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A Comprehensive Examination of Optimization Techniques and Photovoltaic Systems in Energy Management Systems

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Abstract
The Energy Management System (EMS) has the potential to enhance transmission operators' understanding of transmission and sub transmission networks as a whole. It has the capability to function as either a completely integrated system or as an independent system. The utilization of this technology facilitates the integration of renewable energy sources, ensures the dependability of the microgrid, and maximizes cost and economic efficiency within the interconnected power market. Energy Management Systems (EMSs) must successfully address dispatch optimization difficulties related to the available production and storage capacity in order to fulfill technoeconomic and environmental objectives. The inclusion of market data, real-time microgrid status and operational restrictions, as well as fabrication and demand forecasting data, is crucial in this context. Nevertheless, ongoing research is being conducted to create a system that minimizes capital expenses and functions solely on renewable energy sources. This necessitates the implementation of a hybrid system that is affordable for the typical individual. The primary objective and influence of the study is to provide information on current demand response programs and ideas for optimizing energy management systems. Furthermore, this research provides a thorough examination of demand response and optimization tactics, solar systems, and their diverse methodologies, alongside contemporary energy management systems.

Index- Energy *Management System, Optimisation methods, Photovoltaic system, Demand response system, Grid connected system.*

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I. Introduction

Energy has gained increasing importance in various aspects of our lives in recent decades. The affordability, acceptability, efficiency, and accessibility of energy are undeniably crucial factors for the progress of society and the attainment of an elevated quality of life [1,2]. Access to energy is crucial in the contemporary developing economy for initiating and sustaining thriving and efficient households [3]. Until recently, the global energy industry was mostly controlled by polluting and non-renewable energy sources, which had significant adverse impacts on both the economy and ecological, such as air pollution and global warming. In order to avert a disastrous 1.5°C increase in global temperatures since pre-industrial times, it is imperative that all energy production worldwide be sourced exclusively from clean, zero-emitting renewable sources by the year 2050 [4]. Several scholarly articles suggest that rural towns in developing nations could harness electricity to benefit their inhabitants, namely for water-related services [5, 6], agricultural activities, healthcare, education, and commercial activities [7, 8]. The absence of electricity in rural regions has been linked to the exacerbation of disparities within communities, leading to rural-urban migration and further straining urban infrastructure systems [8–10]. The electrification of rural areas in emerging nations presents challenges in terms of energy generation and transmission networks [7]. The current trajectory of the transmission system indicates that there will be a persistent lack of enough funding for new transmission lines in the coming decades, mostly due to the increasing supply and demand dynamics [11, 12]. The significance of improved distribution systems is consequently growing.

Energy management is widely recognized as a crucial and unique strategy for enabling the functioning of smart grids. The concept of "energy management" can be extended to encompass a wide range of subjects. The definition mentioned above refers to the practice of overseeing, controlling, and conserving energy in a structure, institution, or distribution network [13]. The fundamental focus of research and development in the field of energy management systems lies in the exploration of innovative technologies that effectively combine energy-saving strategies with materials designed to minimize energy inefficiency. Nevertheless, the level of focus on customers' altered behavior was not proportional. To enhance consciousness regarding energy-inefficient behaviors, it is advisable for customers to first monitor their power consumption and subsequently limit it once they have acquired the necessary information [14]. Organizations, both governmental and non-governmental, actively promote and support the advancement of energy efficiency. Nevertheless, the limited effectiveness of basic saving recommendations and peer device comparisons might be attributed to their timing and location [15]. Consequently, end users are need to make substantial changes in their behavior in order to adopt environmentally friendly practices [16].

Renewable energy (RE) is presently experiencing the most rapid growth among energy sources, with nuclear power and fossil fuels following suit. Renewable energy, as depicted in Figure [1], encompasses any viable form of energy derived from natural sources, including but not limited to solar, wind, hydro, biomass, waves, tides, and geothermal sources. The increasing popularity of renewable energy can be attributed to its sustainability and minimal environmental footprint. Consequently, recent scholarly investigations have delved into this subject matter. It presents a feasible approach for producing sustainable energy and addressing the problem of global warming. Solar energy is widely regarded as the most efficient and ideal form of renewable energy. Scientists argue that sunlight energy provides a comprehensive answer to the current global energy dilemma, as the quantity of solar energy that reaches the Earth in an hour is equivalent to the total energy consumed by mankind each year. In addition, although now meeting only 1% of the global electric energy needs, solar systems have the potential to decrease CO2 emissions by 40 million tons annually. Solar cells, solar power plants, and solar collectors are currently meeting the global demand for clean energy, among other practical uses of solar energy collection.

