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Original Article

AI-Driven Adaptive Energy Management of PV-Battery Integrated Owerri Urban Distribution Network Using MATLAB with Real-Time Uncertainty Handling

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Abstract *- Growing deployment of distributed renewable energy resources is essential to realizing sustainability and carbon neutrality in contemporary power networks. Nevertheless, the increasing penetration of these resources in power distribution networks can create operational uncertainties due to solar intermittency, stochastic load variations, and voltage instability. Thus, efficient coordination of these dispersed resources needs smart energy management schedules that have the capability to adapt dynamically under varying operational situations. This work proposes a PV–battery integrated 82-bus Owerri urban distribution network model using MATLAB/Simulink. To address the real-time uncertainties in solar generation and load demand, an AI–based energy management framework is proposed. This is done through a framework that integrates RL with PSO to dynamically cooperate with photovoltaic generation, battery energy storage, and grid power. BFS methodology is adopted for the computation of power flow applied to the distribution grid under stochastic operating conditions for the evaluation of voltage stability and power loss performance. Numerical results showed that the proposed AI-based energy management system is superior to traditional manual control strategies. It was equally observed that the RL-based controller enhanced the voltage magnitude from 0.86 to 0.96 p.u. while the value of real power loss declined by 42.9% (210kW-120kW). The findings validated that the proposed adaptive AI-based energy management can significantly increase the incorporation of PV systems, voltage stability, and operational resilience for forthcoming smart network distribution systems, in line with standards stipulated by IEEE, NERC, and NEMSA.*

Keywords *- Battery energy storage, Energy Management system, Particle swarm optimization, Photovoltaic systems, MATLAB.*

1. Introduction

Power distribution network in Nigeria is witnessing increasing load demand, poor voltage performance, and disturbances not only as a result of obsolete infrastructure, rather highly unpredictable load demand. The integration of solar photovoltaic (PV) with battery storage could be a solution to cut down dependency on the existing conventional fossil-based power sources, that is environmentally hostile due heavy carbon contents it emits to the atmosphere. In spite of environmental friendliness and sustainability of RES, more especially PV systems, it brings along issues of high cost of installation, intermittency, and uncertainty, making operations and control difficult [1], [2], [3].

Cities in Nigeria with high population density, such as Owerri, there is an urgent need to manage the stochastic solar PV power, demand variations, and the SOC constraints of the battery in real time, because traditional EMS models used for such purposes do not perform optimally under rapidly changing conditions, nor effectively coordinate distributed resources on the feeder, and fail to explicitly model uncertainties.

Although recent research has addressed various optimization and AI algorithms for EMS, there are still three main gaps: (1) The majority of existing studies validate their results using established IEEE benchmark systems instead of practical cases of urban grids from Africa [4], [5]; (2) AI or optimization models have been frequently utilized in isolation, lacking integration to improve adaptability to changing situations [6], [7]; and (3) Uncertainty in the solar power generation system and loads has not been adequately considered in their control strategy [8], [9].

This research makes several innovations, which set it apart from previous studies:

- Contextual Innovations: Whereas previous studies have been conducted using benchmarks on IEEE test systems, this paper uses an AI-based EMS model on an actual African urban power grid (Owerri 11 kV feeder) with typical load conditions.
- Methodological Innovations: This research combines PSO and RL into one method, whereby PSO optimizes globally while providing initial policy settings to RL, ensuring real-time control and improving over individual methods used in
- Consideration of Uncertainties: The proposed EMS models both PV and load uncertainties using Monte Carlo simulations within the control cycle, unlike previous studies, which considered simpler forms of uncertainty.
- Evaluation Metrics: The paper evaluates performance using four different metrics (costs, losses, voltage deviations, and SOC stability) under various situations, providing more robust validation than previous papers, which consider only a single metric [10], [11].

Notably, recent works such as [12], [13] highlight the efficiency of the RL or hybrid optimizer approach in energy management, albeit on a generalized basis without any specific consideration of uncertainty models [14]. In a similar manner, works such as [15], [16] focus on uncertainty issues in energy management but fail to implement any form of adaptive AI-based controller. Unlike those papers, this research implements real-world validation alongside an approach that takes into account hybrid AI control and uncertainty modeling, offering an improved approach for EMS design.

