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A Review of Energy Management of Multi-microgrid Power Systems in the Presence of Uncertainty of Distributed Generation Resources

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ABSTRACT

Uncertainties in renewable generation and load demand are challenges to the efficient operation of renewable energy systems. This paper aims to review energy management systems for multi-microgrid networks under uncertainty. This review primarily focuses on uncertainty modeling approaches for multi-microgrid energy management, while also providing an integrated discussion on communication architectures, hierarchical control strategies, and market-oriented coordination. Therefore, the paper serves as a hybrid survey—comprehensive in structure yet focused in its analytical depth on uncertainty and distributed optimization frameworks. It provides an overview of optimization techniques and control strategies to address issues related to uncertainty in renewable generation, load demand, and network dynamics. This paper is organized as follows: we first introduce the concept of multi-microgrid networks, discuss the relevance of efficient energy management systems in such systems, then we analyze the impact of uncertainty on the economic and environmental performance of multi-microgrid networks and present approaches to mitigate their effects. The novelty of this review is to provide an integrated conceptual framework of uncertainty modeling, distributed optimization and machine-learning-based forecasting, as well as a critical comparative synthesis of recent studies (2020–2024). Specifically, 50 recent studies are analyzed, with probabilistic and robust optimization methods representing nearly 45% of the reviewed works, and machine-learning-based forecasting models accounting for 30%. Comparative analysis reveals that hybrid ML–robust frameworks achieve the best trade-off between cost-efficiency and reliability, highlighting trends and gaps in current research.

Keywords: Uncertainty, reliability, energy management, multi-microgrid networks.

1 Introduction

A microgrid is a set of loads, distributed generation sources, and energy storage devices that are coordinated to serve reliable power to the distribution grid from a common connection point. A microgrid can operate in both grid-connected and stand-alone modes. In the former case, the power can flow both from the microgrid to the main grid and vice versa, depending on the balance of power and other operating conditions. The latter case means that the microgrid is isolated from the main distribution grid, energy exchange is not possible, and the total power generated by the microgrid must always be equal to the local demand. The ability to operate in both modes is one of the main characteristics of microgrids. The microgrid can be used to support the main grid when needed, participate in energy exchange if it is mutually beneficial, or disconnect the main grid when required to reduce the load on it and provide a reliable energy supply for local loads [1].

The main components of microgrids can be different and depend on their features, e.g., local resources, system topology, the geographical characteristics of the installation site, and whether grid-connected or stand-alone mode should be given priority. Photovoltaic arrays and wind turbines are examples of resources that require converters. Non-critical loads can be simply connected/disconnected by a conventional circuit breaker. They can also be interfaced by a power electronic converter that can be used for more flexible control but can increase the level of unwanted harmonics [2].

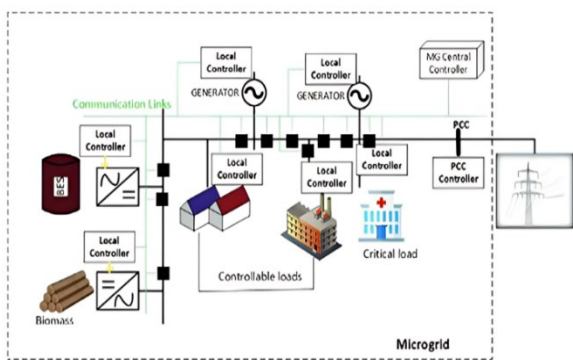


Figure 1: Microgrid structure and connection to the upstream grid

Distributed generation resources can be connectable or non-connectable units based on their controllability. Fossil fuel generators, like diesel generators, are connectable units whose power output can be controlled at all times. However, distributed generation resources that are based on renewable energy sources have an intermittent power output that cannot be controlled, and therefore these units usually operate at their maximum power output capacity at all times. A non-connectable unit can become a connectable unit if it is combined with an energy storage device and a proper controller. The long-term vision for microgrids of the future is complete independence from fossil fuel generation, and this hard-to-achieve goal can be reached by coordinating the

charging and discharging of storage devices with demand response schedules. In order to assure proper operation of a microgrid, control functions can be implemented using centralized, decentralized and distributed approaches. In practice, most of the research is focused on the centralized structure, since this is the dominant control architecture in power grids. In a centralized approach, there is a central controller that monitors and controls all distributed resources and local loads; all calculations and decision-making are done by the central controller. Since all the computation takes place in a single node, the system is sensitive to single-point failures [5]. The control of the microgrid in a decentralized approach is physically distributed in a decentralized infrastructure, i.e., the components of the microgrid are controlled by multiple local agents and these agents are coordinated by the energy management system. One of the key advantages of this architecture is its scalability and reliability; new components can be added to the microgrid without interfering with the microgrid or updating the control algorithm, and the distributed nature of the system is immune to single-point failures. A distributed approach is similar to the decentralized one, but it also allows for coordination and cooperation of individual components. Table 1 summarizes the control levels in microgrids along with their corresponding time scales and key performance functions.

Table 1 – Microgrid Control Hierarchy: Time Scales and Key Functions

Control level	Time scale	Performance
Primary	Millisecond, second	<ul style="list-style-type: none"> Voltage and frequency control Active and reactive power sharing control Islanding detection
Secondary	Seconds, minutes	<ul style="list-style-type: none"> Energy Management System Voltage and frequency deviation compensation. Grid-connected/isolated mode transition. Demand-side management
Third party	Minute, hour, day	<ul style="list-style-type: none"> Grid/Microgrid Power Flow Coordination Microgrid Cluster Coordination

Table 2 presents a concise comparison between this paper and major review articles published in Applied Energy, Renewable & Sustainable Energy Reviews, and Energy Reports. Unlike previous studies that focused on either control hierarchy or single-layer optimization, the present review uniquely integrates uncertainty modeling, distributed optimization, and machine-learning forecasting in a unified EMS framework for MMG systems. This review primarily focuses on uncertainty modeling approaches for multi-microgrid energy management, while also providing an integrated discussion on communication architectures, hierarchical control strategies, and market-oriented coordination. Therefore, the paper serves as a hybrid survey—comprehensive in structure yet focused in its analytical depth on uncertainty and distributed optimization frameworks.

Table 2 – Comparison of Existing Review Papers on MMG (Multi-Microgrid) Energy Management Systems (2020–2024)

Reference	Focus Area	Coverage Period	Key Gap / Limitation	Distinctive Contribution of This Work
RSER (2021)	Centralized control of microgrids	2010–2020	Lacks uncertainty and ML integration	Adds stochastic + ML forecasting layers
Applied Energy (2022)	Market mechanisms and coordination	2014–2021	Neglects distributed optimization	Incorporates privacy-preserving distributed EMS
Energy Reports (2023)	EMS of hybrid microgrids	2018–2023	Limited multi-objective comparison	Provides unified quantitative synthesis

1.1 Research gap and contributions

While a large body of literature exists for the energy management of microgrids and networked (multi-)microgrid systems, several important gaps remain for such systems to be used for practical deployment with high shares of renewable energy and achieve their full potential in terms of performance. The majority of reviews and surveys exist for the various methods that have been proposed to date – such as stochastic/probabilistic methods, interval/fuzzy methods, robust optimization, hybrid formulations, and data-driven/machine-learning enhanced forecasting – but most works consider these techniques in isolation rather than as part of an integrated, scalable framework for multi-microgrid energy management [5].

