# Optimization Approaches for Microgrid Energy Management

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The microgrids (MG) is a single controllable local power network with distributed energy sources (solar Photovoltaics (PV), wind energy, diesel generator, fuel cell, wave energy, etc.), ESS, controllable distributed loads (households, commercial, industrial, etc.), and advanced energy management systems (EMSs). It can be operated alone or in connection with the utility grid.

Keywords: energy management ; functions ; metaheuristic approaches

## 1. Introduction

Many studies have been conducted based on the system's topologies, architectures, and operating modes [1][2][3]. For instance, the stochastic character of installed RESs can be controlled and optimized by a dependable power supply to customers while maintaining appropriate operating conditions for the storage system, electricity bill, and occupancies. Suggested energy management systems (EMS) optimization mechanisms are shown in **Figure 1**.

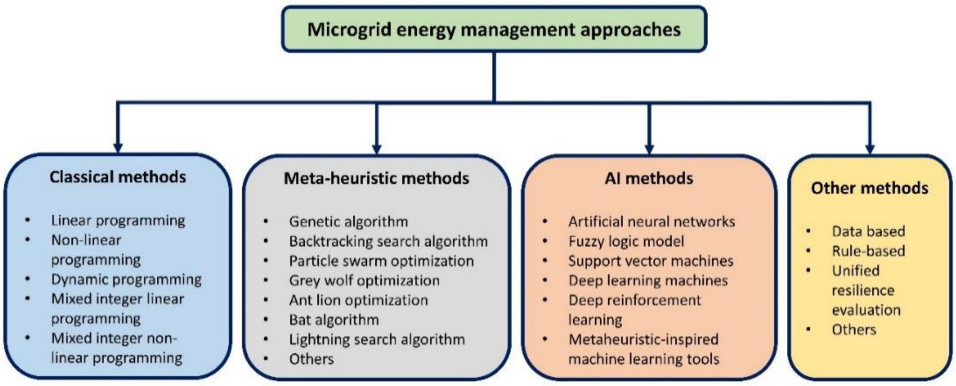


**Figure 1.** Control and optimization approach of EMS.

## 2. Objective Functions and Constraints

The deployment of EMS optimization techniques outlines the primary target functions, including power quality, dependability, pollution, and costs [4][5][6][7]. The fundamental goal of utilizing economic objective functions, for example, is to reduce the price of power. For cost reduction in microgrids (MGs), many formulations have been investigated. For example, the cost minimization problem was framed as a dynamic economic load dispatch problem [8]. Jafari et al. [9] suggested an electrical market approach for improving the dependability of islanded multi-MG networks. A techno-economic goal function was used to account for the MG owners' profit while enhancing the system's reliability. For the probabilistic modeling of renewable energy resources (RER) and loads, distribution functions were employed, and an electrical market strategy was developed to increase the profit of the MG owners.

However, power quality, particularly power loss, continues to be a significant concern for system dependability. Murty et al. [10], who examined a multi-objective EM in a MG system, enhanced a helpful literature study for multi-objective EM. Techno-economic analysis and energy dispatch were given for independent and grid-connected MG infrastructure with hybrid renewable energy resources (RER) and storage devices. Following the definition of the system's restrictions and goal functions, appropriate optimization methods are needed to guarantee power flows between the installed RER/storage and the MGs and between the MGs and the utility grid. The remainder of this section is devoted to a review of critical approaches found in the literature. The energy management system is a computerized system comprised of a software platform that provides essential support for the effective generation and transmission of electrical energy [11]. This platform also ensures adequate security of the energy supply with minimal cost.