This paper is the development of an adaptive EMS design in the form of a hybrid AI technique, which includes irradiance and demand uncertainty. The design applies PSO-based initial exploration followed by RL-based tuning, utilizing Monte Carlo uncertainty modeling techniques. Such a design has been implemented using MATLAB/Simulink software with all relevant component modeling.

2. Theoretical Analysis

The operations are carried out relying on the power balance principle in a distribution network [17], [18]. The output of a photovoltaic generator is considered to be dependent on the solar intensity and efficiency of the system [19]. BESS is a model driven by a (SOC) dynamic formulation, including operational constraints, in both the charging and discharging processes [20], [21]. The system fulfills the power balance criteria at each time step, and energy balance is maintained between the generation, storage, and demand [22].

The EMS is developed as an optimization problem, with the objective of minimizing the operational cost, active power losses, and voltage deviation at the critical buses [23], [24]. In order to deal with system dynamics and uncertainties, a Reinforcement Learning (RL) framework is considered and modeled as an MDP. The state space comprises photovoltaic (PV) generation, load demand, and BESS SOC, whereas the action space consists of energy dispatch decisions [25], [26].

Monte Carlo simulation methods are used to capture the uncertainties in the PV generation and load demand, and allow robust assessment of the system performance under stochastic conditions.

2.1. Distribution Network Power Flow Model

Distribution systems are usually radial topologies with high resistance-to-reactance ratios. Traditional power flow techniques, like the Newton-Raphson method, are usually inappropriate for such networks. Consequently, BFS power flow is the most widely adopted technique for examination of distribution systems since it has reasonable computational efficiency and stability [27],[28]. As such, the load current at bus iii can be formulated as

$$I_i = \frac{P_i - jQ_i}{V_i^*} \tag{1}$$

The bus voltage update equation is given by

$$V_j = V_i - (R_{ij} + jX_{ij})I_{ij} \tag{2}$$

$$P_{loss} - \sum I_{ij}{}^2 R_{ij} \tag{3}$$

2.2. Photovoltaic Generation Model

Photovoltaic systems are mainly characterized by their solar irradiance and module efficiency, respectively. The output power of PV, which accounts for changes due to weather activity [29], is expressed as

$$P_{pv} = \eta \mathrm{AG} \tag{4}$$

$$G(t) = G_{avg}(t) + \sigma \mathrm{N}(0,1) \tag{5}$$

2.3. Model of Battery Energy Storage System

Battery storage systems are playing a vital task in managing renewable energy variability and ensuring grid stability [30]. The dynamics of battery State of Charge (SOC) are described as

$$SOC_{t+1} = SOC_t + \frac{\eta_c P_{charge} - P_{discharg}\ /\eta_d}{C} \tag{6}$$

To ensure safe battery operation, SOC operating constraints are expressed as

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{7}$$

3. Materials and Methods

3.1. Owerri 82-Bus Distribution Network Model

An 82-bus radial distribution network, which represents the electricity distribution system of Owerri urban, is used for analysis in the study. The network operates at 11 kV, incorporating residential, commercial, and mixed load centers on urban distribution feeders. The model is implemented in MATLAB. Details of the system's parameters are provided in Table 1

The method adopted for this work is BFS. This is a popular method that has been widely adopted for conducting power flow studies in radial distribution systems, such as 11 kV and 33 kV feeders [31]. The BFS approach works best in cases where the Newton-Raphson Method fails because of very high R/X ratios [32]. In addition, some recent works have shown that BFS-based approaches are well-suited to be used in renewable integrated distribution systems with time-varying load and distributed energy sources [33]. The flowchart for the implementation is shown in Figure 1