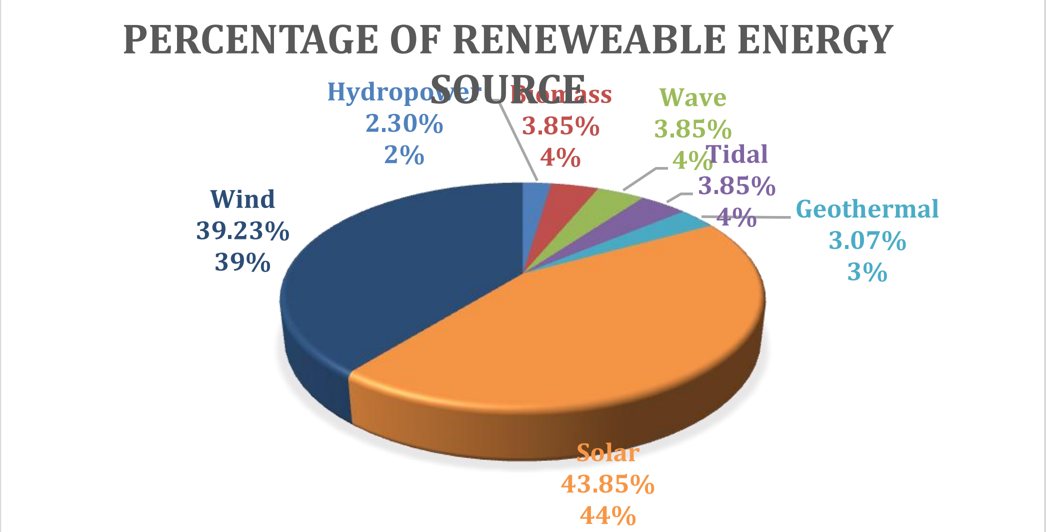

Figure 1: Various sources of renewable energy

Renewable energy (RE) has garnered significant interest in photovoltaic (PV) systems due to their numerous advantages in comparison to electric energy production derived from fossil fuels [17]. The utilization of PV technologies for solar power generation has shown significant growth in recent years. It offers the benefits of minimal maintenance expenses, absence of rotating or mobile components, and negligible global repercussions. However, the efficiency of converting solar energy into electrical energy is quite poor, ranging from 18 to 23%. Photovoltaic power generation offers several advantages, such as its environmentally friendly and non-polluting characteristics, its capacity to generate electricity in close proximity to the consumer with minimal upkeep, and its remarkably extended lifespan [18]. Multiple strategies exist for optimizing the power generation capacity of a solar grid array. The Maximum Power Point Tracking (MPPT) control approach for photovoltaic (PV) systems was introduced as a means to ascertain the maximum power output of the PV grid array [19]. The calculation was performed for each of the two perturbations. The Estimate-Perturb-Perturb (EPP) technique greatly enhances the tracking precision and speed of the MPPT control [20]. Multiple studies have shown that urban and industrial loads receive the most attention, despite government efforts to increase grid transmission and power generation, because of their higher demand and political importance. The utilization of the state-of-charge (SOC) of the energy storage system (ESS), dynamic electricity tariffs, and solar power availability is employed in the optimization technique to strategically allocate energy resources and determine the optimal timing for grid connection or disengagement.

In order to address the present energy problem, it is imperative to devise a pragmatic method for harnessing power from incoming solar radiation. In recent years, there has been a notable reduction in the sizes of power conversion systems. The field of power electronics and material science has witnessed significant progress, enabling engineers to develop highly efficient and small devices capable of withstanding substantial power requirements. The increased power density exhibited by these technologies also presents a drawback. The utilization of multi-input converters capable of efficiently handling voltage fluctuations is increasingly prevalent. Nevertheless, these systems lack the necessary competitiveness to serve as the primary power generation source in highly competitive markets because to their exorbitant production costs and subpar efficiency. If solar cell manufacturing technology continues to advance at its current pace, the use of these technologies would undoubtedly rise. The implementation of modern power control techniques, including Maximum Power Point Tracking (MPPT) algorithms, has significantly enhanced the operational efficiency of solar modules, thereby establishing it as a viable and effective application of renewable energy.

The subsequent sections of the paper are organized as follows. Section II compiles the research on energy management systems and associated strategies. Section III subsequently examines EMS optimization methodologies. Section IV focuses on the PV system and its independent and grid connections. The concluding reflections are further expounded upon in Section IV.

