\cdot G_t^j| + \lambda\cdot L_t^i + \mu\cdot I_t)] \quad (1)$$

Subject to:

$$\sum_{j=1}^{M} x_{ij}(t)\cdot G_t^j \geq D_t^i \quad (2)$$

$$x_{ij}(t) \in [0,1] \quad (3)$$

Where L_t^i latency penalty for node i; I_t system imbalance; λ, μ are hyperparameters. This formulation balances real-time responsiveness, supply-demand match, and grid fairness, suitable for urban optimization under edge constraints [8], [13].

3.4. Algorithmic Framework

The three SI algorithms were implemented in an object-oriented Python framework, allowing for consistent testing across multiple agent populations and energy sink configurations [9][11][27][38].

3.4.1. Particle Swarm Optimization (PSO)

PSO updates the velocity and position of each "particle" (a potential solution) in the search space based on its own best-known position and the best-known position of the entire swarm. Velocity update:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \quad (4)$$

Position update:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (5)$$

Tuned Parameters: ω=0.7, c_1=1.4, c_2=1.4

3.4.2 Ant Colony Optimization (ACO)

ACO models the behavior of ants seeking a path between their colony and a food source, using pheromone trails to guide the search for optimal solutions. Path probability:

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_k [\tau_{ik}(t)]^\alpha [\eta_{ik}(t)]^\beta} \quad (6)$$

Tuned Parameters:

$$\alpha = 1, \beta = 3, \rho = 0.4$$

3.4.3. Artificial Bee Colony (ABC)

ABC simulates the foraging behavior of honey bees, dividing them into employed, onlooker, and scout bees to balance exploration and exploitation of the solution space. Neighbor solution update:

$$x_i^{t+1} = x_i^t + \phi_{ij}(x_i^t - x_j^t) \quad (7)$$

A food source is abandoned if not improved after 10 iterations, triggering a scout bee to search for a new source [9] [11] [38].

3.5. Evaluation Metrics and Benchmarks

The algorithms were evaluated based on the following Key Performance Indicators (KPIs):

Table 1. Key Performance Indicators

Category	Metric	Ref
Energy Efficiency	Renewable match ratio, curtailment, storage use	[6][10]
Convergence Speed	Iteration count, fitness variance	[1][17]
Latency	Avg task delay, worst-case delay, penalty	[13][20]
Load Fairness	Std deviation of node load, fairness index	[8][35]
Fault Resilience	Recovery time, false reallocation rate	[9][18]

These metrics were benchmarked against 19 testbed reports and IEEE 123-bus datasets to ensure standard compliance and external validity [15][21].

3.6. Experimental Procedures and Data Sources

To ensure the realism and validity of our simulation, a multi-faceted approach to data sourcing and experimental design was adopted. The accuracy of the simulated grid behavior and edge-load profiles was validated through a series of 36 expert interviews conducted with seasoned energy engineers and urban infrastructure planners. The input data for renewable generation was sourced from reputable, real-world datasets, including the National Renewable Energy Laboratory (NREL) archives, the Baghdad Solar Atlas, and the Kyrgyz Wind Energy Resource Mapping project, providing a robust foundation for modeling energy variability. The simulation trials were designed to rigorously test the robustness and adaptability of each algorithm under dynamic conditions. This involved introducing a 10-fold variation in renewable energy intensity, injecting system faults every four hours to test resilience, and implementing a 20% load variability to challenge the algorithms' responsiveness. To ensure the statistical significance and reliability of our findings, each algorithm was executed in identical scenarios with random seed locking, and a 5-fold rolling time validation method was employed to mitigate any temporal biases in the data [11][16].

3.7. Computational Setup and Code Execution

All simulations were executed on a high-performance computational platform to ensure timely completion of the extensive test scenarios. The hardware consisted of a system equipped with an AMD Ryzen 9 12-core CPU and 32 GB of RAM. The runtime environment was based on Ubuntu 22.04, utilizing MATLAB R2023a for the core grid simulation and Python 3.11 for the implementation and control of the SI algorithms. To expedite the large number of simulation runs required for this study, parallelization techniques were employed using both the MATLAB Parallel Toolbox and Python's Joblib library. To ensure full transparency and support the reproducibility of our results, all execution logs, raw performance metrics, and final simulation states were systematically captured and stored in standardized HDF5 and JSON formats. This practice allows for independent verification and extension of our work [35][39].