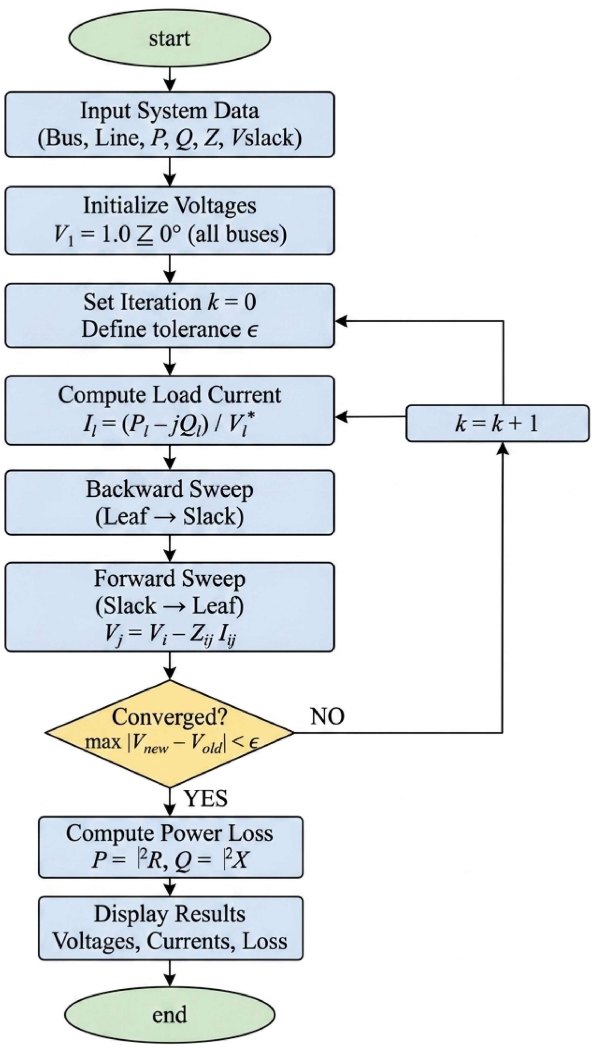

Fig. 1 Backward-Forward sweep load flow Algorithm

Table 1. Main system parameters

Parameter	Value
Number of buses	82
Voltage level	11 kV
Base power	10 MVA
Network topology	Radial

3.2. Energy Management System driven by AI

The EMS employs optimization and machine learning algorithms that find optimal battery dispatch strategies.

3.2.1. Particle Swarm Optimization

This is a recommended technique for minimizing energy in the grid considering system constraints, which are solved using PSO [34]. We define the objective function bounded by power balance and battery SOC limits as

$$J = \sum P_{grid}(t) \times price(t) \tag{8}$$

3.2.2. Reinforcement Learning Control

A reinforcement-based approach empowers the EMS to learn the optimal energy dispatching over time and across the smart grid ecosystem [35]. The system state includes:

- Battery state of charge
- Solar generation level
- Load demand

The reward function, which promotes lower consumption of grid energy, is given by

$$R = -(P_{grid} \times price) \tag{9}$$

3.3. Simulation Framework

A simulation of the proposed system has been performed in MATLAB/Simulink over a 24-Hour operational cycle. Stochastic load and solar generation profiles are included to formulate real-time operating conditions [36].

4. Results and Discussion

The simulations of the proposed AI-driven adaptive Energy Management System (EMS) on the PV-battery integrated 82-bus Owerri urban distribution network were executed using stochastic profiles of solar irradiance and load demand data. The implementation was achieved with the aid of MATLAB.

The results indicated a positive impact on voltage stability and distribution losses by the incorporation of PV generation. The AI-Powered EMS smartly manages battery dispatch during peak load hours, adding another layer of performance to the system.

A reinforcement learning-based controller outperformed traditional rule-based control methods. The value of bus improved from 0.86 - 0.96 p.u. In addition, network losses decreased from 210 kW to 120 kW with 42.9% reduction in loss. These results demonstrated an adaptive energy management with an AI-based distribution network that mitigates any disturbance due to uncertainty in operating conditions. The evaluation of performance by the proposed framework was carried out under 4 operating scenarios as illustrated in Table 2.