The main research gaps that motivate this review are identified below:

- **Absence of data-driven, holistic, and robust frameworks:** Although a majority of the recent literature has focused on state-of-the-art forecasting (ML-based) or robust/stochastic optimization in isolation; a relatively small number of the literature propose a holistic architecture that couples short-term ML forecasts and robust/chance constrained schedulers that also aim at reducing conservatism, while guaranteeing feasibility in real-time operation [6].
- **Privacy, cybersecurity and information-sharing limitations:** Distributed and ADMM-like algorithms have been more and more proposed for multi-microgrid coordination, but real-world adoption is limited due to privacy, cybersecurity in the communication layer and information-sharing issues. Limited literature has studied privacy-preserving distributed optimization methods while considering communication delays, packet loss, and attack models [7].
- **Neglected operational constraints across shared connection points:** While many publications focus on the optimization of individual microgrids or make

assumptions of idealized exchange capacity, the limitations and constraints of transmission/thermal limits, protection coordination and meshed interaction across the common coupling point are often simplified or neglected. This may result in infeasible recommendations when applied to realistic distribution networks [8].

- **Limited market-aware, real-time coordination:** Although the works on the energy trading and transactive energy among microgrids, the integration of the market mechanism and the real-time dispatch under uncertainty is at an early stage when the participants are heterogeneous stakeholders with different, possibly conflicting, goals [9].
- **Scalability and benchmark/testbed scarcity:** Many of the proposed algorithms are demonstrated to perform well in small test systems; however, few have been demonstrated in large scale realistic cases or on hardware-in-the-loop testbeds with communication, measurement noise and cyber-physical effects.

Motivated by the research gaps identified above, the contributions of this review article can be summarized as follows:

- A short taxonomy of uncertainty-modeling approaches for multi-microgrids, along with their strengths, weaknesses and conditions of applicability.
- A unified conceptual framework that couples ML-based short-term forecasting, uncertainty quantification, privacy-preserving distributed optimization (ADMM variants) and realistic network constraints — provided as a reproducible blueprint for researchers and practitioners.
- A comparative table of recent (2020–2024) studies, with a systematic summary of their main goal, uncertainty model, solution method and key assumptions/limitations.
- Actionable recommendations and a prioritized list of open research directions (cybersecurity-aware coordination, market-integration under uncertainty, scalable solvers, real-world testbeds).

The above contributions are expected to (i) identify where the current research efforts are focused, (ii) unveil the under-explored but potentially high-impact research avenues and (iii) offer a practical starting point for the design of resilient, privacy-conscious and scalable energy management systems for multi-microgrid deployments.

2 Multi-microgrid systems

The ever-increasing integration of distributed generation resources into the distribution networks, on one hand, and the growing interest in microgrids implementation, on the other hand, the logical step to further enhance the operation of microgrids is their clustering into so-called microgrid clusters. The recently introduced concept of multi-microgrid represents a high level structure, established at medium voltage level by connecting individual microgrids at their common connection point and can be established either by segmenting the preexisting distribution network or installing new distributed

sources and energy storage to serve local loads. Multi-microgrid systems are classified based on the type of power they operate with, namely AC, DC, and hybrid types. AC multi-microgrid systems can be straightforwardly integrated with the existing distribution networks. The control of DC type is simpler, as it does not require any reactive power management nor frequency regulation; however, appropriate power converters are necessary for connecting to the conventional distribution networks. Hybrid multi-microgrid systems have the potential to harness the benefits of both of the aforementioned types and realize more flexibility [10]. The objective function for the multi-microgrid energy management optimization problem can aim at minimizing the operating costs or, on the contrary, maximizing the benefit of electricity trading, customer satisfaction, and utilization of renewable resources. The operating costs can be minimized by maximizing the use of available renewable energy generation, purchasing electricity at the lowest price and selling it at the highest price, and capitalizing on the heterogeneity of load and generation profiles across the microgrids. These objectives are complimentary to each other and therefore very often the common practice is to model a multi-objective problem that optimizes a weighted sum of those objectives. Constraints that are considered in the model also depend, to a great extent, on how the problem is formulated; therefore, power and energy balance constraints are a common feature, but the operating constraints of microgrid components are different and greatly vary on the type of generation that is considered [11]. In this regard, it is of the utmost importance to account properly for the limitation of power transmission capacity through the common connection point when taking into account the power exchanges between microgrids and the active distribution network, which is mostly neglected in the available literature.

2.1 Radial topology

Each microgrid is directly connected to the main grid and energy exchanges take place through the distribution bus, which is a very common radial topology.

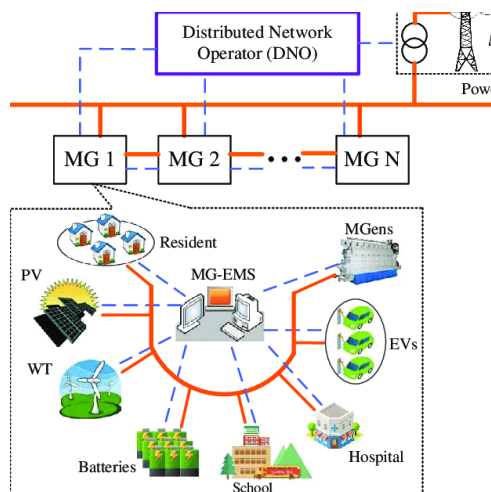


Figure 2: Multi-microgrid system with radial topology [12]

In this topology, there is an exchange of information between each of the components inside the microgrids and the microgrid energy management system to target optimal control of all local resources, coordinated by the distribution network operator. If one of the microgrids is not able to satisfy the demand, or has a large amount of renewable energy production, the energy exchange required can only be done through the main grid [12].

2.2 Daisy chain topology

In this topology, neighboring microgrids are able to share energy and information in both directions. Moreover, each microgrid is able to exchange energy and information with the main grid. The internal structure of a microgrid resembles that of the radial topology. This topology results in a highly coupled energy applications, which imposes additional constraints on the network. The energy management system should also be able to operate correctly with only non-critical information from neighboring microgrids in order to ensure user privacy [13].

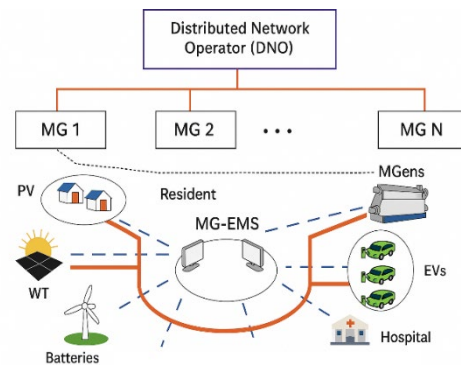


Figure 3: Multi-microgrid system with daisy chain topology [13]

2.3 Mesh topology

In the considered configuration, all the microgrids are interconnected to each other as well as to the main grid and exchange energy and information, which is not realistic.