II. The Solar Power System

Solar energy has attracted considerable interest among researchers due to its widespread availability, cost-efficiency, and safety. This session aims to provide a thorough and inclusive examination of the diverse applications of solar energy, as depicted in Figure 2. Solar energy is characterized by its ample availability, cost-effectiveness, absence of transportation requirements, and non-environmental impact. Humanity's adoption of solar energy has initiated a new era marked by energy preservation and a decrease in pollution. Solar energy can be classified into two main applications, namely passive and active, in the context of sustainable development. Applications of passive solar energy have the ability to capture energy without the requirement of converting light or heat into different forms [18–20]. Active solar energy applications, on the other hand, entail the transformation or retention of solar energy for diverse purposes. Solar thermal and photovoltaic (PV) are two distinct categories that can be further differentiated.

The conversion of solar radiation into electrical energy occurs through the interaction of solar radiation with a semiconductor material [21]. The building sector has been able to efficiently utilize solar energy technology for air conditioning, heating, and hot water due to advancements in the solar thermal conversion device industry. Multiple demonstrations have been undertaken by the solar thermal conversion sector, which is actively involved in research related to solar water heating systems and the integration of buildings with the construction industry. Scientific and technological research has incorporated solar air cooling.

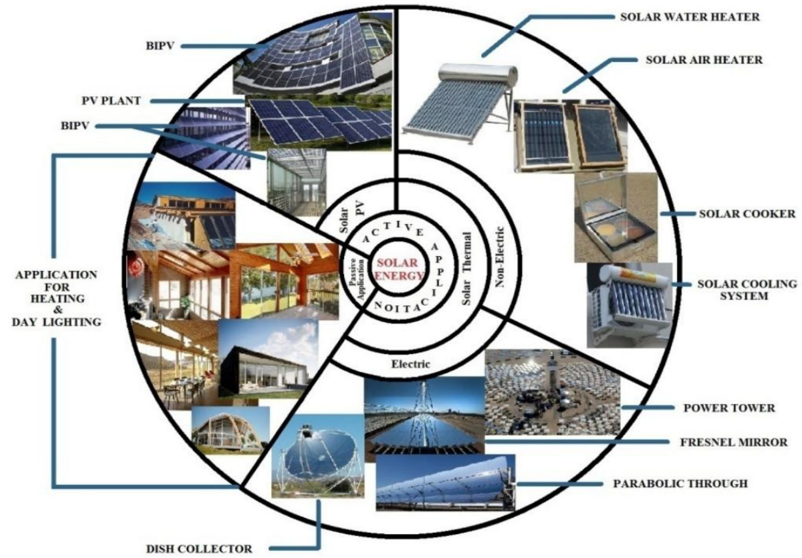

Figure 2: Applications of solar energy

The successful functioning of microgrids, whether connected to the main power grid or operating independently, is highly dependent on the successful deployment of energy management systems. The aforementioned methodologies are of utmost importance in ascertaining the numerical output and/or voltage levels of individual Distributed Generation sources. The difficulty in energy management in microgrids lies in determining the optimal energy generation from the current generators, in order to accomplish certain operational objectives. EMS should be entrusted with the task of overseeing the operation of storage systems linked to the microgrid. The tactics tend to be classified into two main categories: communication-based and communication-less. The operating position of each Distributed Generator (DG) in the Microgrid (MG) is determined through the transmission of system information utilizing a communication-based mechanism. The appropriate communication method is determined by taking into account various factors, including the spatial distance between power sources, the level of security, the financial consequences, and the array of technologies available, which include fiber-optics, microwave, infrared, PLC, and/or wireless radio networks. There are two major categories of energy management techniques: centralized and decentralized. The amalgamation of these two ideas leads to the establishment of both centralized and decentralized schemes [22] [23].

Figure 3 illustrates that in a centralized structure, a solitary control center possesses the power to determine the operational thresholds of distributed generators (DGs). A design for a Centralised Energy Management System (CEMS) is proposed by Olivares et al. [24]. In this system, a central unit is responsible for collecting crucial data from various components of the microgrid. The purpose of this data collection is to optimize the system and define the control system inputs for the next period. The input variables of CEMS encompass various factors, such as the projected power output of non-dispatchable generators, the anticipated local load, the level of charge in the storage system, the operational limitations of dispatchable generators and storage systems, the security and reliability constraints of the microgrid, the status of microgrid interconnection, and the forecasting of main grid energy prices. A multi-stage optimization procedure is performed to identify the ideal operational set points for achieving a predetermined target within a specified timeframe, after collecting all the input variables. The CEMS system's output variables comprise binary decision variables that ascertain the connection or detachment of loads for load shifting purposes. Furthermore, these variables also function as reference values for the control system of each transmittable distributed generation (DG).

