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Advances in Optimization Algorithms for Renewable Integration and Production-Side Management in Smart Grids

Fatima Zohra EL ARGOUBI Houssam Eddine CHAKIR* Mohamed EL KHAILI* Karim CHOUKRI* Mehdi ET-TAOUSSI**

* EEIS-Lab, ENSET Mohammedia, Hassan II University, Casablanca

Abstract. The integration of renewable energy sources into modern power grids has led to challenges in balancing generation and demand, maintaining grid stability, and ensuring operational efficiency. The smart grid paradigm, bolstered by AI, IoT, and advanced optimization algorithms, offers a promising platform to address these issues. Energy Management Systems (EMS) play a crucial role in coordinating distributed energy resources, enhancing forecasting, and optimizing generation scheduling while minimizing costs and emissions. A systematic review of recent algorithmic developments in production-side energy management for smart grids reveals four dominant categories: deterministic algorithms, metaheuristics, artificial intelligence-based methods, and hybrid approaches. The findings highlight the shift from conventional optimization to intelligent, adaptive, and hybrid solutions that combine forecasting, optimization, and control, underscoring the importance of advanced algorithms in enabling reliable, efficient, and sustainable operation of future smart grids.

1 Introduction

The worldwide energy shift, driven by decarbonization goals and increasing electricity consumption, presents significant problems for power generation systems [1]. The rising penetration of intermittent renewable energy sources (solar, wind, biomass, and hydro) has changed the power grid into a complex and uncertain ecosystem, needing intelligent management systems to ensure the balance between production and consumption [2,3].

The smart grid paradigm, reinforced by the rapid deployment of the Internet of Things (IoT), Artificial Intelligence (AI), and distributed computing (edge/fog computing), provides an improved platform to optimize production and enhance network resilience [2,4]. Energy Management Systems (EMS) play a crucial part in scheduling, dispatching, and optimizing energy flows while dealing with renewable variability, grid stability, and power quality difficulties [5].

Energy management algorithms, including deep learning, multi-agent systems, and metaheuristics, are crucial for improving renewable energy forecasting, optimizing unit commitment and generation scheduling, integrating distributed resources (DERs) Virtual Power Plants (VPPs), microgrids, and lowering operational costs while meeting environmental constraints [6,5,7].

The smart grid paradigm has evolved through successive stages (Fig. 1), each reflecting technological and structural transformations of modern power systems. The initial stage was marked by the deployment of advanced information and communication technologies (ICTs) to enable real-time monitoring and data acquisition. This was followed by the emergence of smart distribution systems, where local electricity markets, virtual power plants (VPPs), and data-driven coordination mechanisms became central to managing distributed energy resources (DERs). As decarbonization targets accelerated, grids entered a new phase characterized by high renewable energy penetration, requiring artificial intelligence (AI)-based forecasting, flexible scheduling, and energy storage integration to ensure stability and reliability. The most recent stage involves the large-scale integration of inverter-based resources and advanced power electronic devices, which redefine system dynamics and necessitate novel control strategies, grid-forming converters, and protection schemes to secure the transition toward 100% renewable power systems [8].

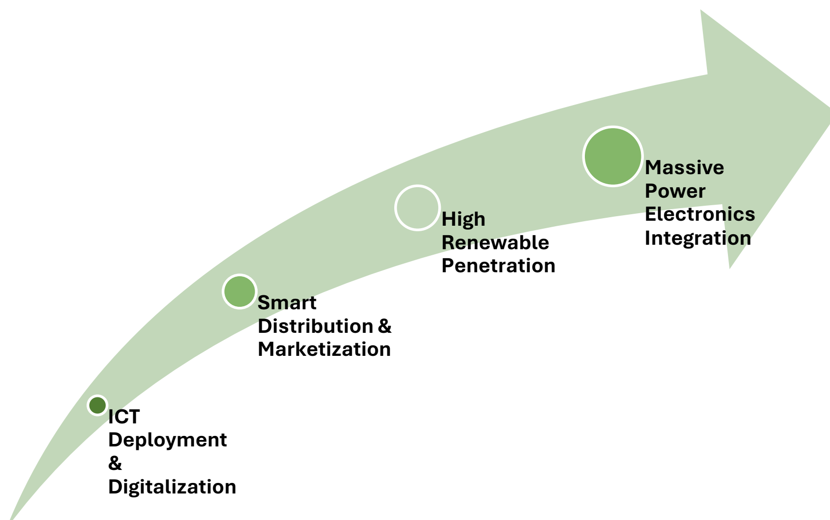

Fig.1. Evolution Stages of Smart Grids

This work seeks to provide a critical overview of recent algorithmic improvements in energy management on the production side. By evaluating recent works (2020-2025), it analyses trends, existing constraints, and prospects.