## 3. Classical Methods

The classical approaches mainly concentrate on optimizing the energy resources and transmission with the mother grid. Still, a lot of work is needed to focus on the battery depth of discharge, greenhouse gas emissions, the privacy of customers, and system reliability. Two well-known classical solution methods of the EMS optimization approaches are (a) linear and nonlinear programming methods and (b) dynamic programming and rule-based methods. Several researchers used these strategies to solve the EMS control approaches. For example, Sukumar et al. [12] presented an EMS combining continuous run mode, power-sharing mode, and on/off mode. While the constant run and power-sharing modes were solved using the linear programming optimization method, the on/off mode was solved using the mixed-integer linear programming method (MILP). In most linear programming approaches, the constraints and objective functions are linear functions with whole-valued and real-valued choice variables. This methodology is frequently used for system analysis and optimization because it is a versatile and powerful tool for tackling big and complicated issues, such as distributed generating and MG systems. Vergara et al. [13] used a non-linear programming method to minimize the cost of a residential three-phase MG. The initial development of the non-linear model was then converted into the MILP. The results showed that the converted method experienced less error and computational time than the nonlinear three-phase optimal power flow formulation. Heymann et al. [14] presented a dynamic programming optimization method. The comparative results showed that this method was more effective in operational cost and computation time than the classical non-linear and MILP methods. Wang et al. [15] presented a Lagrange-programming neural networks (LPNN) approach for the efficient control and administration of MG systems, with the primary goal of lowering the total cost of the MG. This study divided the load into four categories: controlled load, thermal load, price-sensitive load, and critical load, with variable neurons and Lagrange neurons coupled to provide optimal MG operation scheduling.

More complicated problems that can be discretized and sequenced are solved using dynamic programming approaches. The investigated issues are generally divided into subproblems that are addressed optimally, and the acquired answers are then overlaid to produce an optimum solution for the original problem [16]. A rule-based solution approach is utilized for grid-connected and islanded modes of the MG [17]. As a result, rule-based approaches are commonly used to implement the EM system, since they do not require any future data profiles to decide, making them more suited to real-time applications. Bukar et al. [18], for instance, provided a rule-based EMS in which a rule-based algorithm was utilized to implement RER use priority and control the power flow of the suggested MG components. A nature-inspired optimization method was employed to optimize the MG system's operations with respect to long-term capacity planning. The proposed objective function's primary purpose was to reduce the cost of energy in MG systems and the chance of power supply failure. Rule-based techniques for controlling and optimizing energy flow in MG systems have been presented in other papers. Merabet et al. [19] devised a control method to ensure power compatibility with the EMS for various resources in the MG. The hybrid system in the MG was experimentally validated using a real-time control system. The findings indicated that the suggested technique kept the MG subsystems running smoothly under various power-generating and consumption situations. Luu et al. [20] investigated a method for constructing the optimal EM for a MG-connected system that considered the cost of energy trading with the main grid, as well as the cost of battery aging. The authors employed a dynamic programming technique to reduce the system's cash flow while optimizing the power supply from the main grid. Unlike traditional techniques, dynamic programming algorithms may be thought of as mathematical optimization methods that can break down a complex issue into smaller sub-problems that can then be addressed recursively. They can make the best judgments. However, they come at a high cost in processing, making them challenging to implement in embedded devices. **Table 1** demonstrates the review of classical techniques for the microgrid EMS in recently published articles.

**Table 1.** Review of some recent literature on classical techniques for microgrid energy management.

| Ref. | Method | Contributions | Application | Key Findings |
|---|---|---|---|---|
| **Moazeni and Khazaei [21]** | **MILP** | **Minimizing the daily cost of energy** | **Water-energy microgrid system** | **Water sector energy demand was decreased by maintaining a cleaner supply to the energy sector** |
| **Vitale et al. [22]** | **Dynamic programming** | **Development of a fast reduced-order sub-model** | **Islanded and grid-tied microgrids** | **Achieved reduced payback period through the proper capacity exploration** |