The CEMS (Cluster Energy Management System) proposed by Korpas and Holen [25] is designed for a microgrid that incorporates hydrogen storage and wind generation. The methodology employed by this system is dynamic linear programming (LP). Additionally, the researchers in reference [26] utilize a Cluster Energy Management System (CEMS) for a microgrid that combines photovoltaic and storage technologies. They implement a combination of linear programming solution technique and heuristics in their study. Conversely, [27] proposes a solely heuristic optimization method. The utilization of several evolutionary approaches for optimizing CEMS is observed in references [28, 29]. CEMS offers a significant benefit by enabling thorough monitoring of the microgrid, making it ideal for systems that require strong interoperability among system resources. The primary limitations of CEMS, however, encompass diminished adaptability resulting from the need for modifications for each supplementary element (such as generators and storage systems), along with substantial computational demands.

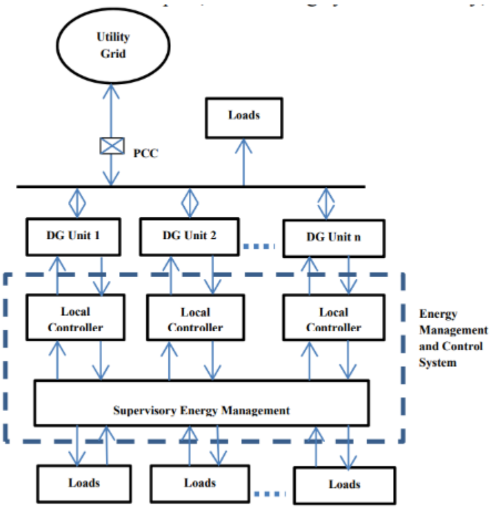

Figure 3: Centralized Energy Management System [30]

Chen et al. [31] introduced a smart energy management system (SEMS) as a means to enhance the operational efficiency of the microgrid. The system is comprised of three primary modules, namely power forecasting, energy storage system (ESS) management, and optimization. The prediction module assumes responsibility for predicting the solar output power and the load behavior. The main objective of the ESS management module is to enhance the efficiency of the storage system in order to achieve the specified energy flow. In addition, the SEMS simplifies the optimization of smart ESS management, economic load dispatch, and distributed generation (DG) operation into a single-objective optimization issue. The desired aspect of the optimization problem is modified according to the execution strategy in order to maximize operational profit whilst minimizing expenses associated with microgrid operation.

In their recent study, Elkholy et al. [32] introduced a Smart Energy Management System (SEMS) that incorporates artificial intelligence (AI) and a field-programmable gate array (FPGA) in an isolated microgrid. This system provides intelligent, secure, consistent, and synchronous energy management capabilities. Two multi-objective optimization techniques, Gorilla Troops Optimizer (GTO) and Reptile Search Algorithm (RSA), are employed to address the optimization difficulty. The study aims to achieve three main objectives: the reduction of operational expenses, the mitigation of power supply failure risks, and the optimization of power consumption by the dummy load. The results illustrate the superiority of the RSA algorithm in achieving the objectives of the objective functions. The experimental testing yielded a minimum running cost of 166.2423 dollars during a time frame of 100 minutes. The utilization of RSA results in a cost reduction of around 6.467%, while the GTO achieves a savings of 6.0363%. The developed SEMS reduces electricity wastage caused by phantom loads. Moreover, it attains the minimum likelihood of power supply loss, almost zero, which is considered the optimal value since it ensures uninterrupted power supply.

III. Optimization Techniques In EMS

The implementation of energy management systems is crucial in facilitating the shift into intelligent systems for residential, structural, commercial, and communal purposes. These systems contribute to the enhancement of energy system planning, dispatch, resilience, and operation. In order to enhance the ability to adapt to changes in demand, market pricing, and environmental conditions, several systems are employed to efficiently manage the production and utilization of energy. An engineer must employ data analytics, control, simulation, and optimization approaches to develop an EMS that can forecast electric demand, model and simulate electrical systems, optimize operations, and analyze trade-offs. The system's advantage is improved by utilizing optimization techniques in certain scenarios, while considering the system's limits as indicated by the formulation. In the present scenario, the achievement of the intended objective requires the application of an appropriate optimization process. The optimization strategies employed for EMS are illustrated in Figure 4 [33].

The utilization of EMS optimization methodologies establishes significant target functions, including power quality, reliability, environmental impact, and cost. An exemplary example is the main goal of employing economic objective functions, which is to reduce the cost of electricity [34-37].

Numerous formulations have been investigated in order to mitigate costs in microgrids (MGs). The setting of cost reduction presents an example of a dynamic economic load dispatch problem [38]. In their study, Jafari et al. [39] suggested utilizing the energy market to improve the dependability of isolated multi-microgrid networks. A techno-economic objective function was utilized to improve the reliability of the system and consider the financial interests of the MG owners. Energy quality, namely power loss, remains a significant obstacle to the dependability of systems. The research conducted by Murty et al. [40] performed an extensive examination of existing literature on multi-objective evolutionary modelling in a microgrid system, providing substantial contributions to the area.