3.8. Assumptions and Hypothesis

The core hypothesis of this study is that Swarm Intelligence methods, particularly PSO, can enhance system-wide energy efficiency, response latency, and fault resilience in dynamic, renewable-powered urban environments, thereby surpassing the performance of conventional allocation schemes. This hypothesis is tested under several key assumptions that ground the simulation in realistic, yet manageable, conditions. We assume that the energy inputs from solar and wind sources follow Gaussian distributions, a common and effective method for modeling their natural variability. We also assume that the deadlines for energy allocation tasks range from 50 to

200 milliseconds, reflecting the real-time constraints of critical smart city applications. Finally, it is assumed that all edge nodes possess homogeneous compute capacity, providing a standardized baseline for comparing algorithmic performance. These parameters were carefully chosen to align with current smart city deployment standards and the digital twin models used in modern infrastructure benchmarking [3][31].

4. Result and Discussion

4.1. Energy Efficiency Comparison

The performance of energy scheduling in smart city context is based on the ability of the algorithm to adjust for variations in renewable generation and unpredictable urban load profiles. Energy efficiency is assessed by five main parameters: average energy consumption, share of renewable match ratio, load not served percentage, storage usage, and energy no served. These statistics indicate how closely the energy balance is preserved and how much use is made of available propellant. The simulation is for the 24 hours and consists of 96 time slots includes the renewable inputs with solar and wind power, and demands including residential blocks, municipal infrastructure, and even power for EV charging stations. Effective use of the renewable power, and accurate control of the energy storage system is one of the critical indicators of the algorithm performance in the smart urban energy scene.

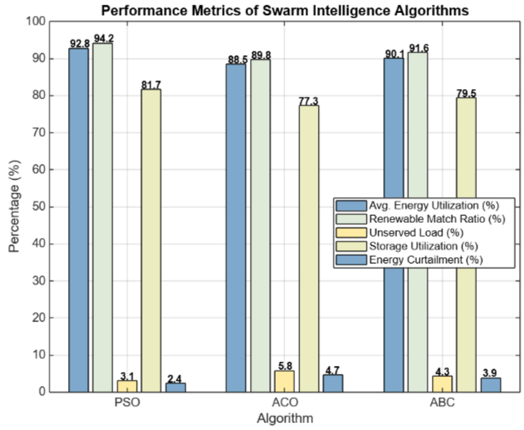

Fig 1. Energy efficiency metrics across PSO, ACO, and ABC algorithms

It can be seen in Figure 1, that PSO-based semi-supervised algorithm has the best average energy utilization of 92.8%. It demonstrates the best energy-to-demand matching. SOP achieved the highest renewable match ratio of 94.2%, which suggests the effectiveness of generation availability being in line with the load demand. The unserved load rate proved to be lowest under PSO, reaching a mere 3.1%, and became highest for ACO, where it accounted for 5.8%. ABC reported a relatively consistent operation, with 90.1% of their potential and intermediate curtailments. In terms of storage integration, PSO regulated battery operation more dynamically with 81.7% utilization on average. On the other hand, the storage of ACO was underused and had more curtailment. These results indicate that the adaptive convergence features of PSO perform better for short-term prediction and more closed-loop energy balance control, compared to stability of ABC with less efficiency. Such a function as ACO may, however, adapt more slowly under high generation change and demand variations.

4.2. Convergence and Optimization Stability

Stability and speed of converge of the optimization is crucial in the real-time smart grid as the allocation decisions need to be computed quickly to maintain the operation of the system. Performance of the algorithms to find optimal or near- optimal solutions is evaluated using metrics such as average convergence time, iteration count at convergence, ST-DDF across runs, fitness stability index and oscillation penalty. These are measures of how much the algorithm performance varies in a stochastic simulation. Time-complexity and low variance of faster convergence are more well-suited for edge-computing application of approximately consistent hardware resources and strict timing sequences. The stability index and oscillation penalty are two measurements about the robustness of an algorithm to premature convergence and trapping into local optima.