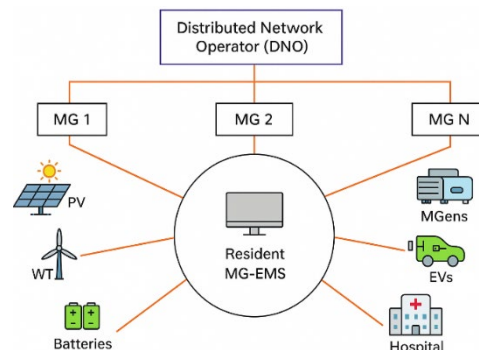


Figure 4: Multi-microgrid system with mesh topology [14]

The purpose of this formulation is to obtain a simple topological configuration for the implementation of the

distributed optimization algorithms. Such a kind of topologies do not exist nor are not planned to be used in practice [14].

There are several topologies for multi-microgrid configuration and each one of them influences its operational flexibility and robustness. Since no particular configuration seems to be widely recognized in the literature, several typical topologies are highlighted in this study and are summarized in Table 2. The main three considered configurations are the radial, the daisy chain, and the mesh. The radial configuration is the simplest one, with only one MG connected to the grid, while in the daisy chain configuration all MGs are connected to each

other, and one of them to the grid, usually the first. In the mesh structure, all MGs are interconnected.

The overview of multi-microgrid structures lays the groundwork for understanding the operational challenges under uncertainty. Building on this, Section 3 introduces uncertainty modeling techniques—including load and renewable generation variability—which directly inform the formulation of EMS (Energy Management System) optimization problems, thereby linking structural characteristics with control and decision-making strategies.

Table 2- Comparative characteristics of multi-microgrid topologies

Topology	Description	Advantages	Limitations	Typical Applications
Radial	Each microgrid directly connected to the main grid; exchanges only via the distribution bus.	Simple structure; easy integration with existing distribution networks; well-studied.	Limited flexibility; energy exchange only through main grid; vulnerable to single-point failures.	Rural or small-scale networks where central operator manages flows.
Daisy chain	Neighboring microgrids exchange energy/information bidirectionally and also connect to the main grid.	Greater flexibility; allows local energy sharing; reduces dependency on main grid.	Higher coordination complexity; requires additional communication and control; privacy concerns.	Urban clusters with diverse resources and strong coupling among microgrids.
Mesh	All microgrids interconnected with each other and with the main grid.	Theoretically allows maximum flexibility; suitable for distributed optimization studies.	Impractical for real deployment; very high infrastructure and coordination requirements.	Mainly used in theoretical research and algorithm development.

3 Energy management system

A special form of hierarchical architecture, a nested structure, is mentioned in some literature sources. In it, microgrids are assigned to a number of hierarchical levels and communicate their information from the bottom up. The EES (Energy Storage System) of all microgrids of the centralized type, connectable units and controllable loads are all centralized at the level of a common controller, which is also responsible for communication between microgrids, participation in auctions, change of operating modes and control functions for stability. It optimizes the objective function of all microgrids. Such a scheme implies high computational capabilities for the central controller, since with the addition of RES, the optimization problem increases in size. Coordination in this case is greatly simplified due to the presence of only one controller, but it requires exchange of information, for example, about generation costs or load profile with the central controller, which the microgrids may not want to do [15].

4 Data Flow and Practical Implementation

In the proposed framework, the data flow begins with the forecasting layer, which produces short-term predictions for renewable generation and load demand. These predictions are then transferred to the uncertainty modeling layer, where forecast uncertainty is quantified using probabilistic or fuzzy models.

Next, the distributed optimization layer leverages these uncertainty parameters to calculate optimal dispatch strategies while considering system constraints. Finally, the decision-making layer executes these strategies, ensuring reliable and efficient operation of the network.

For practical implementation, this architecture can be realized using hierarchical controllers combined with cloud-based distributed EMS platforms. A typical testbed could involve IEEE 33-bus or 69-bus systems, allowing for scalable validation in smart grid scenarios.

5 Uncertainty modeling

One of the unique aspects of power system operation and planning is that the decision-making problem is under a high level of uncertain information. It has been reported that the traditional and deterministic methods in power system studies are not capable to address the uncertainties existent in power system studies. Therefore, various uncertainty modeling methods have been introduced for modeling and introducing the electricity market under uncertainty. The existing uncertainty modeling methods include probabilistic methods, feasibility methods, combined feasibility-probabilistic methods, information gap decision theory, and robust optimization. The primary purpose of the existing methods is to quantify the impact of uncertain input parameters on the system's output parameters. However, the main differences between these methods are in the use of different methods to describe the uncertainty of the input parameters. For example, in probabilistic methods, a probability density function is considered, while in the fuzzy method, a membership function

is assigned to model the uncertain parameters. A brief description of uncertainty modeling using the mentioned methods is provided in Table 3.

In the proposed framework, stochastic methods model uncertainties as random variables with specified probability distributions, enabling scenario-based optimization. Probabilistic approaches generalize this by quantifying

uncertainty via likelihood functions or probability densities, without strictly defined distributions. Interval-based methods, in contrast, represent uncertainties as bounded ranges, treating all values within the bounds as equally feasible. These distinctions are consistently applied in the manuscript to prevent conceptual overlap.

Table 3: Different methods for modeling uncertainty of distributed generation resources