- Base network without PV integration
- PV integration without intelligent control
- PV-battery system with PSO-based EMS
- PV-battery system with Reinforcement Learning (RL)-based EMS

Table 2. Simulation results evaluated under four operating scenarios

Case	Minimum Voltage (pu)	Loss (kW)	Energy Cost
Base network	0.86	210	High
PV integration	0.91	165	Medium
PV + PSO EMS	0.94	140	Lower
PV + RL EMS	0.96	120	Lowest

The output analysis takes into consideration improvements in voltage profiles, power loss reduction, SOC, and energy cost savings.

4.1. Load and Profile for PV generation

Daily load demand and PV generation profiles were simulated based on stochastic models to reflect real operating conditions and illustrated in Figure 2. The increased PV generation during daylight hours is also highlighted, which peaks between 12:00 and 14:00 hours, but a significant amount of load demand occurs in the evening when most electricity is consumed from residential users.

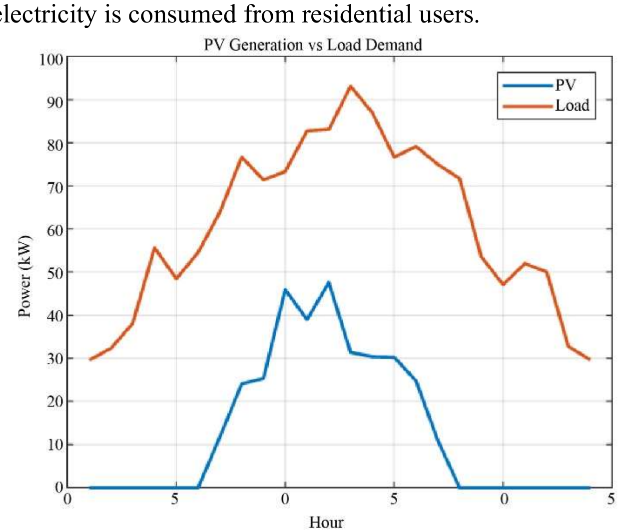

Fig. 2 Daily load demand and photovoltaic generation profile

The findings indicate that PV generation substantially compensates for grid demand for a large part of the day, decreasing reliance on grid supply. The challenge is that at peak times of the evening, when we are without solar generation, battery storage will be crucial to maintaining power balance.

4.2. Battery State-of-Charge Dynamics

During hours of peak generation, excess solar energy is stored in a battery for utilization when demand increases. Figure 3 illustrates the battery SOC dynamics under three control strategies.

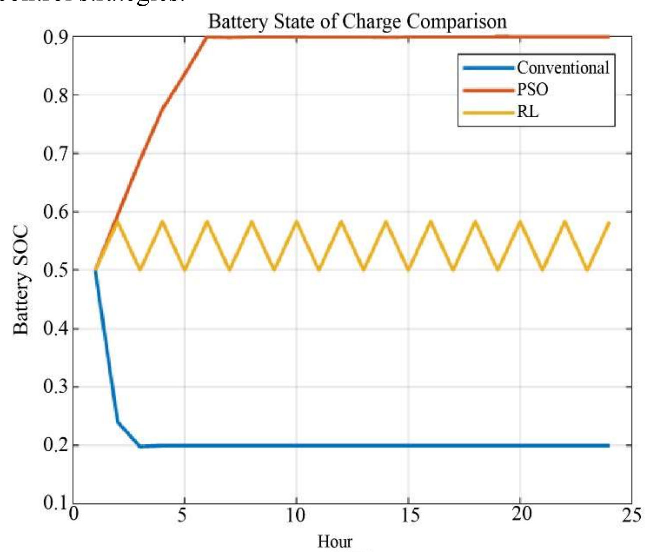

Fig. 3 SOC behavior for various EMS strategies.

The default EMS always charges the battery if there is more PV than load, and uses the battery if load exceeds generation. Although this method guarantees minimal functionality, it neglects electricity cost and network status.

