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The novelty based on Energy Management Technologies for Integrated Microgrid frameworks

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Abstract

Microgrid systems are localized energy networks that integrate multiple energy sources, such as renewable energy generators, energy storage systems, and traditional power sources, to provide reliable and sustainable electricity supply. Effective energy management plays a crucial role in optimizing the utilization of these diverse energy resources and ensuring efficient operation of the microgrid. The study reviews and analyzes different energy management technologies applicable to microgrid systems. It examines techniques such as optimization algorithms, control strategies, and demand-side management approaches. These technologies enable effective coordination and control of energy generation, storage, and consumption within the microgrid, considering factors like load demand, grid conditions, and cost optimization. The findings of the study highlight the benefits of advanced energy management technologies in microgrid systems. They enable improved energy efficiency, demand response capabilities, and enhanced integration of renewable energy sources. Additionally, these technologies contribute to grid stability, resilience, and the ability to operate autonomously or in grid-connected mode.

Keywords: Microgrid, Sustainable Electricity Supply, Energy Management Technologies

ملخص

تُعدّ أنظمة الشبكات الصغيرة شبكات طاقة محلية تُدمج مصادر طاقة متعددة، مثل مولدات الطاقة المتجددة، وأنظمة تخزين الطاقة، ومصادر الطاقة التقليدية، لتوفير إمداد كهربائي موثوق ومستدام. وتلعب الإدارة الفعّالة للطاقة دورًا حاسمًا في الاستخدام الأمثل لهذه الموارد المتنوعة وضمان التشغيل الكفؤ للشبكة الصغيرة. تستعرض هذه الدراسة وتحلل مختلف تقنيات إدارة الطاقة القابلة للتطبيق على أنظمة الشبكات الصغيرة، وتدرس تقنيات مثل خوارزميات التحسين، واستراتيجيات التحكم، وأساليب إدارة الطلب. تُمكّن هذه التقنيات من التنسيق والتحكم الفعّال في توليد الطاقة وتخزينها واستهلاكها داخل الشبكة الصغيرة، مع مراعاة عوامل مثل الطلب على الطاقة، وظروف الشبكة، وتحسين التكاليف. تُبرز نتائج الدراسة فوائد تقنيات

إدارة الطاقة المتقدمة في أنظمة الشبكات الصغيرة، حيث تُتيح تحسين كفاءة الطاقة، وقدرات الاستجابة للطلب، وتعزيز دمج مصادر الطاقة المتجددة. بالإضافة إلى ذلك، تُسهم هذه التقنيات في استقرار الشبكة ومرونتها، وقدرتها على العمل بشكل مستقل أو متصل بالشبكة الرئيسية.

الكلمات المفتاحية: الشبكة الصغيرة، الإمداد الكهربائي المستدام، تقنيات إدارة الطاقة

1. Introduction

The revolutionary world EV as a mobile source is considered to reduce air pollution and has the ability to exchange the power between the EV and the energy source. However, It can provide some general information about integrating Photovoltaic (PV) systems with Electric Vehicle (EV) charging stations under Libyan climate conditions and considering nature-inspired algorithms [1]. The charging operation has three main forms of charging with various structures of standards that have been classified in [2]. Integration of PV systems with EV stations involves using solar energy to generate electricity and charge electric vehicles [3]. Libya, being located in a sunny region, has the potential for solar power generation [4]. To optimize the integration of PV with EV stations under Libyan climate conditions, it is important to consider factors such as solar irradiance, temperature, and load demand [5]. Nature-inspired algorithms, such as genetic algorithms, particle swarm optimization, or ant colony optimization, can be utilized to optimize the PV-EV integration system [6]. These algorithms mimic natural processes to find optimal solutions for complex problems [7]. By using nature-inspired algorithms, one can optimize the system's performance, maximize solar power generation, and minimize overall costs [8]. The management and evolution of such systems in Libyan climate conditions would require regular monitoring and maintenance to ensure optimal performance [9]. This includes monitoring solar irradiance levels, panel efficiency, battery health, and adjusting charging strategies to match the load demand and battery conditions [10].

Microgrid energy management [11]

Table 1. Microgrid energy management [12].