Probabilistic Modeling Method	Concept	Advantages	Disadvantages	Reference	Objective function
Stochastic Modeling	This method uses probability theory to characterize the uncertainty associated with distributed generation resources. This involves defining probability distributions for the relevant variables and performing statistical analysis.	Probabilistic modeling provides a comprehensive representation of uncertainty, enabling risk assessment and decision-making under uncertainty. It shows the probability of different outcomes.	This method can be computationally intensive, especially for high-dimensional problems. Choosing appropriate probability distributions and interpreting results can be difficult.	[16]	Minimizing distribution network losses using reactive power optimization
Interval Analysis	Introduces randomness into the system model. Stochastic processes are used to describe the behavior of distributed generation resources over time.	It captures the temporal variability of resources, provides insights into system dynamics, and accounts for different sources of uncertainty.	Computational complexity can be high and simplifications are required for long-term simulations.	[17]	Increasing distribution network resilience against severe floods
Fuzzy Logic	Interval analysis represents uncertainties using intervals or ranges rather than exact values. This method provides upper and lower bounds for the behavior of the system.	It is computationally efficient, provides guaranteed bounds, and is useful when exact probability distributions are not available.	May yield very conservative results, may not provide probabilistic insights, and may not show correlations between uncertainties.	[18]	Minimizing energy consumption costs over the entire time horizon
Machine Learning	Fuzzy logic extends traditional logic by allowing partial truth values, which allows for the representation of uncertain or uncertain information. Membership functions define the degree of membership in a set.	It handles ambiguous information, offers a flexible modeling approach, and incorporates expert knowledge.	Can be difficult to define appropriate membership functions and rules, may not provide accurate probabilistic assessments.	[19]	Identifying weaknesses in the reliability testing system and installing distributed generators based on it
Hybrid Method	Machine learning techniques learn patterns and relationships from historical data to model uncertainty. They include regression, classification, and reinforcement learning.	It captures complex relationships, adapts to changing conditions, handles high-dimensional data, and provides probabilistic predictions.	Depending on the available data and their quality, interpreting results and ensuring model generalizability can be challenging.	[20]	Minimizing energy costs without affecting production and minimizing environmental impacts
Robust Optimization	Hybrid methods combine several methods to take advantage of their strengths. For example, combining probabilistic modeling with machine learning	It comprehensively represents uncertainty, solves specific challenges, and takes advantage of multiple techniques.	Higher complexity, requires expertise in multiple domains, requires careful design and validation.	[21]	Minimizing microgrid operating costs
Sensitivity Analysis	Robust optimization seeks to find solutions that are optimal for a range of uncertain scenarios. It considers worst-case or best-case scenarios within defined sets of uncertainties.	Provides solutions that are less sensitive to uncertainty, ensures feasibility or performance assurance	May be conservative and does not fully exploit sparse resources, may be difficult to define appropriate uncertainty sets.	[22]	Energy management of active distribution networks with the presence of energy storage and demand flexibility
Probabilistic Modeling Method	Sensitivity analysis shows how changes in uncertain parameters affect the behavior of the system. This analysis helps prioritize uncertainties and understand their impact.	Provides insights into critical uncertainties, guides decision-making, and helps focus resources on impactful factors.	It does not provide a complete picture of the uncertainties, and may not show interactions between uncertainties.	[23]	Optimizing the total cost of the energy system

Table 3 gives the taxonomy of frequently used uncertainty modeling approaches. Figure 5 shows the tree diagram associated with Table 3.

Besides, Table 4 reviews the recent related research on multi-microgrid energy management (MEM) in the period of 2020–2024. The important features of the works such as main objective, the types of uncertainty model, used algorithm, and their advantages and disadvantages are discussed. In this way, the comparison of recent works is performed, the state-of-art of research area is defined, and the research gaps that are the main motivations for this study are revealed. Under high renewable energy penetration, probabilistic and ML-based

forecasting methods achieve higher adaptability and prediction accuracy but are sensitive to data quality and computation burden. Conversely, robust optimization ensures system feasibility and stability but tends to yield conservative results, often sacrificing cost-efficiency. Hybrid frameworks that combine probabilistic forecasts with robust scheduling demonstrate superior resilience and flexibility. Therefore, such hybrid approaches are increasingly recognized as promising candidates for uncertainty-aware multi-microgrid operation. Motivated by the identified research gaps and the comparison of the recent works, in Fig. 6, we present a conceptual architecture for uncertainty-aware EMS of multi-microgrid systems.

Table 4: Comparative review of recent studies (2020–2024) on multi-microgrid energy management under uncertainty

Reference	Objective / Focus	Uncertainty Modeling	Solution Method	Strengths	Limitations	Main Findings / Limitations
[5]	EMS for DC microgrids considering battery degradation	Probabilistic (battery lifetime models)	MILP	Considers realistic battery degradation; cost-optimal scheduling	High computational complexity; limited scalability	Effective in optimizing battery usage and cost, but scales poorly with system size پززی
[10]	Multi-microgrid EMS: architecture and scheduling	Mixed (stochastic + heuristic)	Hierarchical coordination	Provides detailed architecture; considers communication issues	Simplified network constraints; limited robustness	Good architectural framework and comms modeling; limited robustness under severe uncertainties
[8]	Energy management in transmission-mode multi-microgrids	Robust optimization	Bilevel optimization	Models transmission capacity; enhances resilience	Conservative results; no market interaction	Strengthens grid resilience; may be overly conservative, ignores market dynamics
[7]	Multi-area islanded hybrid microgrids	Stochastic modeling	Scenario-based MILP	Captures temporal variability; improves resilience	Many scenarios → high computational burden	Captures variability effectively; computationally intensive for large systems
[4]	Resilience-oriented planning of mobile storage	Probabilistic risk-based	Mixed-integer programming	Enhances resilience against outages	Focus on resilience; less on cost/market	Strong resilience focus; cost and market aspects underexplored
[11]	Enhancing cybersecurity in distributed microgrids	Not explicit (focus on comms)	Review + framework	Comprehensive survey of communication protocols	No quantitative optimization model	Thorough communication survey; lacks quantitative EMS modeling
[14]	Reactive power flow optimization	Hybrid (Taguchi + metaheuristic)	Dandelion algorithm	Effective hybrid approach	Validation only on small systems	Shows potential of hybrid optimization; applicability to large systems untested
[16]	MPC for distributed resources	Probabilistic forecast error	Model Predictive Control	Adaptive MPC; handles forecast errors	Computationally demanding	Improves forecast handling; high computational burden may limit real-time use
[12]	Deep learning-based demand response	Machine learning (forecasting)	Deep learning + MILP	Captures nonlinear patterns; improves demand response	Needs big data; generalization uncertain	Captures complex demand patterns; dependent on large datasets and generalizability
[18]	Smart EMS using ML	ML-based probabilistic	Reinforcement learning	Adaptive, scalable	Requires training data; low explainability	Adaptive and scalable EMS; low transparency and need for training data

The proposed architecture envisions integrating the four main layers including the short-term forecasting, uncertainty modeling, distributed optimization, and decision-making. As such, the proposed architecture manifests how machine-learning-based forecasting and robust optimization can be coupled with privacy-preserving distributed coordination for realizing scalable, resilient, and market-compatible EMS solutions.

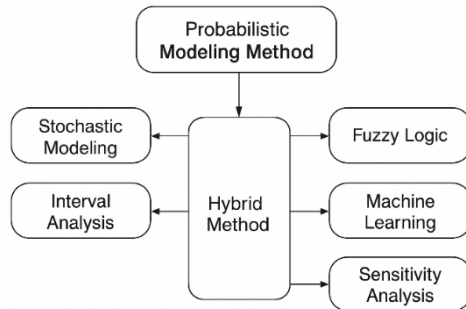


Figure 5: Tree diagram of uncertainty modeling approaches

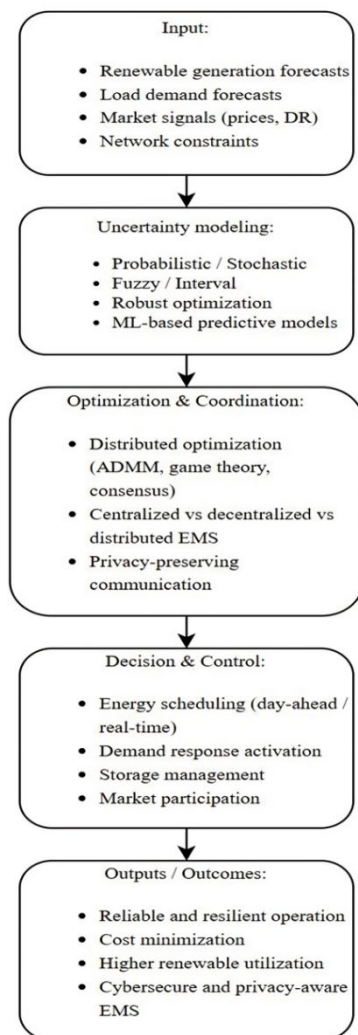


Figure 6: conceptual architecture for uncertainty-aware EMS of multi-microgrid systems [12]