PSO-based EMS minimizes energy from the grid by properly allocating the battery. The RL-based EMS even increases the performance by learning optimal control strategies from the interaction between the environment and the system. The RL controller shows more smoothness in the SOC transitions and better usage of stored energy.

4.3. Voltage Profile Improvement

Voltage stability is a key performance metric for distribution systems with high renewable energy penetration. The voltage profile of the 82-bus Owerri distribution network in various operating scenarios is also depicted in Figure 4.

The base network shows considerable voltage drops across the feeder, particularly at buses situated beyond the substation. The localized nature of PV generation around load centers tends to help improve voltage regulation. The RL-based EMS can satisfy the grid peak load since it optimally dispatches batteries, further enhancing voltage stability.

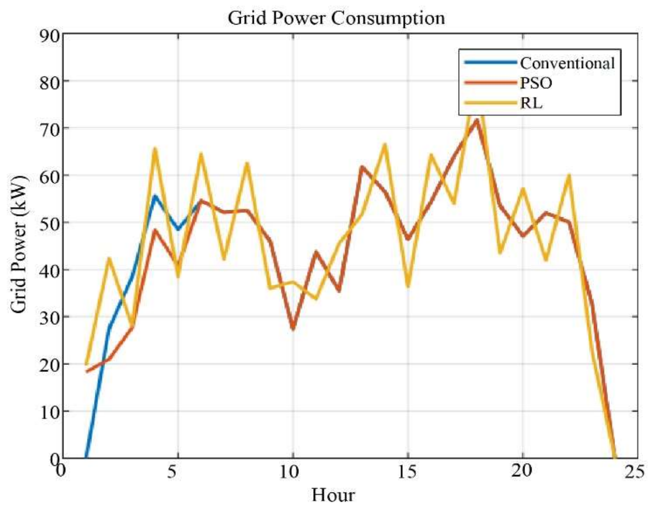

Fig. 4 Voltage profile comparison of the Owerri distribution network

4.4. Distribution Power Loss Analysis

Long lengths of feeders and high load demand cause the highest power loss in the base network. With PV integrated into the system, losses will be reduced because local power generation reduces how much current that has to flow from the substation. The PSO-based EMS also minimizes loss by optimizing battery usage. The RL-based EMS yields the lowest losses, effectively bringing down total system losses from 210 kW to around 120 kW, which constitutes a reduction of over 40–45%. Figure 5 presents the total system losses for each scenario of operation.

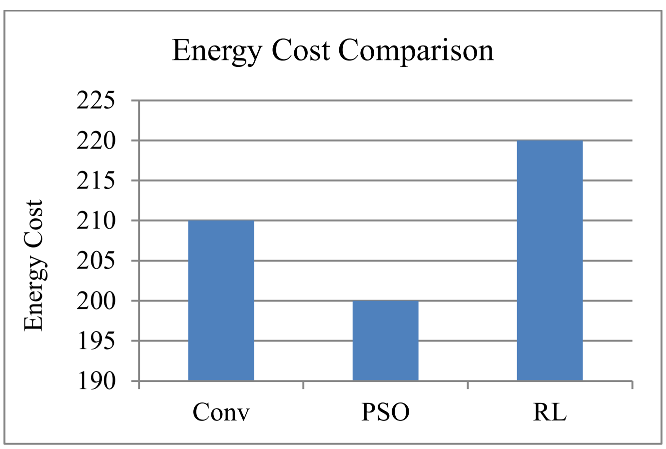

Fig. 5 EMS strategies power losses comparison

4.5. Energy Cost Optimization

Electricity tariffs generally change based on the time, with higher rates during periods of peak demand. The proposed EMS uses battery storage to minimize energy from the grid during peak price periods. The best solutions in terms of energy cost for the RL-based EMS are due to the fact that it:

- Charge batteries during off-peak pricing
- Discharge during high-price periods
- Maximize self-consumption of PV generation