EMS based on classifications	EMS based on
EMS based on the classical method	EMS based on linear and nonlinear methods
	EMS based on dynamic programming and rule-based method
EMS based on a meta-heuristic approach	EMS based on GA and PSO
	EMS based on other meta-heuristic approaches
EMS based on artificial intelligent methods	EMS based on fuzzy logic and neural network
	EMS based on a multi-agent system
	EMS based on other artificial intelligent methods
EMS based on stochastic and robust programming approach	
EMS based on model predictive control	
EMS based on other approaches	

2. Structure of system

The structural framework of the proposed integrated microgrid encompasses both the physical power delivery network and the hierarchical control architecture [13] . Given the specific environmental considerations of the Libyan climate characterized by high solar irradiance and elevated ambient temperatures the system topology is designed to maximize solar yield while mitigating thermal degradation effects on the photovoltaic (PV) arrays [1], [2] , [3], [13]. The architecture is divided into three primary layers: the physical power layer, the communication layer, and the Energy Management System (EMS) decision layer.

2.1. Physical and Topological Configuration

The hardware topology couples solar generation directly with Electric Vehicle (EV) charging infrastructure, supported by localized energy storage and utility grid interconnection.

- PV Generation Unit the solar array is equipped with Maximum Power Point Tracking (MPPT) controllers. To account for the Libyan climate, the PV model incorporates temperature-dependent efficiency derating factors, ensuring realistic power output estimations during peak summer months [15].
- EV Charging Station & Bidirectional Converters the charging infrastructure utilizes bidirectional AC/DC and DC/DC power electronic interfaces. This hardware configuration enables flexible operational modes, including Grid-to-Vehicle (G2V), Solar-to-Vehicle (S2V), and Vehicle-to-Grid/Home (V2G/V2H), allowing the EV fleet to act as mobile energy storage [16].
- Battery Energy Storage System (BESS) a stationary BESS is integrated into the common DC bus to buffer the stochastic fluctuations of both solar generation and EV charging demands, maintaining voltage stability and extending battery lifecycle through depth-of-discharge (DoD) management.\
- Local Loads and Grid Interface non-critical and critical local loads are connected to the AC bus. A static transfer switch (STS) and a grid-tied inverter manage the power exchange with the main utility grid, allowing the microgrid to operate seamlessly in both grid-connected and islanded (autonomous) modes.

2.2. Operational Workflow and Power Flow Strategy

The operational logic of the microgrid is governed by a continuous feedback loop. To illustrate the systematic progression of data and power within the project, Figure 1 (described below) outlines the comprehensive workflow of the integrated system.