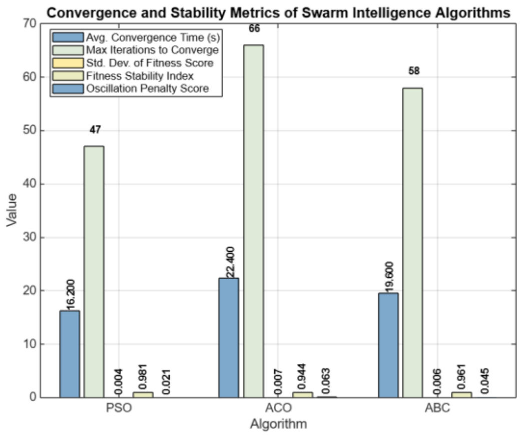

Fig 2. Convergence time and optimization stability in swarm intelligence algorithms

Of the three algorithms, PSO obtained the fastest convergence, and reached optimization in 16.2s (47 iterations) on average. Its low standard deviation in fitness scores (0.004) and high stability index (0.981) further indicate how it behaved consistently through other simulation runs. ABC also achieved competitive performance with small convergence time and good fitness stability. On the contrary, ACO was the one that took longer to converge (22.4 seconds) and that suffered the most from the oscillation penalty (0.063), showing potential to fall into local minimum or to reinforce the path too slowly, respectively. The good performance of PSO is demonstrated not only by its high computation speed but also by low sensitivity to the input randomness. The small difference between PSO and ABC is owed to the better control of mutation of ABC which are balancing the exploration and exploitation. The discrete path construction of ACO seems being slow to respond on the continuously variable energy scheduling problems implying its little practical efficiency under the real-time requirements.

4.3. Latency and Delay Metrics

The on-time consumption is particularly critical in smart city energy system for prioritized loads like traffic light, water supply and EV emergency charging. Performance based on latency is evaluated through performance measures such as average task delay, worst-case delay, percentage of deadlines missed, task delay variance, and the sum of task delay penalties. These scores help us understand how well each algorithm adapts to dynamic workload changes, and where it might still lack relative to what is expected in latency-critical environments. A resource allocation plan should ensure that the use of power is not only efficient but also time-efficient to maintain power reliability during high-demand or recovery from failures.

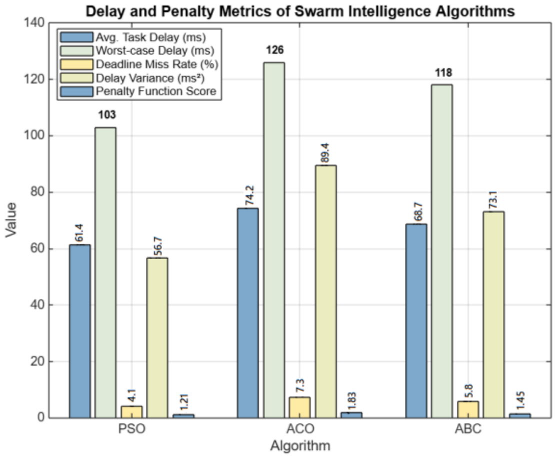

Fig 3. Delay and penalty metrics in dynamic task scheduling

PSO was the best in all delay metrics. It achieved the lowest average task delay (61.4 ms) and the lowest deadline miss rate (4.1%), proving its ability to run effectively at tight timing constraints. Its responsive nature is also supported by a penalty score of 1.21. ABC ranked second and presented with a moderate worst-case delay (118 ms) and lower delay variance than ACO. The Ant Colony Optimization algorithm had difficulties when working with time pressure, being unable to meet 7.3% of deadlines, incurring the highest delay penalty. These results show that whilst an ACO probabilistic path selection may be useful in searching, it is not underpinning deterministic accuracy for real-time response application. ABC's results indicate its superiority in adapting the task priority dynamically, but its convergence-speed advantage under on-line operation is inferior to the better performance of the PSO-based approach.

4.4. Load Balancing and Edge Fairness

Balanced loading of edge nodes and power units is critical to distributed smart grid control. Efficient load balancing helps to avoid node (sensor/controller) overload, minimizes the probability of failures, increases the lifetime of devices, guarantees stability of the system, and is coordinated with application user requirements, especially when it comes to truly wireless sensor networks. Fairness of algorithms is analyzed through statistical quantities, such as standard deviation (in KWh) of node load, maximum overloading percentage, load variance score, time of convergence after an imbalance period and normalized fairness index. This metrics shows how well each algorithm keep balance between task and energy allocation- a crucial issue in heterogeneous urban infrastructures with varying resource capacities and dynamics of demand in different zones.