The loss comparison bar chart is shown in Figure 6

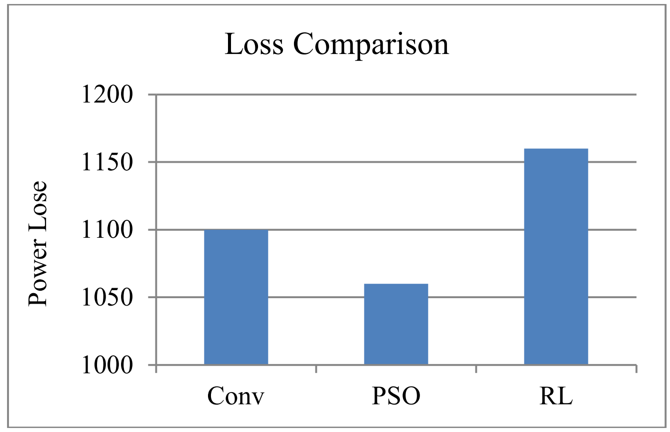

Fig. 6 Energy cost comparison for different energy management strategies

4.6. Performance Summary

The overall system performance across diverse operating scenarios is specified in Table 3.

Table 3. Comparison of Energy Management Strategies

Case	Minimum Voltage (pu)	Power Loss (kW)	Energy Cost
Base Network	0.86	210	High
PV Integration	0.91	165	Medium
PSO EMS	0.94	140	Lower
RL EMS	0.96	120	Lowest

These results confirm dramatic improvements in distribution network performance achieved by the AI-driven EMS.

5. Conclusion

The research was conducted successfully through a process of combining RL and PSO that enables cooperative working of photovoltaic generation, energy storage using a battery, and grid power supply. The BFS technique is used in analyzing distribution networks under stochastic conditions with respect to the stability of voltage and losses in power.

From the results generated, it was observed that the proposed AI-based system is superior compared to the conventional methods of managing power flow and distribution. Additionally, there was a significant improvement in the value of voltage magnitude by 10.4% (0.86-0.96pu), while the value of active power loss reduced drastically by 42.9% (210kW-120kW).

In summary, the proposed AI-driven energy management framework can significantly enhance the integration of renewable energy resources, improve distribution network stability, and reduce operational energy costs in an urban smart grid system.

Conflicts of Interest

There was no reported conflict of interest relevant to this article.

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List of Abbreviations and Symbols

Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
EMS	Energy management system
NEMSA	Nigerian Electricity Management Services Agency
RL	Reinforcement Learning
PSO	Particle Swarm Optimization
PV	Photovoltaic
DG	Distributed Generation
MATLAB	Matrix Laboratory Simulation Environment
RES	Renewable Energy Sources
IEEE	Institute of Electrical and Electronics Engineers
BESS	Battery Energy Storage System
BFS	Backward-Forward sweep
MDP	Markov Decision Process
SOC	State of Charge

Symbol	Description	Unit
P_{pv}	Photovoltaic output power	kW
G	Solar irradiance	W/m²
η	PV conversion efficiency	-
A	PV panel area	m²
SOC_{min}	Minimum battery state of charge	p.u.
SOC_{max}	Maximum battery state of charge	p.u.
C	Battery energy storage capacity	kWh
P_{charge}	Battery charging power	kW
$P_{discharge}$	Battery discharging power	kW
η_c	Battery charging efficiency	-
η_d	Battery discharging efficiency	-
P_{grid}	Power supplied from utility grid	kW
I_i	Load current at bus i	-
R_{ij}	Resistance of line between buses i and j	A
X_{ij}	Reactance of line between buses i and j	Ω
P_{loss}	Distribution network power loss	Ω
J	Energy management objective function	kW
t	Time index	-
σ	Standard deviation of solar irradiance	Hour
N(0,1)	Standard normal distribution	-