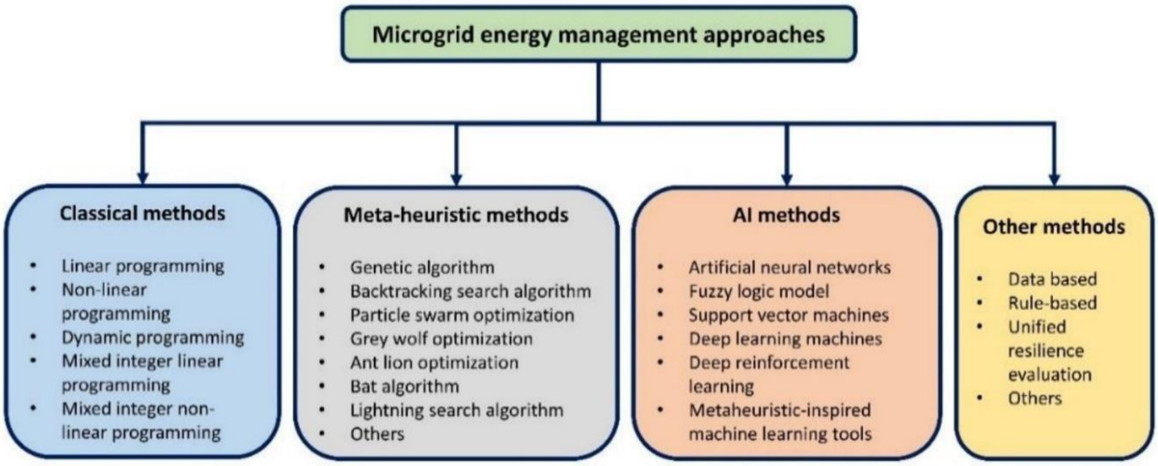

Figure 4: Optimisation Approach of EMS [33]

i) Classical optimization techniques

The optimization of energy resources and transmission within the architecture of the mother grid is primarily prioritized by traditional methodologies. The prioritization of battery drainage depth, greenhouse gas emissions, client confidentiality, and system reliability requires further effort. Linear and nonlinear programming approaches, in addition to dynamic programming and rule-based methods, are two well-established classical solution methodologies for EMS optimization strategies. Several researchers employed these ways to tackle the EMS control methods. Figure 5 illustrates the traditional optimization methods.

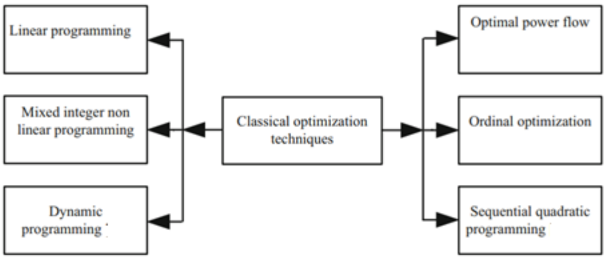

Figure 5: Classical Optimization Techniques

According to Sukumar et al. [41], three distinct modes were introduced for an Energy Management System (EMS), namely on/off, power-sharing, and continuous run. The on/off mode was addressed using the mixed-integer linear programming approach (MILP), while the continuous run and power-sharing modes were addressed using the linear programming optimization methodology. Choice variables, which can be either whole-valued or real-valued, are frequently included in linear programming systems alongside linear objective functions. This methodology is frequently utilized for system analysis and optimization due to its effectiveness and adaptability in tackling complex and broad problems, such as dispersed manufacturing and MG systems. In their study, Vergara et al. [42] utilized a non-linear programming approach to mitigate the expenses associated with a three-phase residential microgrid. The MILP model was derived from the initial non-linear model. In contrast to the nonlinear three-phase optimum power flow formulation, the converted technique demonstrated enhanced accuracy and required less computational time.

The optimization technique based on dynamic programming was developed by Heymann et al. [43]. The comparative analysis revealed that this particular method exhibited superior performance in terms of operational expenses and computation time when compared to the usual MILP and non-linear approaches. In their study, Wang et al. [44] introduced a Lagrange-programming neural networks (LPNN) method to effectively regulate and oversee MG systems, aiming primarily to decrease the overall expenses associated with MG. This study categorized the load into four unique groups, namely regulated load, thermal load, price-sensitive load, and critical load, in order to enhance the efficiency of scheduling MG activities. Within each group, there was a connection between variable neurons and Lagrange neurons. In order to tackle complex problems that may be broken down and structured in a sequential fashion, dynamic programming methodologies are utilized.