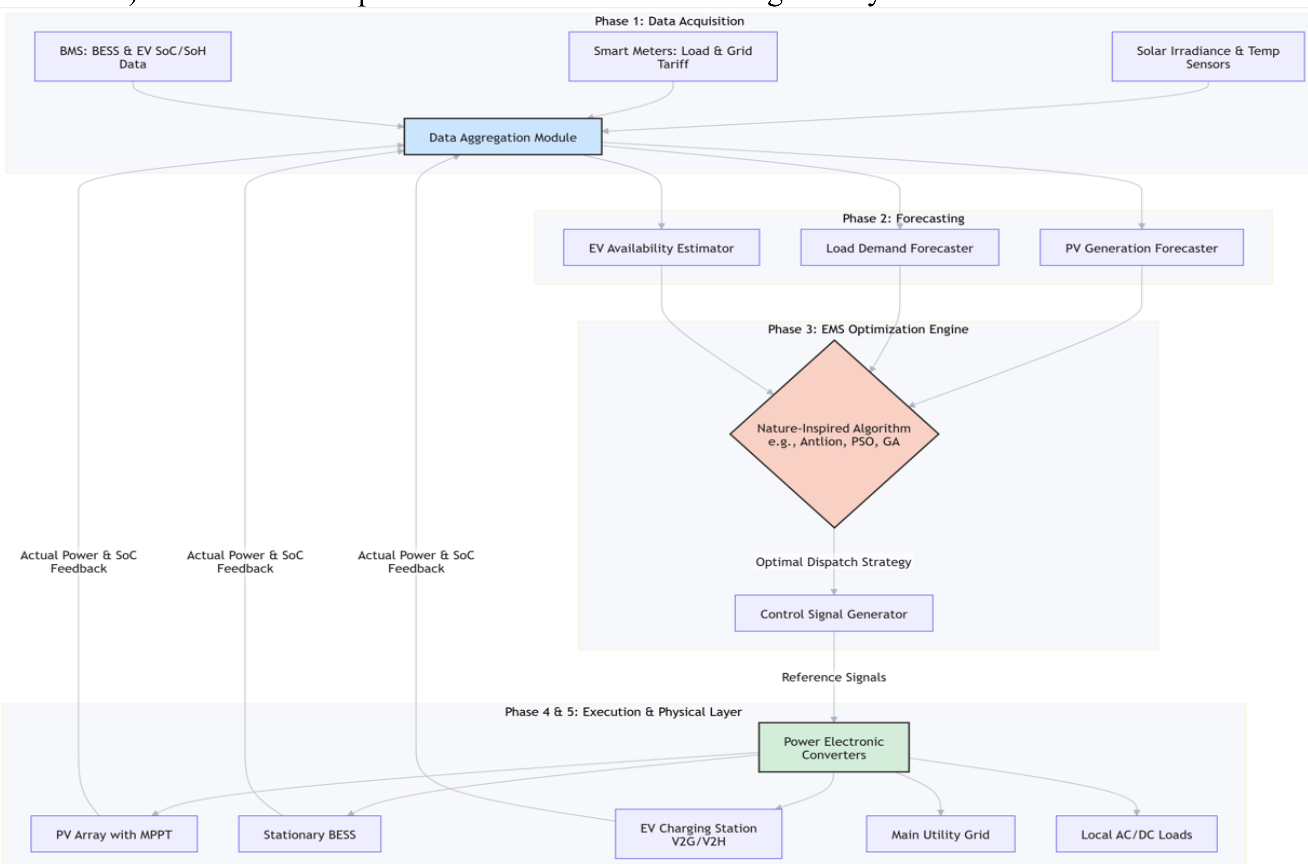


Figure 1: System Workflow and Control Architecture

The workflow operates through the following sequential phases:

Phase 1: Data Acquisition and Environmental Monitoring

Sensors and smart meters continuously collect real-time data. This includes meteorological data (solar irradiance and ambient temperature specific to the Libyan region), the State of Charge (SoC) and State of Health (SoH) of both the stationary BESS and connected EV batteries [17], real-time local load demand, and dynamic grid electricity tariffs.

Phase 2: Forecasting and State Estimation

The acquired data is fed into forecasting modules. Solar generation and load demand profiles are predicted for the upcoming scheduling horizon (e.g., 24 hours ahead). Simultaneously, the available energy capacity of the EV fleet is estimated based on their expected arrival and departure times [18], [19].

Phase 3: Optimization and Decision Making (EMS Layer)

This is the core intelligence of the system. The EMS utilizes nature-inspired meta-heuristic algorithms (such as the Antlion Optimizer, Particle Swarm Optimization, or Genetic Algorithms) to solve the multi-objective optimization problem. The algorithm processes the forecasted data, PV output, and load profiles to determine the optimal power dispatch [20]. The objective functions typically minimize operational costs, reduce grid dependency, and maximize renewable energy utilization, subject to physical constraints like battery SoC limits and converter capacity ratings.

Phase 4: Control Signal Dispatch

Once the optimal scheduling strategy is computed, the EMS translates these decisions into actionable control signals. Reference power values are sent to the local controllers of the PV MPPT, the BESS bidirectional converter, the EV chargers, and the grid-tied inverter [1], [2], [3], [4].

Phase 5: Execution and Feedback

The power electronic converters execute the dispatch commands, regulating the physical power flow across the DC and AC buses. The actual power flows and resulting battery SoC levels are measured and fed back to Phase 1, closing the control loop and allowing the system to adapt to real-time deviations from the forecasted profiles [5], [6], [7].