Comparative and Critical Analysis

Various uncertainty-handling and optimization methods have been critically analyzed to identify their comparative strengths and weaknesses. Stochastic approaches provide probabilistic insight but are computationally demanding; robust optimization ensures reliability but may be conservative; interval and fuzzy approaches are simple yet lack probabilistic interpretation; and machine-learning-based methods are adaptive but depend on data quality. Hybrid approaches, combining ML-based forecasting with robust or chance-constrained optimization, provide a balanced trade-off between accuracy and robustness.

This comparative perspective offers a guideline for selecting suitable strategies based on system scale, data availability, and required reliability level. To provide a measurable comparison, several studies were analyzed for quantitative metrics.

Table 5: Recent studies for quantitative metrics

Reference	Year	Method	Cost Reduction (%)	RES (Renewable Energy Source) Utilization (%)	Computation Time (s)	Key Remarks
[21]	2021	Stochastic MILP	8.5	72	1200	Realistic small-scale case
[22]	2022	Robust ADMM	5.1	65	300	Conservative but reliable
[23]	2024	ML-based RL	9.3	78	260	Fast and adaptive approach

These results show that hybrid and ML-based approaches generally achieve better renewable utilization while maintaining acceptable computational efficiency.

Numerous solution methods and algorithms based on the distributed optimization technique have been reported in the literature for solving such problems, including methods based on game theory, hierarchical decision making, ADMM algorithms, consensus algorithms, heuristic methods, and dual decomposition [24-31]. If the problem under study has a decomposable structure or can be mathematically manipulated into a form that has such a structure, then only the distributed optimization approach can be used, and these subproblems can be solved locally, and the optimal solution for all microgrids can be obtained by sharing information through an iterative algorithm [31-41]. The implementation approach of the distributed solution algorithm changes depending on the type and structure of the optimization problem, and for each type of problem, methods such as Benders decomposition and Dantzig-Wolf decomposition are applied, respectively. The dual decomposition method has been applied to many optimization problems that can benefit from a distributed solution [41-48]. Therefore, the optimization model is considered according to equation (1).

$$\begin{aligned} \min \sum_{i=1}^I f_i(x) \\ \text{s. t. } g_i(x) \leq a_i \\ \sum_{i=1}^I h_i(x) \leq b \end{aligned} \quad \text{Eq 1}$$

where:

- x_i denotes the local decision vector (generation, storage, and exchange variables) for microgrid i ,
- $f_i(x_i)$ is its local objective function (e.g., operation cost, emission, or power loss),
- $g_i(x_i)$ represents the local operational constraints,
- $b_i = A_i x_i$ defines coupling constraints among microgrids, e.g., power balance at the point of common coupling.

Where $f(x)$ the objective function is a convex, quadratic, and separable function with respect to the variables x ; $g(x)$ is a separable function across the variables x that represents a set of inequality constraints of the problem; $h(x)$ is a function related to another set of problem constraints, but not separable across the variables x ; b are the values on the right-hand side corresponding to the inequality constraints. On the basis of the properties above, the dual decomposition method is applied to the problem to relax the difficult constraints.

$$\begin{aligned} \max_{\lambda} \left\{ \min_x \sum_{i=1}^I f_i(x) + \lambda [b - \sum_{i=1}^I h_i(x)] \right\} \\ \text{s. t. } g_i(x) \leq a_i \end{aligned} \quad \text{Eq 2}$$

the resulting subproblems. At each iteration, the dual variable is updated using an appropriate optimization scheme, such as the subgradient method or cutting-plane approaches, depending on the smoothness of the dual function. Each subproblem corresponds to a local optimization task for a specific microgrid, which minimizes its own Lagrangian function while considering the current value of λ . The updated dual variable λ^{k+1} is then obtained based on the aggregated coupling constraint violations across all subsystems. This iterative process continues until convergence is achieved—i.e., when the difference between successive dual variables or the primal residuals falls below a predefined threshold. The method ensures coordination among all microgrids while maintaining privacy of local data and achieving a global optimal solution under convexity assumptions.

$$\lambda^{k+1} = \lambda^k + \alpha^k s^k \quad \text{Eq 3}$$

where α^k is the step size at iteration k , and $x_i^{(k)}$ is the local optimal solution at iteration k . Convergence of the algorithm is guaranteed if the objective function is convex and the step-size rule satisfies diminishing or square-summable conditions. The step size α can be chosen following different rules. For a fixed step size, the sub-gradient algorithm will converge to a bound on the optimal value in a finite number of steps which will depend on the step size. The iterative procedure is the following: at each step it starts with the dual variable set to a fixed value, then it solves the sub-problem independently with the dual variable as a parameter. Then the previous process is repeated by solving the sub-problems with the new dual variables. The above process is iterated until convergence. It is important to note that the sub-gradient algorithm is very sensitive to the chosen step size α because it progresses in an oscillating way towards the optimal value. This causes the

main drawback of the algorithm because it makes very difficult the choice of a suitable stopping criterion. In general, the algorithm stops after a fixed number of iterations. Variable step sizes could enhance the speed of convergence of the algorithm but it strongly depends on the problem under consideration. Moreover, the objective function must be convex with respect to the coupled variables of the problem to ensure convergence.

Following the review of recent MMG EMS studies and their uncertainty models, Section 5 integrates these insights into a conceptual EMS architecture. Here, forecasting, modeling, and optimization layers are shown to interact coherently, demonstrating how theoretical models translate into practical control strategies across multi-microgrid systems.

6 Discussion

In synthesizing the information from the previous sections, several insights emerge on uncertainty modeling and optimization techniques for multi-microgrid energy management. First, although significant advances in stochastic and robust optimization have been made in recent years, most works considered here represent uncertainty in a rather simplistic way by assuming that random variables are independent, or by not accounting for temporal correlation of renewables generation and load profiles. This often results in models that may be solvable and work well in simulations, but become less robust in practice under realistic operating conditions.

Figure 7 presents a bubble chart illustrating the frequency of uncertainty modeling methods (probabilistic, fuzzy, robust, ML-based) versus their occurrence in recent studies. The chart provides a visual taxonomy showing how forecasting and optimization approaches co-occur across reviewed works, thereby highlighting dominant research trends between 2020 and 2024.