The rule-based solution technique [45] is employed to address the grid-connected and islanded modes of the MG. The utilization of rule-based methodologies in the construction of an EM system is more appropriate for real-time applications due to their ability to avoid the need for selecting future data profiles. The authors Bukar et al. [46] proposed a rule-based Energy Management System (EMS) that successfully regulated the power distribution of individual MG components and prioritized the utilization of Renewable Energy Resources (RER) through the implementation of a rule-based algorithm. The effectiveness of the MG system in terms of long-term capacity planning was improved by the utilization of a nature-inspired optimization technique. The main aim of the proposed goal function was to reduce energy expenses and limit the risk of power supply failure in distributed generation (MG) systems. Prior research has developed rule-based approaches to regulate and enhance the efficiency of energy transfer in MG systems. The control approach for multiple resources in the MG was developed by Merabet et al. [47] in order to assure power compliance with the Energy Management System (EMS). A real-time control system was employed to undertake an experimental verification of the hybrid system in the MG. The findings of the study demonstrated that the suggested approach successfully maintained the optimal performance of the MG subsystems under different power generating and consumption conditions. The study conducted by Luu et al. [48] examined a methodology for determining the optimal EM strategy for a microgrid (MG) system, considering the expenses related to energy trading with the primary grid and battery deterioration. In contrast to conventional methods, dynamic programming algorithms can be understood as mathematical optimization techniques that have the ability to decompose a complicated problem into smaller sub-problems, which can then be solved iteratively. Individuals have the capacity to make decisions that are optimal. The incorporation of embedded systems poses a considerable obstacle owing to their elevated computational expenses. Table 1 presents a comparative analysis of traditional optimization methodologies employed by different authors.

Table 1: Comparison of different Classical Optimization Methods used by different authors

Authors	Methods	Contributions	Implementation	Results
Pippia et al. [45]	Rule-based	Enhanced energy management in a grid-connected microgrid comprising renewable energy sources, loads, and ESS.	Implemented in grid-connected microgrids	Outperformed MILP with significant reduction in calculation time, with almost no performance loss.

Bukar et al. [46]	Rule-based	Development of a queuing theory-based energy management method.	Applied in long-term capacity planning for MG	Aims to reduce energy expenditures while enhancing system dependability.
Moazeni and Khazaei [49]	MILP	Minimization of daily energy costs.	Implemented in water-energy microgrid system	Reduced water sector energy consumption achieved by adopting greener energy supply.
Vitale et al. [50]	Dynamic programming	Creation of a fast reduced-order sub-model.	Utilized in islanded and grid-tied microgrids	Achieved reduced payback period through adequate capacity investigation.
Pedro et al. [51]	MINLP	Modelling of an imbalanced three-phase electrical distribution system with droop control.	Applied in islanded microgrids	Resulted in average maintenance load reductions and cost reductions.
Balderrama et al. [52]	Linear programming	Identification of an open-source modelling framework bridging field practices and stochastic methodologies.	Implemented in community microgrid	Recommended sturdy and optimum system designs with minimal community expenses.
Sankar et al [53]	Linear programming	Utilized dual active bridge converter and mode switching algorithm for bidirectional power exchange.	Implemented in hybrid microgrids	Enabled selling excess energy to the main grid, increasing income, and providing power from the main grid during demand shortfall.
Iqbal et al. [54]	Non-linear programming	Development of a peer-to-peer energy-sharing strategy.	Applied in community microgrid	Reduced total device faults compared to typical sharing systems.
Liu et al. [55]	Stochastic programming	Developed multi-period investment planning scheme.	Utilized in islanded microgrid	Achieved better economic and synergetic results compared to standard paradigm.

Restrepo et al. [56]	Optimization- and rule-based EMS		Implemented in Canadian Renewable Energy Laboratory	Produced superior overall performance compared to rule-based EMS with equivalent communication channels while ensuring stability.