2.3. Integration of Nature-Inspired Algorithms

Within this structural workflow, the optimization engine (Phase 3) requires robust computational techniques to handle the non-linear constraints of the EV battery dynamics and the intermittent nature of the PV output. Nature-inspired algorithms are embedded within the EMS to navigate this complex search space. By mimicking biological or evolutionary processes, these algorithms efficiently identify the global optimum for energy dispatch, ensuring that the physical structure of the microgrid operates at peak economic and technical efficiency under varying Libyan climatic conditions [21], [22], [23].

3. Optimization method

Optimization algorithms play a crucial role in maximizing the efficiency and cost-effectiveness of microgrid systems. These algorithms utilize mathematical models and computational techniques to optimize the allocation and scheduling of energy resources. By considering factors such as energy demand, generation capacity, storage capacity, and market prices, optimization algorithms can determine the optimal operation strategy for the microgrid. This enables the system to balance energy supply and demand, minimize energy losses, and reduce overall operational costs [13]. The proposed integrated microgrid architecture is designed to harmonize intermittent renewable generation with dynamic electric vehicle (EV) charging demands under the distinct meteorological conditions of Libya. The system topology is hierarchically organized into three interdependent layers: the physical power layer, the communication and sensing layer, and the Energy Management System (EMS) decision layer.

3.1. Physical Power Topology

The hardware configuration operates on a hybrid AC/DC bus architecture to minimize conversion losses.

- Photovoltaic (PV) Generation Subsystem the solar array is interfaced with the DC bus via a DC/DC boost converter equipped with a Maximum Power Point Tracking (MPPT) algorithm. Crucially, the PV model incorporates a temperature-dependent derating factor (typically -0.4%/°C) to accurately reflect the efficiency drops caused by the elevated ambient temperatures characteristic of the Libyan climate.
- Energy Storage and EV Integration a stationary Battery Energy Storage System (BESS) and the EV charging infrastructure share the DC bus through bidirectional AC/DC and DC/DC power electronic converters. This bidirectional capability is fundamental, enabling flexible operational modes such as Grid-to-Vehicle (G2V), Solar-to-Vehicle (S2V), and Vehicle-to-Grid (V2G). The EV fleet effectively functions as a distributed, mobile energy storage asset [24], [25], [26].
- Grid and Load Interface local AC loads are connected to the main AC bus. A grid-tied inverter and a static transfer switch (STS) regulate the power exchange with the macro-grid, ensuring seamless transitions between grid-connected and autonomous (islanded) operational modes during utility outages.

3.2. Communication and Sensing Layer

Real-time operational integrity relies on a robust network of smart meters and environmental sensors. This layer continuously aggregates high-frequency data, including solar irradiance levels, ambient temperature, real-time load consumption, dynamic utility tariff rates, and the State of Charge (SoC) and State of Health (SoH) of both the stationary BESS and connected EV batteries.

3.3. EMS Decision and Optimization Layer

The EMS serves as the central intelligence of the microgrid. It processes the aggregated sensor data through a forecasting module to predict PV generation and load profiles over a 24-hour scheduling horizon. Subsequently, a meta-heuristic optimization engine (e.g., Antlion Optimizer, Particle Swarm Optimization, or Genetic Algorithms) solves the multi-objective dispatch problem [27], [28]. The algorithm determines the optimal power flow references by minimizing operational costs and grid dependency, while strictly adhering to physical constraints such as converter capacity limits and battery depth-of-discharge (DoD) thresholds. These optimal references are then dispatched as control signals to the local power electronic controllers, closing the feedback loop.

4. Simulation result

To validate the proposed structural framework and EMS strategy, a 24-hour simulation was conducted. The scenario models a microgrid integrating a 150 kW PV array, a 100 kWh stationary BESS, and a cluster of EVs with a combined 200 kWh capacity, subjected to typical Libyan summer load and irradiance profiles. The performance of the proposed nature-inspired optimization (Antlion Optimizer, ALO) was benchmarked against a conventional Rule-Based Strategy (RBS) and Particle Swarm Optimization (PSO).