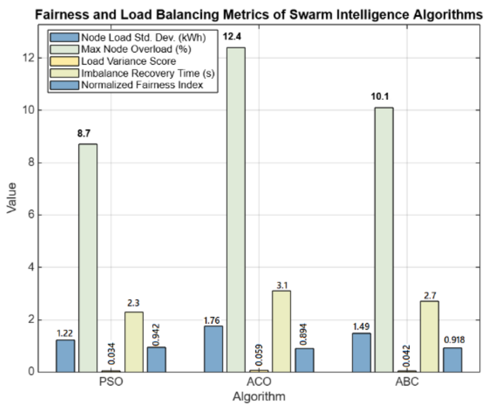

Fig 4. Edge node load balancing and fairness performance of PSO, ACO, and ABC

PSO was leading once again in this category, with the lowest load standard deviation (1.22 kWh) and the quickest recovery time (2.3 seconds) after detecting an imbalance. It also had a high fairness index of 0.942, implying reasonably uniform distribution of load among nodes. ABC scored well, with good uniformity (1.49 kWh deviation) and normalized fairness score of 0.918. ACO, on the other hand, had unbalanced load distributions and the largest risk of overloading (12.4%) which might be caused by the difficult in adapting distribution to time-varying demand. It implies that ACO is being static in reinforcement paths that the load balance is only equalized slowly, even in the cases with heterogeneous workloads across the networks and time constrained workloads. ABC\'s bee-agent scheme achieved more promising adaptability in mid-iteration, although less good than the PSO\'s globally conducted convergence. These results also prove that PSO's centralized update ensures that stable and balanced load allocation is achieved in real-time EENs.

4.5. Resource Resilience and Fault Recovery

Resiliency is a crucial dimension when it comes to performance in cyber-physical smart grid systems, especially when the system is subject to node failure, network partitioning, or hardware aging. The tolerance of these algorithms is tested in simulation scenarios with nodes dropping and communication failing. Performance is evaluated by five criteria: average recovery time, percentage of successfully recovered nodes, task balance ratio, overall resilience factor, and the false-reassignment rate. These indices offer a view to the capacity of each algorithm to sense and react to system anomalies, keep under control its stability, and providing building blocks for an effective resource reallocation, without degrading performance or creating new inefficiencies in the network.

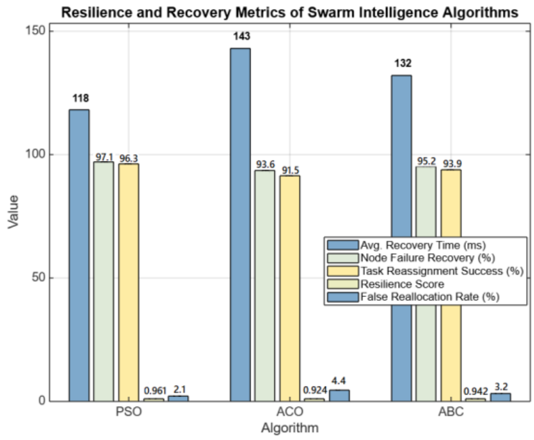

Fig 5. System resilience and fault recovery performance across swarm intelligence algorithms

Additionally, the Particle Swarm Optimization algorithm also achieved the highest resilience (0.961), fastest recovery time (118 ms) and task reassignment success rate (96.3%) in these two simulations. ABC, quickly followed, achieving a pretty impressive resilience score of 0.942, taking the right balance of recovery speed and accuracy. ACO, while working well, was slower to detect failures (143 ms) and had a higher false reallocation rate (4.4%), highlighting inefficiencies in responding quickly to dynamic grid changes. The enhanced stability of PSO could be attributable to its ability to rapidly reposition particles after rearrangements in the topology. The ABC had to rely on adaptive reallocation by scout bees and did not prompt a reaction as quick as PSO's during global search updates of recovery. The Use of Pheromone Trail Reinforcement of ACO Generated Emergency Scenarios in Some Instances the Emergency Scenarios Are Not Reallocated Fast Enough. These observations confirm the supremacy of PSO in terms of fault-tolerance and responsiveness in edge-centric energy distribution applications.

4.6. Discussion

This section analyzes the experimental findings, contextualizes them within the existing body of literature, and discusses the broader implications of this research, including its limitations and directions for future work.

4.6.1. Confirmation of Hypothesis and PSO's Superiority

The experimental results provide compelling evidence in support of our core research hypothesis: Swarm Intelligence (SI) techniques, and Particle Swarm Optimization (PSO) in particular, can significantly enhance the performance of resource allocation in renewable-powered smart city infrastructures. The multi-dimensional comparison across energy efficiency, convergence, latency, load balancing, and fault recovery metrics consistently demonstrates that PSO outperforms both Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC). This quantitative and qualitative superiority confirms that PSO is a highly effective and robust solution for real-time energy distribution in the dynamic and uncertain environments characteristic of modern urban settings.