ii) Heuristic and metaheuristic methodological approaches

In several technical domains such as product distribution, power systems, transportation, communication, and microgrid energy management, heuristic and metaheuristic approaches are commonly utilized in scholarly works to tackle intricate and non-differentiable optimization issues [57]. Two widely used meta-heuristic approaches for addressing the EMS of the MG are the evolutionary algorithm and particle swarm optimization techniques. These approaches are popular due to their capability to examine information simultaneously. Chalise et al. [58] developed a multi-objective Energy Management System (EMS) that focuses on the battery degradation cost and cost-effective load dispatch of a distant Microgrid (MG). The present work investigated the application of a rule-based technique for real-time operation and a genetic algorithm for day-ahead scheduling. The authors in [59] present a PSO-based optimum EMS for both islanded and grid-connected MG modes. The objective function for both the islanded and grid-connected modes was to optimize energy trading profitability with the primary grid while simultaneously minimizing operating and maintenance expenses. The findings indicate that this approach exhibited superior performance compared to the genetic algorithm in terms of computational efficiency and attainment of a global optimal solution. The two most widely recognized methodologies for addressing the EMS are the genetic algorithm and Particle Swarm Optimization (PSO) methods. Other alternative approaches to address this problem include differential evolution [60], grey wolf optimization (GWO) [61], ant colony optimization (ACO) [62], among others.

Paperi et al. [63] developed a heuristic approach to select the optimal operating system for EMS and MG. The study issue was stated as a single-objective optimization problem, with the main target being cost minimization. The metaheuristic-based system developed by Vacca et al. [64] involved the integration of the Harmony search algorithm with enhanced differential evolution. To maintain power consumption below a predetermined level, numerous knapsacks were utilized during periods of high demand. In terms of cost and peak-to-average ratio, the proposed system exhibited superior performance compared to previous metaheuristic systems. Radosavljevic et al. [65] devised an optimal EMS for a grid-connected MG system. This system utilized evolutionary algorithms to account for uncertainties in Renewable Energy Resource (RER) generation, power consumption, and energy pricing.

The EMS of the MG system was addressed by Aghajani et al. [66] using a multi-objective Particle Swarm Optimization (PSO) technique. Wei et al. [67] created a standalone modular microgrid model to minimize the feasible economic dispatch regions, create an optimization model, and determine the most effective operating strategies for the microgrid system. A more advanced genetic method was proposed to address this concern. The employed methodology yielded a solution of exceptional quality and successfully resolved the EMS issues despite several limitations. The meta-heuristic techniques for the microgrid EMS are compiled in Table 2. The analysis that was given made clear that, when it came to tackling microgrid EMS problems with a variety of restrictions and uncertainties, the different meta-heuristic approaches performed satisfactorily in terms of reaching optimal solutions (minimum costs or greatest profits). Furthermore, the authors demonstrated improved or competitive efficacy for their used algorithms in the majority of cases when compared to others. Since all algorithms are stochastic, it is difficult to draw firm conclusions regarding which one is better than the others because, in theory, they should all provide results that are comparable. Furthermore, the appropriate choice of the hyper-parameters affects their effectiveness.

Table 2: Comparison of heuristic and metaheuristic approaches used by different authors

Authors	Methods	Contributions	Implementation	Results

Quazi et al. [68]	NSWOA	Hybridization of Whale Optimization Algorithm (WOA) with non-dominated sorting technique.	Implemented in islanded microgrid.	Yielded optimal results while reducing computational expenses compared to alternative methodologies.
Leonori et al. [69]	GA	Investigated strategies for synthesizing rule-based fuzzy inference systems.	Applied in demand response services.	Resulted in reduced system complexity and a 10% increase in profit creation compared to previous methods.
Hussein et al. [70]	SFOA	Formulated multi-objective problem for controller parameter tuning.	Utilized in inverter-based microgrid.	Led to enhancements in system performance and adaptability.
Almadhor et al. [71]	BAPSO	Determined optimal locations and sizes for solar generation systems.	Employed in PV-based microgrid.	Reduced power loss in transmission and achieved quicker convergence with reduced computational load.
Singh and Gope [72]	GWO	Optimized load frequency control formulation.	Applied in two-area multi-microgrid.	Demonstrated superior performance of GWO-tuned controller compared to other algorithms.
Roslan et al. [73]	LSA	Developed optimal power scheduling strategy.	Utilized in scheduling controller.	Achieved overall cost reductions of 62.5% and 61.98% reduction in carbon dioxide emissions.
Suman et al. [74]	PSO-GWO	Formulated optimal planning problem.	Implemented in rural microgrid.	Successfully reduced average electricity cost by meeting significant portion of load demand.
Soham and Kamal [75]	CE-DE	Optimized for minimization of running costs and pollution reduction.	Benchmarked in microgrids.	Ensured timely convergence and fostered competitor creation.
Moazeni et al. [76]	Evolutionary algorithms	Developed control strategies for power and energy management.	Applied in low voltage microgrids.	Reduced operational expenses and energy wastage, leading to enhanced overall effectiveness.
Hossain et al. [77]	Modified PSO	Proposed optimal battery control strategy for real-time management.	Implemented in grid-tied microgrids.	Successfully reduced operational expenses by 12% over a 96-hour period.
Kavitha et al. [78]	MPO	Solved supply-demand problems to minimize production costs.	Utilized in islanded and grid-tied microgrids.	Achieved approximately 8% increase in profitability by leveraging enhanced optimization capabilities and accelerated convergence.
Tomin et al. [79]	Monte-Carlo tree search algorithm	Developed unified approach for optimal energy and benefits management.	Applied in community microgrids.	Improved quality of energy and reduced levelized cost of energy index by 20% to 40%.