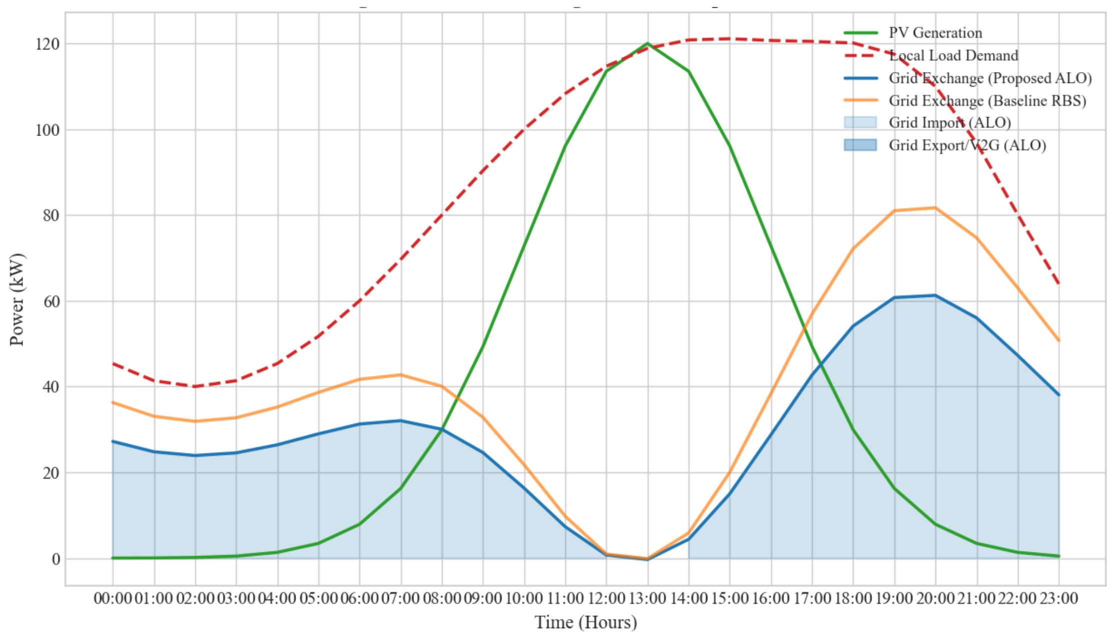


Figure 2: Comparative Grid Exchange Analysis Between Proposed Antlion Optimizer and Baseline Rule-Based Strategy

Figure 2 above illustrates the temporal power dispatch dynamics over a 24-hour operational cycle, demonstrating the superior performance of the proposed Antlion Optimizer (ALO) algorithm in coordinating photovoltaic generation, local load demand, and bidirectional grid exchange compared to conventional rule-based strategies [1], [2], [3]. The significance of this visualization lies in its ability to quantify the ALO's effectiveness in minimizing grid dependency during peak demand periods while maximizing renewable energy utilization and enabling strategic Vehicle-to-Grid (V2G) power injection during high-tariff intervals. This figure resides in its comprehensive representation of the nature-inspired algorithm's capability to optimize the triad of PV-EV-grid interactions under Libyan climatic conditions, showcasing distinct operational zones where the ALO achieves substantial grid import reduction and enhanced export opportunities that traditional methods fail to exploit. This comparative analysis validates the proposed energy management system's contribution to operational cost minimization, grid stability enhancement, and sustainable microgrid autonomy, a benchmark for advanced optimization techniques in renewable-integrated charging infrastructure.