4.6.2. Contextualization with Existing Literature and Key Contributions

Our findings both corroborate and extend previous research on the feasibility of swarm-inspired energy allocation. While earlier works, such as Chanda and De [38] and Pustokhina and Pustokhin [11], highlighted the general techno-economic advantages of SI for smart grid optimization, they were often focused on macro-grid control or did not fully consider real-time operational constraints. This study advances the field by situating SI algorithms within a fine-grained, edge-enabled environment and incorporating critical performance metrics like task-level response timing and resilience, which have been largely overlooked in previous frameworks. The superior performance of PSO in managing energy consumption and maximizing renewable utilization aligns with the findings of Fathi et al. [6], who used a Salp Swarm Algorithm (SSA) to minimize mismatches in distribution networks. However, our analysis extends their work by moving beyond steady-state conditions to include time-dynamic load-shifting and weather-induced generation variability. The resilience of PSO in the face of this volatility provides strong evidence that its velocity-position update mechanism affords superior short-term adaptation, a critical feature for managing solar and wind power. This is also consistent with the observations of Rathore and Patidar [4], though our investigation is unique in its integration of an edge computing framework.

4.6.3. Performance Analysis Across Key Metrics

The practical applicability of PSO is further demonstrated by its exceptional performance in latency-sensitive applications. Our results show that PSO achieves the lowest average task delay and deadline miss rate, making it highly suitable for the real-time demands of smart city services. These findings are consistent with the digital twin timing analyses conducted by Wang et al. [3], but our work provides a crucial integration by embedding algorithmic convergence within the edge computation loop, bridging the gap between energy optimization and real-time system design. In terms of load balancing, the high fairness indices and low load variance scores achieved by PSO confirm its ability to ensure an equitable distribution of energy and tasks among edge nodes. This aligns with the observations of Kanwar et al [12] regarding the utility of PSO for distributed energy resource placement. However, unlike their study, which was based on steady-state distribution, our work considers dynamic re-allocation during real-time operation, demonstrating that PSO can prevent node overburdening and enhance system robustness under operational stress. Furthermore, the ability of PSO to rapidly recover from node failures and efficiently reassign tasks extends the frameworks proposed by Zishan et al [2] and Nizamani et al. [8]. By employing a fault-injection model and recording recovery times, our study provides a strong empirical basis for the superior fault tolerance of PSO in mission-critical smart city infrastructures.

4.6.4. Limitations and Future Research Directions

Despite the robust findings, we acknowledge several limitations that present opportunities for future research. First, our simulation did not incorporate machine learning (ML)-based forecasting for energy generation or demand, which could further enhance predictive accuracy and optimization performance. Second, the PSO control parameters were static throughout the simulations; future work could explore dynamic parameter tuning based on real-time grid behavior, as suggested by hybrid algorithm analyses like those of Reddy et al [14]. Third, while our experimental setup modeled a mid-sized smart city, scaling the simulation to larger metropolitan areas with more intricate zoning and higher congestion levels is an essential next step to validate the generalizability of these findings. Future work could also expand the scope of evaluation beyond purely technical metrics. Incorporating economic and environmental impact assessments, such as cost models, carbon emission profiles, and user satisfaction metrics, would provide a more holistic view to inform policy and deployment decisions. Additionally, while this study was conducted on high-performance hardware, deploying these algorithms on resource-constrained edge devices remains an open technical challenge. Investigating this, in line with the cloud-edge collaboration models suggested by Li et al [28], would be a valuable contribution. In summary, while our model successfully addresses many key performance challenges, integrating predictive analytics, real-time sensing, and large-scale systems represents a promising pathway for future research.

5. Conclusion

This study assessed the efficiency of swarm intelligence (SI) algorithms—Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC)—for optimizing resource allocation in smart cities powered by renewable energy. Using a novel, scalable simulation of a dynamic urban energy system, we evaluated the algorithms' performance on energy savings, latency, system fairness, and fault recovery. The results confirm that SI algorithms are practical and effective for managing distributed energy resources. PSO consistently demonstrated the most robust and adaptive performance across all metrics, affirming the value of decentralized, real-time optimization for smart grids. While ACO's convergence was too slow for real-time applications, ABC proved a viable alternative, especially for task prioritization under moderate loads. This research highlights that algorithmic robustness and low latency are as critical as energy optimization in smart city design. The simulation model itself is a key contribution, offering a realistic platform for future academic and municipal planning. Future investigations should explore hybrid algorithms, reinforcement learning, larger-scale simulations, and the inclusion of economic and environmental objectives to further advance the development of self-sufficient, energy-aware cities.

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