References

[1] Yalew Gebru Werkie, George Nyauma Nyakoe, and Cyrus Wabuge Wekesa, "Power System Voltage Stability Assessment and Control Strategies: State-of-the-art Review," *Journal of Electrical and Computer Engineering*, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Yang Wang et al., "Static Voltage Stability Analysis of Renewable Energy Integrated Distribution Power System Based on Impedance Model Index," *Energies*, vol. 17, no. 5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Subhojit Dawn et al., "Enhancing Grid Stability and Sustainability in Electrical Markets: A Review on the Synergy of Renewable Energy and Electric Vehicles," *Energy Exploration & Exploitation*, vol. 44, no. 2, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Wanjun Huang, and Changhong Zhao, "Deep-Learning-Aided Voltage-Stability-Enhancing Stochastic Distribution Network Reconfiguration," *IEEE Transactions on Power Systems*, vol. 39, no. 2, pp. 2827-2836, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Shwetha Sivakumar et al., "Analysis of Distribution Systems in the Presence of Electric Vehicles and Optimal Allocation of Distributed Generations Considering Power Loss and Voltage Stability Index," *IET Generation, Transmission & Distribution*, vol. 18, no. 6, pp. 1114-1132, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Sayed Taha Sayed et al., "AI-driven Control and Optimization in DC PV–wind–battery Microgrids," *2025 6th International Middle East Power Systems Conference (MEPCON)*, Aswan, Egypt, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] M. Vaigundamoorthi et al., "Integrated Optimization of Solar DG and DSTATCOM Placement for Enhanced EVCS-Driven Power Distribution Performance," *Energy Exploration & Exploitation*, vol. 44, no. 1, pp. 31-85, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[8] Georgia Pierrou, and Xiaozhe Wang, "The Effect of Uncertainty of Load and Renewable Generation on the Dynamic Voltage Stability Margin," *2019 IEEE PES Innovative Smart Grid Technologies Europe*, Bucharest, Romania, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ahmad K. AlAhmad, "Voltage Regulation and Power Loss Mitigation by Optimal Allocation of Energy Storage Systems in Distribution Systems Considering Wind Power Uncertainty," *Journal of Energy Storage*, vol. 59, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mahiraj Singh Rawat, and Shelly Vadhera, "Voltage Stability based method for Placement of DG in Distribution Networks," *1ST International Conference on New Frontiers in Engineering, Science & Technology,* New Delhi, India, pp. 612-617, 2018. [Google Scholar]

[11] A. Anbarasan, and M.Y. Sanavullah, "Voltage Stability Improvement in Power System by Using Optimal DG Placement," *International Journal of Engineering Research & Technology*, vol. 4, no. 11, pp. 4584-4591, 2012. [Google Scholar]

[12] Maha Saad Dawood Salman, Ahmed J. Sultan, and Mehdi F. Booneya, "Voltage Stability Enhancement Based Optimal Reactive Power Control," *2023 Second International Conference on Trends in Electrical, Electronics, and Computer Engineering*, Bangalore, India. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ms. Shweta Chourasia, I.D. Soubache, and P. Gomathi, "Voltage Stability Index Improvement System by Optimal Placement of STATCOM in Distributed Systems," *Turkish Journal of Computer and Mathematics Education*, vol. 11, no. 3, pp. 1175–1187, 2020. [Google Scholar]