| Ref. | Method | Contributions | Application | Key Findings |
|---|---|---|---|---|
| Pedro et al. [23] | MINLP | Modeled an unbalanced three-phase electrical distribution system with droop control | Islanded microgrids | Reduced average maintenance load and cost curtailments |
| Balderrama et al. [24] | Linear programming | Identified an open-source modeling framework to bridge the gap between field practices and two-stage stochastic modeling approaches | Community microgrid | Recommended robust and optimal system configurations with a minimal impact on the final costs for the community |
| Iqbal et al. [25] | Non-linear programming | Modelling of a peer-to-peer energy-sharing strategy | Community microgrid | Minimized overall device errors (~25%) compared to traditional sharing mechanisms |
| Liu et al. [26] | Stochastic programming | Development of a multi-period investment planning scheme | Islanded microgrid | Achieved better economic and synergetic performances compared to the traditional model. |
| Restrepo et al. [27] | Optimization- and rule-based EMS | Development, implementation, and commissioning of different EMS strategies for testbed microgrid | Canadian Renewable Energy Laboratory | Yielded better overall performance over the rule-based EMS using similar communication links while maintaining stability. |
| Bukar et al. [28] | Rule-based | Development of a rule-based energy management scheme based on queuing theory. | Long-term capacity planning for MG | The optimization problem minimizes energy costs and maximizes system reliability. |
| Almada et al. [18] | Rule-based | Management and control of a microgrid with distributed energy resources under standalone operation, grid connection, and transition between the aforementioned operating modes | AC microgrid | MG control and management techniques work well under all operating conditions |
| Rippia et al. [17] | Rule-based | Enhancing the energy management of a grid-connected microgrid comprised of renewable energy sources, loads, and ESS | Grid-connected microgrids | The rule-based method performed better than the MILP while ensuring nearly no performance loss by offering a sizable decrease in computation time |

## 4. Heuristic and Metaheuristic Approaches

Heuristic and metaheuristic methods are frequently used in the literature to solve complex and non-differentiable optimization problems from various engineering fields, including transportation, communication, power systems, product distribution, and microgrid energy management [29]. Among many approaches, the genetic algorithm and particle swarm optimization methods are two popular meta-heuristic methods to solve the EMS of the MG, due to their parallel computational ability. Chalise et al. [30] formulated a multi-objective EMS concentrating on a remote MG's economic load dispatch and battery degradation cost. This work considered day-ahead scheduling using a genetic algorithm and real-time operation using a rule-based approach. A PSO-based optimal EMS for both islanded and grid-connected modes of the MG has been proposed in [31]. The objective functions for the islanded and grid-connected modes were to minimize the operational and maintenance costs and maximize the energy trading profit with the primary grid. The results show that this technique provided a better solution than the genetic algorithm in terms of the global optimum solution and the time of computation. Apart from these two well-known solution approaches, the genetic algorithm and PSO methods of the EMS, there are other approaches, such as differential evolution [32], gray wolf optimization (GWO) [33], ant colony optimization (ACO) [34], etc.

Paperi et al. [35] presented a heuristic technique for determining the best functioning and EMS of the MG system. The research topic was framed as a single-objective optimization problem, only focusing on cost reduction. Khan et al. [36] presented a metaheuristic-based system by combining the Harmony search algorithm with improved differential evolution. During peak periods, several knapsacks were utilized to ensure that power consumption was below a predetermined threshold value—the suggested system beat existing metaheuristic approaches in terms of cost and peak-to-average ratio. Ref. [37] suggested a genetic algorithm-based optimum EMS system for a grid-connected MG system that considered electricity price, power usage, and RER generation uncertainty. The multi-period gravitational search method solves a deterministic EM issue [38]. Aghajani et al. [39] employed a multi-objective PSO method while addressing the EMS of the MG system. Wei et al. [40] created a standalone modular microgrid model to shorten the feasible economic dispatch regions, formulate an optimization model, and define optimum microgrid system operating strategies. An improved genetic algorithm was proposed to investigate this problem. The employed strategy was capable of solving the EMS problems with many constraints and produced a high-quality solution. Prasant and Joseph [41] developed a methodology for evaluating the techno-economic and environmental efficiency of supplying uninterrupted electricity to a microgrid composed of seven components—wind turbines, solar PV, lead-acid batteries, fuel cells, biodiesel generators, electrolyzes, and small-scale hydrogen tanks—in Tucson, Lubbock, and Dickinson, TX, USA. They measured the configurations with the lowest levelized cost of energy (LCOE) using the genetic algorithm. **Table 2** summarizes the meta-heuristic methods for the microgrid EMS. It was evident from the presented analysis that the various meta-heuristic approaches showed satisfactory performances in achieving optimal solutions (minimal costs or maximum profits) while solving microgrid EMS problems with various constraints and uncertainties. Besides, in most of the cases the authors reported better or competitive efficacy for their employed algorithms compared to others. However, it is challenging to come up with solid conclusions about the superiority of any specific algorithm, as they all should provide similar results ideally due to their stochastic nature. Besides, their efficacy also depends on the proper selection of the hyper-parameters.