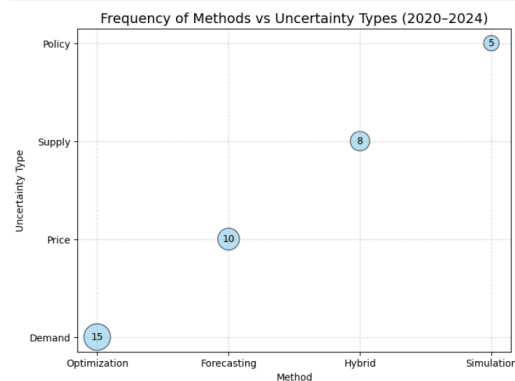


Figure 7: Quantitative Synthesis

Second, even though distributed ADMM, game-theoretic, and consensus-based approaches have received increasing attention, there is still limited evidence on their scalability and convergence speed for large-scale multi-microgrid clusters. While most of the existing works show the feasibility of such

methods on small test networks, the performance under realistic communication delays, packet losses, or cyberattacks is rarely analyzed. This leaves the questions whether, and if so how, these distributed approaches can be deployed in the field in large smart distribution grids.

Third, by comparing the techniques and application areas in the survey, it can be seen that very little work has been done on machine learning-based forecasting with subsequent integration in optimization models. While some recent publications adopt deep learning or reinforcement learning for prediction or for joint scheduling and control, only few provide a hybrid architecture where the predictive models are coupled to robust or chance-constrained optimization. Such hybridization of data-driven and optimization-based methods would potentially reduce the conservatism of robust approaches and lead to more adaptive solutions.

Another interesting trend can be found in the role of market mechanisms for economic coordination among microgrids. While a number of frameworks for transactive energy and peer-to-peer trading have been proposed, most studies still consider either a centralized decision maker or not conflicting objectives of independent stakeholders. However, from a practical perspective, a multi-microgrid system is a multi-agent system with often contradicting interests, so an exclusive focus on optimization does not represent reality sufficiently well.

From a resilience perspective, the surveyed literature shows that microgrids can be used to enhance local reliability of supply during extreme events. However, most of the existing works on this topic are case-specific and not directly generalizable to large interconnected networks. In addition, the cybersecurity aspect is almost never considered as part of the optimization models, but rather discussed separately in the context of communications. A fully cyber-physical approach is required to enable secure operation under uncertainty.

These observations also inform the potential directions of future multi-microgrid EMS research. It is clear that while theoretical advancements and tractable modeling assumptions are still needed, especially for large-scale systems, the next step of EMS research must include real-world implementation constraints. These can include hardware limitations, regulatory or market-driven incentives, as well as a wide range of operational constraints. Standardized benchmarks and hardware-in-the-loop testbeds would be highly beneficial to enable fair comparison and quick translation of advanced optimization models into practice.

The proposed framework offers significant practical value for both academic research and industrial applications. It can support smart-city energy coordination, real-time utility scheduling, and regulatory policy evaluation. Moreover, its modular and flexible design allows for seamless integration with existing industrial EMS platforms, facilitating deployment in real-world operational environments. This highlights the potential for the framework not only to advance theoretical research but also to address industry challenges in energy management and planning.

7 Conclusion & Future work

This review paper has provided a detailed discussion on different aspects of energy management for multi-microgrid systems under renewable and load uncertainties. We started by categorizing existing uncertainty modeling approaches and then performed a survey of the methods for optimization and coordination in uncertain multi-microgrid environments. A critical assessment of the existing literature (2020–2024) was done to show the main recent trends and reveal the most important gaps in order to promote further research toward real-scale and practical applications.

Despite the promising results, practical implementation of the proposed models faces several challenges. Computational limitations arise in large-scale MILP and scenario-based models, which can be mitigated using parallel and distributed solvers such as ADMM. Moreover, ML-based approaches heavily rely on high-quality data, and leveraging synthetic or hybrid datasets can enhance model robustness. Data exchange among distributed agents may also raise privacy and cybersecurity concerns, for which differential privacy and encrypted communication can be effective solutions. In addition, many theoretical studies overlook real market constraints; thus, incorporating regulatory rules and transactive mechanisms is essential for real-world deployment.

To the best of our knowledge, the main contributions of this paper are threefold. First, we surveyed and compared different uncertainty modeling approaches. The state-of-the-art (2020–2024) literature in this domain was summarized to provide a comparative overview on the existing approaches, including classical (probabilistic and fuzzy), data-driven, and machine learning-assisted uncertainty frameworks. Second, we identified existing gaps and presented a conceptual framework that may serve as a blueprint for future development in this domain, providing a one-stop-shop reference that can connect disparate research works. The conceptual framework here is comprised of interrelated and integrated building blocks, including forecasting and uncertainty modeling, distributed optimization, and market-aware decision making in presence of uncertainty. Third, by critically reviewing the literature, we pointed out potential application venues, use cases, and industry relevance.

Potential practical implications. The discussion and framework developed in this paper reveal that EMS frameworks based on distributed, scalable, and uncertainty-aware architectures can be the most valuable enablers for achieving high resilience and sustainability of the overall power system in near- and midterm time scales, especially when deployed in the emerging context of smart city ecosystems. In this regard, the integration of machine learning-based short-term forecasting and uncertainty modeling methods with robust or stochastic optimization-based decision making under uncertainty can be expected to lead to high reliability in the operational planning of the interconnected microgrids. However, distributed privacy-preserving

approaches for multi-stakeholder decision making are of critical importance for this to be feasible in real-world deployments. Although this review strived to cover the main aspects of coordination, optimization, and distributed decision-making in MMG energy management, several important dimensions remain beyond its current scope. The key limitations and future research directions are summarized as follows:

- **Hardware-in-the-loop validation:** Future studies should employ hardware-in-the-loop (HIL) platforms to validate the proposed EMS frameworks under realistic operational conditions.
- **Communication and interoperability standards:** Further work is needed to address interoperability protocols and communication reliability for large-scale multi-microgrid coordination.
- **Long-term techno-economic assessment:** Comprehensive economic and lifecycle analyses are essential prerequisites for real-scale deployment of EMS frameworks.
- **Hybrid data-driven and robust frameworks:** Combining the predictive power of machine learning with distributionally robust or stochastic optimization can enhance adaptability and reduce conservatism.
- **Cyber-resilient EMS architectures:** Future EMS designs should embed cybersecurity and resilience mechanisms at every level of system decomposition.
- **Benchmark testbeds and datasets:** Developing open benchmark datasets and testbeds will enable fair comparison and validation of proposed algorithms.
- **Integration of multi-energy and market-aware systems:** Expanding EMS frameworks to include multi-energy carriers (electricity, heat, and gas) and real-world market dynamics will improve practical applicability.

In conclusion, this review can be regarded as a comprehensive state-of-the-art reference on multi-microgrid EMS frameworks under renewable and load uncertainties. It provides both researchers and practitioners with a structured basis for developing resilient, scalable, and market-compatible energy management systems.