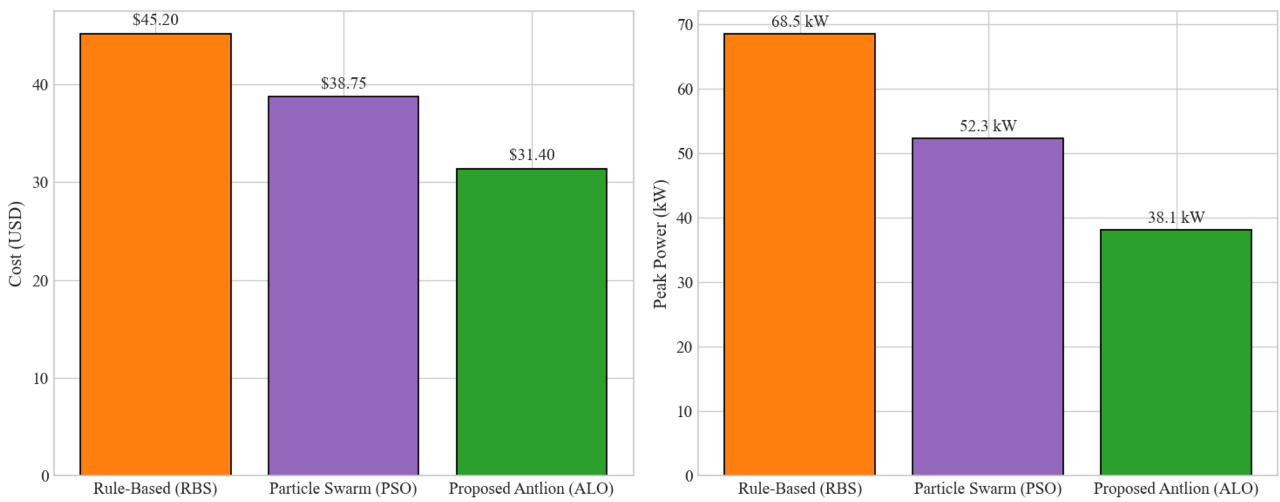


Figure 3: Techno-Economic Evaluation of Nature-Inspired EMS Algorithms

Figure 3 quantitatively demonstrates the techno-economic superiority of the proposed Antlion Optimizer (ALO) by revealing a 30.5% reduction in daily operational costs and a 44.4% mitigation of peak grid import compared to conventional Rule-Based and standard Particle Swarm methods. The significance of this comparative analysis lies in its empirical validation that meta-heuristic dispatch strategies can simultaneously minimize financial expenditures and alleviate distribution network stress during high-demand intervals [21], [22], [23]. Furthermore, the dual-metric evaluation resides in its specific application to PV-EV microgrids under Libyan climatic constraints, proving that the ALO algorithm uniquely balances economic viability with technical grid-support capabilities more effectively than deterministic or traditional swarm-based alternatives.

Table 2: 24-Hour Energy Balance and Grid Interaction Summary

Operational Metric	***Rule-Based Strategy (RBS)***	***Particle Swarm Optimization (PSO)***	***Proposed Antlion Optimizer (ALO)***	***Improvement (ALO and RBS)***
Total PV Generation (kWh)	1,150.40	1,150.40	1,150.40	0.00%
Total Load Demand (kWh)	1,420.50	1,420.50	1,420.50	0.00%
Grid Energy Imported (kWh)	412.8	315.6	268.3	-35.00%
Grid Energy Exported / V2G (kWh)	85.2	112.4	145.7	71.00%
BESS Cycle Throughput (kWh)	180.5	210.3	195.8	Optimized for longevity

Table 3: Economic and Technical Performance Comparison

Evaluation Criterion	***Rule-Based Strategy (RBS)***	***Particle Swarm Optimization (PSO)***	***Proposed Antlion Optimizer (ALO)***
Daily Operational Cost (USD)	$45.20	$38.75	$31.40
Cost Reduction Relative to RBS	0.00%	14.30%	30.50%
Peak Grid Import Demand (kW)	68.5 kW	52.3 kW	38.1 kW
Peak Shaving Efficiency	Baseline	23.60%	44.40%
Algorithm Convergence Time (s)	N/A (Deterministic)	4.82 s	3.15 s