2 Research strategy

This study adopts a systematic research strategy to examine the evolution of energy management algorithms in smart grids, with a focus on the production side. The approach is structured around three main steps (Fig. 2):

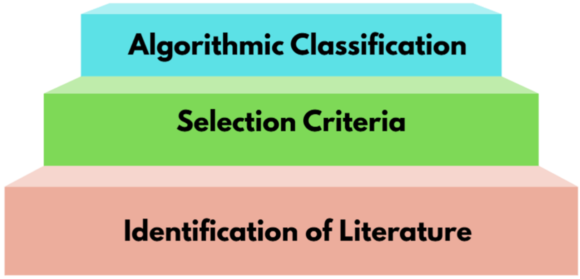

Fig.2. Three-Step Research Strategy

2.1 Identification of Literature

A comprehensive search was carried out using terms including "Smart Grid," "Energy Management Algorithms," "Optimization," "Forecasting," "Artificial Intelligence," "Metaheuristics," and "Reinforcement Learning" across ScienceDirect. To ensure coverage of recent algorithmic developments, Boolean operators and filters were implemented to target works published between 2020 and 2025.

2.2 Selection Criteria

Included only papers that suggested, used, or contrasted algorithmic methods for energy management. Works that were only associated with demand-side management, policy debates, or hardware development were not included. Duplicate entries, articles without methodological detail, and publications written in languages other than English were also excluded.

2.3 Algorithmic Classification

The selected contributions were organized into categories based on the algorithmic techniques employed.

3 Background

3.1 Smart Grid Energy Sources

Smart grid energy sources (Fig .3) combine renewable, conventional, and Energy Storage Systems (ESSs) to ensure reliable and sustainable electricity generation. Their integration enhances flexibility, stability, and efficiency in modern power systems.

3.1.1 Renewable Energy Sources (RESs)

Green, free, and year-round, renewable energy sources (RESs) can be used to generate electricity without the need for sophisticated equipment or sophisticated methods, which lowers the cost of production, transmission, and consumption [9]. Solar energy uses photovoltaic (PV) cells to capture solar radiation and transform it into electrical energy [10]. Wind turbines convert the kinetic energy of wind into mechanical energy, which is then used to produce electrical energy [11], It is a variable, intermittent, and

environment-dependent form of generation [12]. Hydroelectric energy is described as one of the most widely used RES in electric power production, contributing 17% to global energy production and ranking as the third-largest energy source [9]. It involves using water's potential energy to obtain mechanical energy, which is then converted into electrical energy using electric generators and water turbines [9]. According to [13] biomass is listed as one of the most commonly used renewable energy sources in microgrids. The paper [14] mentions geothermal as a type of large-scale sustainable energy plant that might fulfill the goal of energy production. According to [10], vibration energy is one of the various environmental energy sources that can be converted into electrical form for powering devices. d solar to power our daily activities [4–7]. The study emphasizes fuel cell-based hybrid power systems as essential components. To improve system sustainability and efficiency, fuel cells are frequently combined with renewable energy sources and are being taken into account more and more in energy management plans [9].
The use of renewable energy to replace fossil fuels which harm the environment has been extensively investigated in industrialized nations like the US, Australia, France, Germany, Italy, Spain, Turkey, and the UK. This trend is predicted to increase in the future [15].

3.1.2 Fossil-Based and Conventional Sources

Despite the global trend toward the integration of renewable energy sources, conventional and fossil-based energy sources continue to play a significant role in many smart grids and microgrid setups. Because of their dependability, diesel generators are frequently used as supplemental or backup units, particularly in remote or hybrid microgrids [15]. Thermal power plants, driven by coal or natural gas, still account for a significant share of large-scale electricity production worldwide, though they face increasing criticism for their carbon footprint [16]. More broadly, fossil fuels represent a traditional but environmentally costly energy supply option, contributing to greenhouse gas emissions and global warming [17]. Nuclear power, on the other hand, provides a low-carbon alternative with high energy density, but it raises concerns related to safety, waste management, and high capital costs [18].