Disclosure of Potential Conflicts of Interest

The Authors declare that there is no conflict of interest

Reference

- [1] D. E. Olivares, A. Mehrizi-Sani, A. H. Etemadi, C. A. Cañizares, R. Iravani, M. Kazerani, and N. D. Hatziargyriou, "Trends in Microgrid Control" *IEEE Trans. Smart Grid*, Vol. 5, No. 4, pp. 1905-1919, 2014. DOI: [10.1109/TSG.2013.2295514](https://doi.org/10.1109/TSG.2013.2295514)
- [2] M. Ahrari, K. Shirini, S. S. Gharehveran, M. G. Ahsae, S. Haidari, and P. Anvari, "A Security-Constrained Robust Optimization for Energy Management of Active Distribution Networks with Presence of Energy Storage and Demand Flexibility" *J. Energy Storage*, Vol. 84, pp. 111024, 2024. <https://doi.org/10.1016/j.est.2024.111024>
- [3] P. Delgoshaei and J. D. Freihaut, "Development of a Control Platform for a Building-Scale Hybrid Solar PV-Natural Gas Microgrid" *Energies*, Vol. 12, No. 21, pp. 4202, 2019. <https://doi.org/10.3390/en12214202>
- [4] S. S. Gharehveran, S. G. Zadeh, and N. Rostami, "Resilience-Oriented Planning and Pre-Positioning of Vehicle-Mounted Energy Storage Facilities in Community Microgrids" *J. Energy Storage*, Vol. 72, pp. 108263, 2023. <https://doi.org/10.1016/j.est.2023.108263>
- [5] F. Li, C. Cañizares, and Z. Lin, "Energy Management System for DC Microgrids Considering Battery Degradation" *2020 IEEE Power & Energy Society General Meeting (PESGM)*, pp. 1-5, 2020. DOI: [10.1109/PESGM41954.2020.9281580](https://doi.org/10.1109/PESGM41954.2020.9281580)
- [6] V. Amir, S. Jadid, and M. Ehsan, "Probabilistic Optimal Power Dispatch in Multi-Carrier Networked Microgrids under Uncertainties" *Energies*, Vol. 10, No. 11, pp. 1770, 2017. <https://doi.org/10.3390/en10111770>
- [7] M. M. Ibrahim, H. M. Hasanien, H. E. Farag, and W. A. Orman, "Energy Management of Multi-Area Islanded Hybrid Microgrids: A Stochastic Approach" *IEEE Access*, 2023. doi: [10.1109/ACCESS.2023.3313259](https://doi.org/10.1109/ACCESS.2023.3313259)
- [8] S. A. Mehraban and R. Eslami, "Multi-Microgrids Energy Management in Power Transmission Mode Considering Different Uncertainties" *Electr. Power Syst. Res.*, Vol. 216, pp. 109071, 2023. <https://doi.org/10.1016/j.epr.2022.109071>
- [9] D. Gregoratti and J. Matamoros, "Distributed Energy Trading: The Multiple-Microgrid Case" *IEEE Trans. Ind. Electron.*, Vol. 62, No. 4, pp. 2551-2559, 2014. doi: [10.1109/TIE.2014.2352592](https://doi.org/10.1109/TIE.2014.2352592)
- [10] B. Zhou, J. Zou, C. Y. Chung, H. Wang, N. Liu, N. Voropai, and D. Xu, "Multi-Microgrid Energy Management Systems: Architecture, Communication, and Scheduling Strategies" *J. Mod. Power Syst. Clean Energy*, Vol. 9, No. 3, pp. 463-476, 2021. doi: [10.35833/MPCE.2019.000237](https://doi.org/10.35833/MPCE.2019.000237)
- [11] S. S. Gharehveran, K. Shirini, S. C. Khavar, S. H. Mousavi, and A. Abdolahi, "Deep Learning-Based Demand Response for Short-Term Operation of Renewable-Based Microgrids" *J. Supercomput.*, pp. 1-34, 2024. <https://doi.org/10.1007/s11227-024-06407-z>
- [12] M. Shahidehpour, Z. Li, S. Bahramirad, Z. Li, and W. Tian, "Networked Microgrids: Exploring the Possibilities of the IIT-Bronzeville Grid" *IEEE Power Energy Mag.*, Vol. 15, No. 4, pp. 63-71, 2017. doi: [10.1109/MPE.2017.2688599](https://doi.org/10.1109/MPE.2017.2688599)
- [13] M. Najjarpour and B. Tousi, "Probabilistic Reactive Power Flow Optimization of Distribution System in Presence of Distributed Units Uncertainty Using Combination of Improved Taguchi Method and Dandelion Algorithm" *Int. J. Eng., Trans. A: Basics*, Vol. 37, No. 1, pp. 37-47, 2024.
- [14] S. S. Gharehveran, S. Ghassemzadeh, and N. Rostami, "Two-Stage Resilience-Constrained Planning of Coupled Multi-Energy Microgrids in the Presence of Battery Energy Storages" *Sustain. Cities Soc.*, Vol. 83, pp. 103952, 2022. <https://doi.org/10.1016/j.scs.2022.103952>
- [15] F. Langner, W. Wang, M. Frahm, and V. Hagenmeyer, "Model Predictive Control of Distributed Energy Resources in Residential Buildings Considering Forecast Uncertainties" *Energy Build.*, Vol. 303, pp. 113753, 2024.
- [16] M. Lindsay and M. Emimal, "Fuzzy Logic-Based Approach for Optimal Allocation of Distributed Generation in a Restructured Power System" *Int. J. Appl. Power Eng.*, Vol. 13, No. 1, pp. 123-129, 2024. DOI: [10.11591/ijape.v13.i1.pp123-129](https://doi.org/10.11591/ijape.v13.i1.pp123-129)