**Table 2.** Recent literature on meta-heuristic techniques for microgrid energy management.

| Ref. | Algorithm | Contributions | Application | Key Findings |
| --- | --- | --- | --- | --- |
| Quazi et al. [42] | NSWOA | Hybridization of WOA with a non-dominated sorting technique | Islanded microgrid | Achieved optimal solutions with lower computational expenses compared to other reported algorithms |
| Leonori et al. [43] | GA | Investigation of strategies to synthesize rule-based fuzzy inference systems | Demand response services | Reduced the system complexity and maximized profit generation by 10% compared to the referenced solution |
| Hussein et al. [44] | SFOA | Formulation of the multi-objective problem for controller parameter tuning | Inverter based microgrid | Enhancement of system performance and flexibility compared to particle swarm optimization |
| Almadhor et al. [45] | BAPSO | Determination of optimal locations and sizes for the solar generation systems | PV-based microgrid | Reduced transmission power loss and achieved faster convergence with less computational burden |
| Singh and Gope [46] | GWO | Optimization problem formulation for load frequency control | Two-area multi-microgrid | Achieved superior performance with the GWO-tuned controller over the cuckoo search algorithm-tuned controller |
| Roslan et al. [47] | LSA | Development of an optimal power scheduling strategy | Scheduling controller | Savings of 62.5% in overall costs and 61.98% in carbon dioxide emission reduction |
| Shafiullah et al. [33] | GWO | Formulation of the multi-objective problem considering ESS degradation cost | Community microgrid | Generation of quality solutions with a competitive computational effort |
| Suman et al. [48] | PSO-GWO | Formulation of the optimal planning problem | Rural microgrid | Obtained a reduced average cost of electricity by meeting a good portion of the load demand |
| Soham and Kamal [49] | CE-DE | Optimization problem formulation for minimization of running costs and reduction of pollution. | Benchmarked microgrids | Avoided pre-mature convergence and generated competitive solutions |
| Perol et al. [50] | Evolutionary algorithms | Development of control strategies for power and energy management | Low voltage microgrids | Reduced operation costs and energy losses, thus improving overall efficiency |
| Hossain et al. [51] | Modified PSO | Proposed an optimal battery control strategy for real-time management | Grid-tied microgrids | Achieved a 12% reduction in operation costs for a time horizon of 96 h |
| Kavitha et al. [52] | MPO | Solved supply-demand problems to minimize production costs | Islanded and grid-tied microgrids | Generated around 8% higher profit with better optimization ability and faster convergence |

| Ref. | Algorithm | Contributions | Application | Key Findings |
|---|---|---|---|---|
| **Tomin et al. [53]** | **Monte-Carlo tree search algorithm** | **Developed a unified approach for optimal energy and benefits management** | **Community microgrids** | **Improved supplied energy quality and reduced the levelized cost of energy index from 20% to 40%** |

## 5. Artificial Intelligence Methods

Artificial neural networks are an example of a method that is created artificially. They are stochastic approaches that may be utilized to address optimization issues for systems that contain random variables. The fluctuating nature of RER in MG systems is caused by meteorological conditions, which impact electricity generation. Solanki et al. [54] presented a mathematical approach for intelligent load control in a stand-alone MG system. Neural networks were utilized to simulate the loads examined, and a predictive control was applied to manage the energy, based on expected load fluctuation. The EMS based on artificial intelligence primarily concentrated on Fuzzy logic and neural networks [55], as well as multi-agent systems. A fuzzy logic-based EMS with a battery and hydrogen energy storage system for a microgrid has been proposed [56]. The authors claimed that this solution could respond well to required load demands and meet the established technical and economic criteria. Wang et al. [16] formulated a neural network-based EMS for the MG. The objective function is to reduce the overall fuel, operation, maintenance, and emission cost of the generation units. Ghorbani et al. [57] proposed a multi-agent-based EMS approach, where consumers, storage units, generation units, and the grid are considered agents for a grid-connected MG. In this work, the objective function was to reduce power imbalance costs. Results showed that the time required to take the decision was better for the decentralized approach than that of the centralized approach. Among the other known artificial intelligence solution techniques, game theory, the Markov decision process, and theadaptive intelligence technique are remarkable.