3.1.3 Energy Storage Systems (ESSs)

Energy Storage Systems (ESSs) play a fundamental role in smart grids by ensuring stability, flexibility, and reliability in the presence of variable renewable generation. Among them, Battery Energy Storage Systems (BESS) [19], particularly lithium-ion technologies, are the most widely deployed due to their high efficiency, fast response, and scalability for both microgrids and large-scale applications [20]. Stationary battery groups provide centralized storage capacity for load balancing, peak shaving, and backup supply [21]. While vehicle batteries (EVs) are increasingly recognized as mobile storage units through vehicle-to-grid (V2G) integration [21]. In addition, supercapacitors complement batteries by delivering rapid charge–discharge cycles, making them valuable for frequency regulation and short-term stabilization [22]. Together, these storage technologies enhance energy management strategies by mitigating intermittency, supporting economic dispatch, and enabling the integration of high shares of renewable energy into production-side smart grids.

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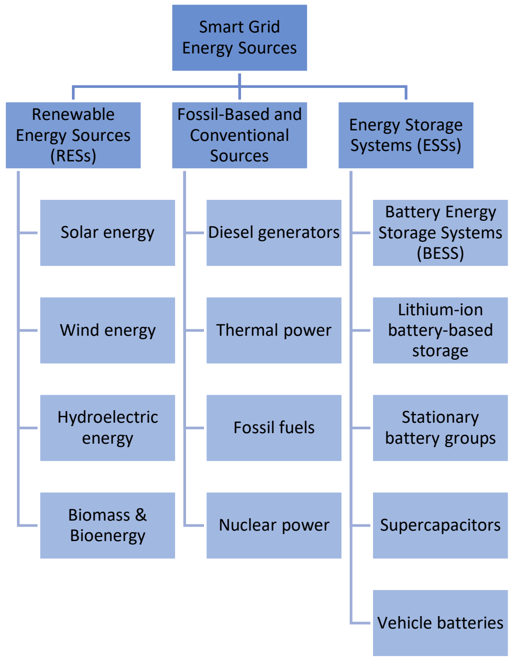

Fig.3. Smart Grid Energy Sources

3.2 Energy Management system (EMS)

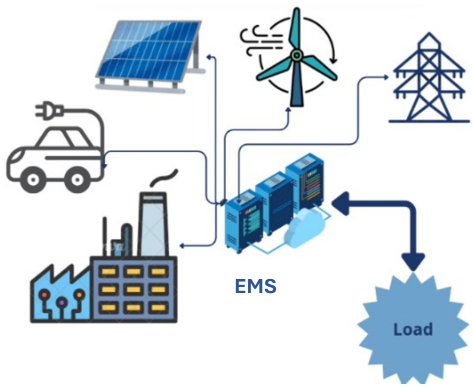

Fig.4. Energy Flow Managed by EMS in Smart Grid

The Energy Management System (EMS) is the controller that optimizes energy production and other operational objectives while calculating power flows to supply electricity to loads steadily (Fig .4) [23]. It plays a crucial role in integrating multiple energy sources within a microgrid, particularly under the economic-emission dispatch (EED) framework. By coordinating generation and demand, the EMS enables efficient utilization and optimization of available energy resources while simultaneously reducing fuel costs and lowering pollutant emissions [24]. The EMS also gathers information and applies algorithms for ptimal Distributed Generator (DG) allocation, minimizing power outages and ensuring stable operation [25].