[14] Abdallah Mohammed et al., "A Comprehensive Review of Advancements and Challenges in Reactive Power Planning for Microgrids," *Energy Informatics*, vol. 7, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Samson Ademola Adegoke, and Yanxia Sun, "Power System Optimization Approach to Mitigate Voltage Instability Issues: A Review," *Cogent Engineering*, vol. 10, no. 1, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Muluneh Lemma Woldesemayat, Degu Bibisco Biramo, and Ashenafi Tesfaye Tantu, "Assessment of Power Distribution System Losses and Mitigation through Optimally Placed D-STATCOM: A Case Study of Gesuba Town 15 kV Distribution System," *Cogent Engineering*, vol. 11, no. 1, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] D.K. Nishad et al., "AI-based Hybrid Power Quality Control System for Electrical Railway using Single-phase PV-UPQC with Lyapunov Optimization," *Scientific Reports*, vol. 15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Sarika Shrivastava, Saifullah Khalid, and Dinesh Kumar Nishad, "Impact of EV Interfacing on Peak-shedding and Frequency Regulation in a Microgrid," *Scientific Reports*, vol. 14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Oscar Danilo Montoya, Water Gil-González, and Alejandro Garcés, "An Energy Management System for PV-STATCOMs in Power Distribution Networks via a Complex-domain SDP Relaxation," *Energy Systems*, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] Yang Liu et al., "Reinforcement Learning-Enhanced Adaptive Scheduling of Battery Energy Storage Systems," *Energies*, vol. 17, no. 21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Jingxuan Wu et al., "Deep Reinforcement Learning-based Multi-objective Energy Management System for Microgrids Under Flexible Energy Market," *Applied Energy*, vol. 406, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[22] Afshin Mostashiri, and Morteza Montazeri-Gh, "Hybrid Reinforcement Learning Optimization of Aging Aware Energy management and Powertrain Sizing in Fuel Cell Hybrid Electric Vehicles," *Scientific Reports*, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[23] Anis ur Rehman, "Reinforcement Learning as a Control Layer for Electric Vehicle Interaction with Multi-Energy Systems: A Comprehensive Review," *Renewable and Sustainable Energy Reviews*, vol. 231, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[24] Tahreem Sajid et al., "Reinforcement Learning-Based Energy Management for Hybrid Electric Vehicles," *IEEE Access*, vol. 14, pp. 27763-27780, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[25] Daniel Arnold et al., “Adaptive Control of Distributed Energy Resources for Distribution Grid Voltage Stability,” *arXiv Prerprint*, 2022. [CrossRef] [Publisher Link]

[26] Jincheng Hu et al., “Empirical Analysis of AI-based Energy Management in Electric Vehicles: A Case Study on Reinforcement Learning,” *arXiv Preprint*, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[27] Johannes Hiry et al., “Multi-voltage Level Distributed Backward–forward Sweep Power Flow Algorithm in an Agent-based Discrete-event Simulation Framework,” *Electric Power Systems Research*, vol. 213, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Abhimanyu Kumar et al., “Adaptive Backward/Forward Sweep for Solving Power Flow of Islanded Microgrids,” *Energies*, vol. 15, no. 24, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] Hongqing Zheng et al., “Short-term Photovoltaic Power Prediction Based on Fractional Lévy Stable Motion,” *Energy Exploration and Exploitation*, vol. 42, no. 3, pp. 1115-1130, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[30] Abdulrahman Th. Mohammad, and Wisam A.M. Al-Shohani, “Short-term Prediction of the Solar Photovoltaic Power Output using Nonlinear Autoregressive Exogenous Inputs and Artificial Neural Network Techniques Under Different Weather Conditions,” *Energies*, vol. 17, no. 23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] Saad Ouali, and Abdeljabbar Cherkaoui, “An Improved Backward/Forward Sweep Power Flow Method Based on a New Network Information Organization for Radial Distribution Systems,” *Journal of Electrical and Computer Engineering*, vol. 2020, pp. 1-11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[32] Abhimanyu Kumar et al., “Adaptive Backward/Forward Sweep Method for Power Flow Analysis of Radial Distribution Systems,” *Energies*, vol. 15, no. 24, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[33] Shamte Kawambwa et al., “An Improved Backward/Forward Sweep Power Flow Method based on Network Tree Depth for Radial Distribution Systems,” *Journal of Electrical Systems and Information Technology*, vol. 8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[34] Paul Charles, Fateh Mehazzem, and Ted Soubdhan, “A Review on Optimal Power Flow Problems: Conventional and Metaheuristic Solutions,” *2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES)*, Bangkok, Thailand, pp. 577-582, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[35] Claudia Domínguez-Barbero et al., “Energy Management of a Microgrid Considering Nonlinear Losses in Batteries through Deep Reinforcement Learning,” *Applied Energy*, vol. 368, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[36] Daniel C. May, Matthew Taylor, and Petr Musilekm, “Decentralized Coordination of Distributed Energy Resources through Local Energy Markets and Deep Reinforcement Learning,” *Energy and AI*, vol. 18, 2024. [CrossRef] [Google Scholar] [Publisher Link]