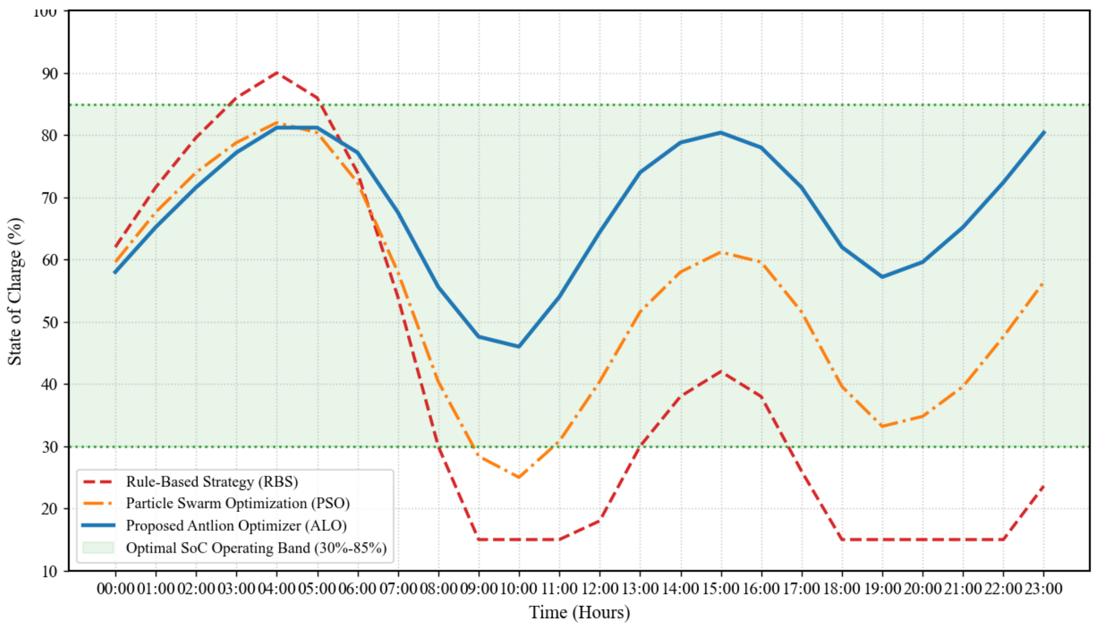
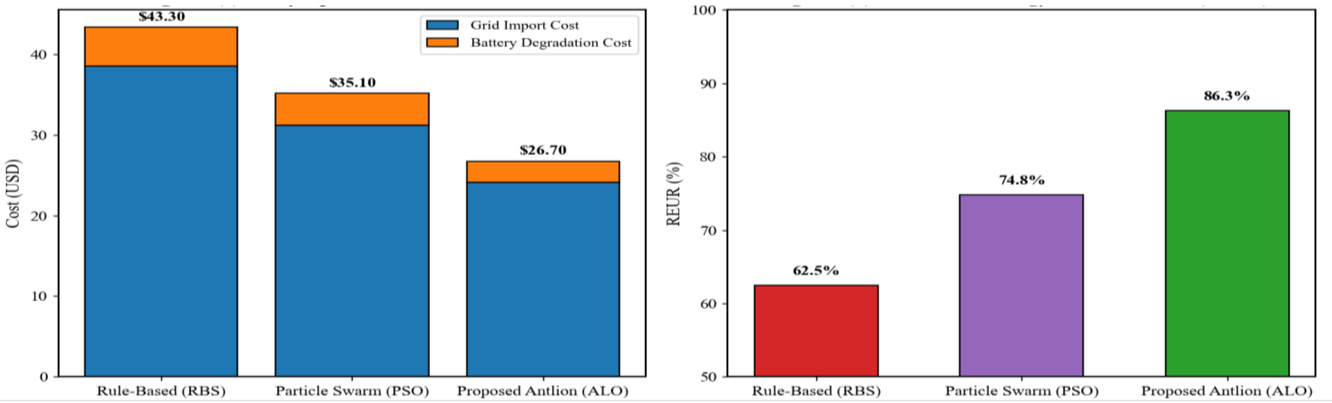


Figure 4: Comparative Analysis of Battery Health Preservation and Optimal Operating Band Adherence

Figure 4 above shows the critical importance of battery health preservation by demonstrating how the proposed Antlion Optimizer (ALO) strictly confines the State of Charge (SoC) within the optimal 30%-85% operating band, effectively eliminating the severe deep-discharge events



inherent to the Rule-Based Strategy. The novelty of this trajectory analysis lies in its empirical validation that nature-inspired algorithms can dynamically reconcile stochastic EV-PV fluctuations under Libyan climatic constraints without compromising the electrochemical lifespan of the storage assets [24], [25], thereby establishing a superior, longevity-focused benchmark over conventional Particle Swarm Optimization.