4 Optimization Algorithms

Recent studies on energy management for microgrids demonstrate significant advancements in the optimization of Maximum Power Point Tracking (MPPT) has improved significantly, based on recent studies on microgrid energy management. according to the study [10], integrating the HHO and HBA algorithms into a hybrid HHO-HBA scheme extends the lifetime of IoT networks by improving convergence, increasing tracking efficiency from 85% to over 95%, and achieving an overall efficiency of 96.18%. [26] suggests a smart microgrid Enhanced Energy Management System (EMS) that maximizes energy flow and operating efficiency by utilizing an upgraded Honey Badger Algorithm (HBA).Simultaneously, [9] demonstrated how an intelligent control method that combines fuzzy logic Control (FLC) with a modified Perturb & Observe algorithm improves PV power output, lowers losses during abrupt irradiance swings, and extends battery life. Both studies demonstrate that hybridized control techniques greatly enhance PV system performance and storage durability, despite being based on different paradigms.
The reduction of expenses and emissions is the subject of a second line of inquiry. According to the study [24], the Lévy Arithmetic Algorithm (LAA) outperforms GA and AOA techniques in reducing emissions to 2233.5 kg and generation cost to 192,152.86 when applied to a PV/wind/diesel microgrid. A similar approach may be seen in [27], which used Gurobi and MILP optimization to compare two battery management strategies: Feed-in Damping (FD) and Self-Consumption (SC). While the SC technique increased emissions, the FD strategy reduced curtailed energy by 15.6%, cut costs by 5.64%, and boosted battery lifespan by almost two years. Both contributions agree on the significance of multi-objective optimization in lowering operating costs and environmental consequences, even if they use different optimization methodologies.
The importance of advanced management algorithms is further shown by research on grid-connected PV-battery systems. [14] showed that an ideal EMS has an annual average performance ratio of 81.1% and lowers grid usage by 43.5% on days with high loads. Additionally, [28]confirmed through tests on a 2.1 kW PV system the ability of an adaptive algorithm that combines Incremental Conductance MPPT with active/reactive power control to preserve power quality and guarantee continuous operation. With the use of real data,[29] suggests a GA-optimized controller for a grid-connected PV, BSS residential microgrid that explicitly models line losses and balances active and reactive power jointly. The ARLM strategy reduces energy costs by 26% compared to AOM and 13% compared to ARM, lowers RMSE voltage drop by more than 60%, increases the average power factor to ≈0.92, and mitigates transmission losses, CO_2 emissions, and BSS aging. These findings demonstrate how EMS optimization and adaptive real-time control work in tandem to improve the robustness of grid-connected devices.
Furthermore, a promising trend is the combination of bio-inspired optimization and artificial intelligence. [21] shown how an LSTM-based predictive model can efficiently coordinate PV, grid, and vehicle batteries while planning charging and optimizing energy flow, lowering demand by 8–20%. Similarly, [30]showed that an enhanced Grey Wolf Optimization in conjunction with an Artificial Neural Network (ANN) lowers THD to 0.83% and improves current tracking. In a similar vein, IGANN-PSOA demonstrated that combining an interpretable neural network (IGANN) with the Portia Spider Optimization Algorithm (PSOA) outperforms conventional techniques, achieving an efficiency of 98.2% and a quick response time of 63 ms. When taken as a whole, this research demonstrate that artificial intelligence (AI) and evolutionary optimization are crucial levers for enhancing microgrid systems' stability, forecasting, and energy quality.

Table 2. Overview of Energy Sources and Algorithms in Recent Smart Grid Studies.

Article	**Energy Source**	**Algorithm**	**Algorithm Family**
[10]	Solar and Wind sources	Honey Badger Algorithm (HBA) and Harris Hawks Optimization (HHO)	Hybrid approaches
[24]	solar photovoltaic (PV), wind turbine (WT), and multiple diesel generators as energy sources	L'evy Arithmetic Algorithm (LAA)	Metaheuristic Algorithm
[27]	photovoltaic (PV) Battery energy storage systems (ESS)	Q learning	AI-Based algorithm
[9]	photovoltaic (PV) diesel generator system energy storage system (batteries)	modified FLC-PO algorithm	Metaheuristic Algorithm
[14]	photovoltaic (PV) Battery energy storage systems (ESS)	-	-
[21]	grid, vehicle batteries, PV system, and the stationary battery group	long-short term based prediction model (LSTM)	AI-Based algorithm
[31]	Stationary bikes Photovoltaic (PV) Battery storage systems (ESS) Main grid	fuzzy logic control (FLC)	Deterministic Algorithms
	photovoltaic (PV)	adaptive energy management algorithm (AEMA)	Deterministic Algorithms
[25]	photoelectrochemical and voltaic cells (HPEV) and fuel cells (FC)	ANNs & IWSOA	Hybrid approaches
[30]	photovoltaic (PV) panels and wind turbines Electric vehicles (EVs) the main grid	Grey Wolf	Metaheuristic Algorithm
[32]	photovoltaic (PV)	sliding mode control	Deterministic Algorithms
[23]	Solar panels (PV), a wind turbine system, a Li-ion battery-based storage system, an electric vehicle (EV), and a DC load	Stochastic Model Predictive Control (SMPC)	control algorithms

5 Conclusion

The review highlights the rapid evolution of energy management algorithms in the smart grid paradigm, focusing on production-side applications. Recent contributions show a shift from conventional optimization techniques to intelligent, adaptive, and hybrid approaches that combine forecasting, optimization, and control. Deterministic methods provide reliability and mathematical rigor, while metaheuristics offer flexibility. Artificial intelligence techniques like neural networks and reinforcement learning show potential for predictive energy management and improved operational efficiency. Hybridization delivers performance gains in cost reduction, emission minimization, and renewable energy integration. Future research should integrate these methods into large-scale, real-time implementations.

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