- [17] A. Akram, S. Abbas, M. Khan, A. Athar, T. Ghazal, and H. Al Hamadi, "Smart Energy Management System Using Machine Learning" *Comput. Mater. Continua*, Vol. 78, No. 1, 2024. <http://dx.doi.org/10.32604/cmc.2023.032216>
- [18] Xing, Xueliang, and Limin Jia. "Energy management in microgrid and multi-microgrid." *IET Renewable Power Generation* 18, no. 15, 2024: 3480-3508. <https://doi.org/10.1049/rpg2.12816>
- [19] Rajaei, Ali, Sajjad Fattaheian-Dehkordi, Mahmud Fotuhi-Firuzabad, and Moein Moeini-Aghtaie. "Decentralized transactive energy management of multi-microgrid distribution systems based on ADMM." *International Journal of Electrical Power & Energy Systems* 132, 2021: 107126. <https://doi.org/10.1016/j.ijepes.2021.107126>
- [20] Yang, Jun, and Changqi Su. "Robust optimization of microgrid based on renewable distributed power generation and load demand uncertainty." *Energy* 223, 2021: 120043.
- [21] R. Singh, Arvind, R. Seshu Kumar, Mohit Bajaj, Chetan B. Khadse, and Ievgen Zaitsev. "Machine learning-based energy management and power forecasting in grid-connected microgrids with multiple distributed energy sources." *Scientific Reports* 14, no. 1, 2024: 19207. <https://doi.org/10.1038/s41598-024-70336-3>
- [22] Shirini, K., Kordan, M. B., & Gharehveran, S. S. (2025). Impact of learning rate and epochs on lstm model performance: a study of chlorophyll-a concentrations in the Marmara Sea. *The Journal of Supercomputing*, 81(1), 265. <https://doi.org/10.1007/s11227-024-06806-2>
- [23] Taherihajivand, A., Shirini, K., & Samadi Gharehveran, S. (2024). Weed detection in fields using convolutional neural network based on deep learning. *Agricultural Engineering*, 47(1), 129-142. <https://doi.org/10.22055/agen.2024.45327.1688>
- [24] Sattari, M. T., Shirini, K., & Javidan, S. (2024). Evaluating the efficiency of dimensionality reduction methods in improving the accuracy of water quality index modeling in Qizil-Uzen River using machine learning algorithms. *Water and Soil Management and Modelling*, 4(2), 89-104.
- [25] Sattari, M. T., Bagheri, R., Shirini, K., & Allahverdipour, P. (2024). Modeling daily and monthly rainfall in Tabriz using ensemble learning models and decision tree regression. *Scientific Journal of Golestan University*, 5(18). [Doi: 10.30488/CCR.2024.433394.1192](https://doi.org/10.30488/CCR.2024.433394.1192)
- [26] Shirini, K., Taherihajivand, A., & Samadi Gharehveran, S. (2023). A review of algorithms for solving the project scheduling problem with resource-constrained considering agricultural problems. *Journal of Agricultural Mechanization*, 8(1), 1-14. [DOR:10.22034/jam.2023.55751.1227](https://doi.org/10.22034/jam.2023.55751.1227)
- [27] Gharehveran, S. S., Shirini, K., Khavar, S. C., & Abdollahi, A. (2025). Optimizing day-ahead power scheduling: a novel MIQCP approach for enhanced SCUC with renewable integration. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, 101022. <https://doi.org/10.1016/j.prime.2025.101022>
- [28] Taherihajivand, A., Shirini, K., & Samadi Gharehveran, S. (2024). An overview of product performance prediction using artificial algorithms. *Journal of Agricultural Mechanization*, 9(3), 1-14. <https://doi.org/10.22034/jam.2024.61899.1276>
- [29] Saeedi, N., Baharvand, D., Shirini, K., & Gharehveran, S. S. (2025). Prediction of electrical energy consumption using principal component analysis and independent components analysis. *The Journal of Supercomputing*, 81(9), 1072. <https://doi.org/10.1007/s11227-025-07505-2>
- [30] Shirini, K., Hajivand, A. T., & Gharehveran, S. S. (2024). A novel deep learning-based method for potato leaf disease classification. 9th Advanced Engineering Days, 9, 462-464.
- [31] Zaki Dizaji, H., Shirini, K., Taheri Hajivand, A., & Monjezi, N. (2024). Modelling variables affecting the yield of sugarcane fields using deep recurrent neural network. *Iranian Journal of Biosystems Engineering*, 55(2), 93-108. [10.22059/ijbse.2025.378958.665557](https://doi.org/10.22059/ijbse.2025.378958.665557)
- [32] Taheri Hajivand, A., Shirini, K., & Samadi Gharehveran, S. (2024). Balancing time and cost in resource-constrained project scheduling using meta-heuristic approach. *Journal of Agricultural Machinery*, 14(2), 215-234. [DOI: 10.22067/jam.2023.81735.1157](https://doi.org/10.22067/jam.2023.81735.1157)
- [33] Samadi Gharehveran, S., & Shirini, K. (2025). A Review of Resilient-oriented Operation Strategies of Electrical Energy Distribution Networks in Critical Situations. *Passive Defense*. [DOI: 10.22067/jpd.2025.123456](https://doi.org/10.22067/jpd.2025.123456)
- [34] Shirini, K., & Samadi, G. S. (2023). A review on algorithms for solving the resource-constrained projects scheduling problems with considering agricultural problems. [DOI: 10.22034/jam.2023.16162](https://doi.org/10.22034/jam.2023.16162)
- [35] Tan, J., Radhi, R. M., Shirini, K., Gharehveran, S. S., Parisooz, Z., Khosravi, M., & Azarinfar, H. (2025). Innovative framework for fault detection and system resilience in hydropower operations using digital twins and deep learning. *Scientific Reports*, 15(1), 15669. [DOI: 10.1038/s41598-025-98235-1](https://doi.org/10.1038/s41598-025-98235-1)
- [36] Ayele, Eyuel Debebe, Javier Ferreira Gonzalez, and Wouter B. Teeuw. "Enhancing cybersecurity in distributed microgrids: A review of communication protocols and standards." *Sensors* 24, no. 3, 2024: 854. <https://doi.org/10.3390/s24030854>
- [37] Shirini, K., Aghdasi, H. S., & Saeedvand, S. (2024). Modified imperialist competitive algorithm for aircraft landing scheduling problem. *Journal of Supercomputing*, 80(10). <https://doi.org/10.1007/s11227-024-05999-w>
- [38] Shirini, K., Aghdasi, H. S., & Saeedvand, S. (2024). A comprehensive survey on multiple-runway aircraft landing optimization problem. *International Journal of Aeronautical and Space Sciences*, 25(4), 1574-1602. <https://doi.org/10.1007/s42405-024-00747-z>
- [39] Shirini, K., Aghdasi, H. S., & Saeedvand, S. (2024). Multi-objective aircraft landing problem: a multi-population solution based on non-dominated sorting genetic algorithm-II. *The Journal of Supercomputing*, 80(17), 25283-25314. <https://doi.org/10.1007/s11227-024-06385-2>
- [40] Oskouei, A. G., Abdolmaleki, N., Bouyer, A., Arasteh, B., & Shirini, K. (2025). Efficient superpixel-based brain MRI segmentation using multi-scale morphological gradient reconstruction and quantum clustering. *Biomedical Signal Processing and Control*, 100, 107063. <https://doi.org/10.1016/j.bspc.2024.107063>
- [41] Gharehveran, S. S., Shirini, K., Khavar, S. C., Mousavi, S. H., & Abdollahi, A. (2024). Deep learning-based demand response for short-term operation of renewable-based microgrids. *The Journal of Supercomputing*, 80(18), 26002-26035. <https://doi.org/10.1007/s11227-024-06407-z>
- [42] Gheibi, Y., Shirini, K., Razavi, S. N., Farhoudi, M., & Samad-Soltani, T. (2023). CNN-Res: deep learning framework for segmentation of acute ischemic stroke lesions on multimodal MRI images. *BMC Medical Informatics and Decision Making*, 23(1), 192. <https://doi.org/10.1186/s12911-023-02289-y>

[43] Samadi Gharehveran, S. (2025). Optimization of the number of batteries and their arrangement in electric vehicles based on multi-objective optimization. *Passive Defense*.

[44] Samadi Gharehveran, S., Nasiri, M., & Ghassem Zadeh, S. (2025). Optimum operation of resilient multi-energy microgrids under low probability and high impact events. *Passive Defense*.