Neural networks are primarily used to regulate, optimize, and detect system characteristics in online and offline applications. Given their capacity to address the system's stability through self-learning and prediction skills, neural networks, unlike prior techniques, can handle issues with nonlinear data in large-scale MG systems [58][59][60]. Despite the solutions' efficacy, intelligent energy management in smart MG systems still needs real-time and predictive control methodologies. **Table 3** illustrates various artificial intelligence methods related to microgrid EMSs.

**Table 3.** Review of artificial intelligence methods related to microgrid energy management.

| Ref. | Technique | Contributions | Application | Key Findings |
|---|---|---|---|---|
| **Dong et al. [61]** | **Fuzzy logic** | **Developed day-ahead fuzzy rules for real-time energy management under various operational uncertainty** | **Multi-energy microgrid** | **Exhibited superior performance compared to the online rule-based and meta-heuristic optimization-based offline scheduling schemes** |
| **Zehra et el. [62]** | **Fuzzy logic** | **Proposed the control strategies for renewable energy resources and battery storage systems** | **DC microgrid** | **Achieved better controllability compared to the sliding and integral sliding mode controllers** |
| **Singh and Lather [63]** | **HBSANN** | **Addressed demand-generation disparity for effective power-sharing between various ESS.** | **Low-voltage DC microgrid** | **Exhibited lower voltage overshoot and settling time compared to conventional strategy** |
| **Nakabi and Toivanen [64]** | **Reinforcement learning** | **Outlined various flexible resources for coordination with priority** | **Microgrid** | **Exhibited the highest model performance and convergence to near-optimal policies** |
| **Tan and Chen [65]** | **NN** | **Designed a multi-objective optimization model for multiple microgrid systems** | **Multiple microgrids** | **Achieved a 36.86% lower forecasting error; obtained better pareto solutions and faster convergence** |
| **Tayab et al. [66]** | **HHO-FNN** | **Developed a hybrid approach for short-term load forecasting** | **Queensland electric market** | **Reduced the mean absolute percentage error ranging from 33.30% to 60.76%** |
| **Priyadarshini et al. [67]** | **EE-RRVFLN** | **Proposed a maximum power point tracking model for multiple PV-integrated MG under partial shading conditions and load uncertainty.** | **PV-BESS integrated microgrid** | **Established the superiority of the employed approach over the conventional and random vector functional link neural networks** |

## 6. Other Methods

Proactive control is one of the most intriguing EMS methods. This technique is based on a mixed-integer optimal control issue, which can be expressed as a mixed-integer nonlinear programming problem [21]. According to the literature, the notion of proactive control for EM in MG systems is seldom applied. For control-based prediction judgments, the notion is particularly appealing. Proactive control can be enhanced in future investigations for EM in MG systems, thanks to the advancement of information and communication technologies, particularly microcontrollers. In addition, the approach can improve the system's performance in existing system disruptions. Amirioun et al. [68] provided a MG proactive control method for dealing with the adverse effects of severe windstorms. When the anticipated windstorm alerts arrived, the method discovered a conservative MG schedule with the fewest susceptible branches operating while the whole load was serviced. The cautious timetable guaranteed that the MG functioned normally before the windstorm, while decreasing the MG's susceptibility when the event arrived. This technique benefited from generation rescheduling, network reconfiguration, parameter tuning of the droop-controlled units, and conservation voltage regulation. Panteli et al. [69] talked about unified resilience evaluation, the operational enhancement method, and a technique for evaluating the impact of severe weather conditions. Another study by Amin et al. [70] combined BESS and PV systems under a hierarchical transactive EM method to lower customer power costs. A cost-benefit analysis technique that integrated PV units with battery storage systems was created for proactive residences. The control algorithm managed the battery's charge/discharge cycle based on a cost-benefit analysis of real-time energy rates and battery costs, providing users with a precise estimate of their investment returns and annual savings. When a proactive system is handled utilizing predictive techniques, the performance of this method may be improved. Reactive Feedback Control and Model Predictive Control were compared with respect to energy used, energy error, and management effort for a specific data center by Rahmani et al. [71]. The research suggested a data center model-based feedback control method to improve service quality, energy consumption, and managerial effort. Moreover, the combination of different approaches mentioned earlier was also used in a few cases for energy management in microgrid systems [72][73][74][75].

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