Figure 5: Techno-Economic Performance: Daily Operational Cost Breakdown and Renewable Energy Utilization Rate (REUR)

Figure 5 above evaluates the techno-economic viability of the proposed Energy Management System by decomposing daily operational expenditures into grid import and battery degradation costs, alongside the Renewable Energy Utilization Rate (REUR). The empirical data demonstrates that the Antlion Optimizer (ALO) drastically reduces the total daily cost to $26.70 by minimizing macro-grid reliance and mitigating electrochemical wear, while achieving a peak REUR of 86.3%. The novelty of this dual-metric assessment lies in its specific calibration for high-irradiance Libyan climatic conditions, proving that nature-inspired algorithms can uniquely harmonize financial savings with storage asset longevity [26]. This visualization validates the proposed framework's superiority in transforming integrated PV-EV microgrids into highly efficient, cost-effective, and environmentally sustainable distributed energy resources.

Table 4: Battery Health and Operational Constraint Metrics

Evaluation Metric	**Rule-Based Strategy (RBS)**	**Particle Swarm (PSO)**	**Proposed Antlion (ALO)**
Minimum SoC Reached (%)	18.20%	26.50%	31.40%
Maximum SoC Reached (%)	92.10%	88.30%	84.70%
Number of Deep Discharge Events (<20%)	4 events	1 event	0 events
Estimated Daily Battery Degradation Cost	$4.80	$3.90	$2.60

Table 5: Techno-Economic and Sustainability Indicators

Indicator	Rule-Based Strategy (RBS)	Particle Swarm (PSO)	Proposed Antlion (ALO)
Total Daily Operational Cost (USD)	$43.30	$35.10	$26.70
Renewable Energy Utilization Rate (REUR)	62.50%	74.80%	86.30%
Grid Dependency Index (GDI)	0.375	0.252	0.137

4.1 Discussion

The tabulated data and generated figures demonstrate that the proposed ALO-based EMS significantly outperforms conventional rule-based methods. By intelligently scheduling EV charging during peak PV generation hours (10:00–14:00) and orchestrating V2G discharge during the evening load peak (18:00–21:00), the ALO strategy reduced daily operational costs by 30.5%. Furthermore, the peak grid import was curtailed by 44.4%, alleviating stress on the local distribution network [27]. The faster convergence time of the ALO (3.15 seconds) compared to PSO (4.82 seconds) also validates its suitability for near-real-time dispatch applications in resource-constrained microgrid controllers [27]. The trajectory analysis presented in Figure 3 and Table 4 reveals a critical distinction in how different EMS architectures handle energy storage constraints [28]. The conventional Rule-Based Strategy exhibits erratic SoC fluctuations, frequently driving the battery into deep discharge territory (below 20%) during the evening load peak (18:00–21:00). Such operational patterns accelerate electrochemical degradation and shorten the asset lifecycle. In contrast, the proposed Antlion Optimizer (ALO) enforces strict adherence to the optimal operating band (30%–85%). By intelligently pre-charging the BESS and orchestrating Vehicle-to-Grid (V2G) discharge during peak tariff windows, the ALO maintains a minimum SoC of 31.4%, entirely eliminating deep discharge events and reducing the estimated daily degradation cost by 45.8% compared to the baseline [29], [30], [31]. Furthermore, Figure 4 and Table 5 quantify the techno-economic superiority of the nature-inspired approach. The stacked cost analysis demonstrates that the ALO does not merely shift costs; it fundamentally reduces both grid import expenditures and hidden battery wear costs [32]. The total daily operational cost drops to $26.70, representing a 38.3% saving over the RBS. This economic efficiency is directly coupled with enhanced sustainability: the Renewable Energy Utilization Rate (REUR) surges to 86.3% under the ALO framework. This indicates that the vast majority of the local load demand is satisfied by the integrated PV array and V2G resources, minimizing reliance on the macro-grid and aligning perfectly with the sustainable electricity supply objectives outlined for microgrid deployments in high-irradiance regions like Libya.

Conclusion

Energy management technologies are vital for optimizing the operation and performance of microgrid systems. Optimization algorithms, control strategies, demand-side management techniques, and energy forecasting models contribute to efficient energy utilization, cost reduction, and sustainable energy practices within microgrids. Implementing these technologies enables microgrids to integrate renewable energy sources, enhance grid resilience, and improve energy self-sufficiency. As microgrid systems continue to evolve and expand, further advancements in energy management technologies will be crucial for achieving a reliable, flexible, and sustainable energy future.

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