(iii) Artificial Intelligence Methods

Artificial neural networks exemplify a prominent example of a method that is artificially developed. Random techniques are employed to address optimization challenges in systems characterized by random variables. The fluctuating characteristics of RER in MG systems are influenced by meteorological factors that impact power generation. The mathematical technique for intelligent load control in a self-contained MG system was presented by Solanki et al. [80]. Neural networks were employed to mimic the loads, while a predictive control system was utilized to manage the energy based on anticipated load fluctuations. The Artificial Intelligence-based EMS principally focuses on Fuzzy logic, neural networks, and multi-agent systems [81]. A microgrid comprising a battery and hydrogen energy storage system has been equipped with a fuzzy logic-based Energy Management System (EMS) [82]. As per the authors' assertions, this particular strategy has the potential to properly address the required load needs while also adhering to the specified technical and economic parameters. Wang et al. [44] created a neural network-based MG EMS. The objective of this function is to reduce the total expenses associated with the fuel, operation, maintenance, and emissions of the generation units. Ghorbani et al. [83] proposed an approach for an Energy Management System (EMS) that involves several agents, including consumers, storage units, generating units, and the grid. This strategy aims to manage energy in a grid-connected Microgrid (MG) by taking into account expected load variance. The findings of the study indicated that the decentralized technique exhibited a shorter decision-making time compared to the centralized approach. Among the several artificial intelligence solution methodologies, game theory, the Markov decision process, and the adaptive intelligence approach are notable.

Neural networks are commonly employed in both online and offline applications for the purpose of managing, enhancing, and identifying system attributes. In contrast to earlier approaches, neural networks has the capability to effectively address the complexities associated with nonlinear data in large-scale MG systems. This is primarily attributed to their inherent ability to enhance system stability through self-learning and prediction capabilities [84]. Irrespective of the efficacy of the proposed methods, the implementation of intelligent energy management in smart microgrid systems necessitates the utilization of real-time and predictive control methodologies. Table 3 illustrates various artificial intelligence approaches used in microgrid Energy Management Systems (EMSs).

Table 3: Comparison of different AI methodologies done by several researchers

Authors	Methods	Contributions	Implementation	Results
Dong et al. [85]	Fuzzy logic	Developed day-ahead fuzzy rules for real-time energy management under various operational uncertainty	Multi-energy microgrid	Demonstrated exceptional performance in comparison to offline scheduling techniques that rely on online rule-based and meta-heuristic optimization.
Zehra et al. [86]	Fuzzy logic	Proposed control strategies for renewable energy resources and battery storage systems	DC microgrid	Outperformed sliding and integral sliding mode controllers in terms of controllability.
Singh and Lather [87]	HBSANN	Addressed demand-generation disparity for effective power-sharing between various ESS	Low-voltage DC microgrid	The observed voltage overshoot and settling time were found to be decreased in comparison to the usual technique.

Nakabi and Toivanen [88]	Reinforcement learning	Outlined various flexible resources for coordination with priority	Microgrid	Demonstrated superior model performance and achieved convergence towards policies that are close to optimal.
Tan and Chen [89]	NN	Designed a multi-objective optimization model for multiple microgrid systems	Multiple microgrids	The forecasting error was reduced by 36.86%, resulting in improved Pareto solutions and accelerated convergence.
Dong et al. [85]	Fuzzy logic	Developed day-ahead fuzzy rules for real-time energy management under various operational uncertainty	Multi-energy microgrid	Demonstrated exceptional performance in comparison to offline scheduling techniques that rely on online rule-based and meta-heuristic optimization.
Zehra et al. [86]	Fuzzy logic	Proposed control strategies for renewable energy resources and battery storage systems	DC microgrid	Outperformed sliding and integral sliding mode controllers in terms of controllability.
Singh and Lather [87]	HBSANN	Addressed demand-generation disparity for effective power-sharing between various ESS	Low-voltage DC microgrid	The observed voltage overshoot and settling time were found to be decreased in comparison to the usual technique.
Nakabi and Toivanen [88]	Reinforcement learning	Outlined various flexible resources for coordination with priority	Microgrid	Demonstrated superior model performance and achieved convergence towards policies that are close to optimal.

Priyadarshini et al. [90]	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	Demonstrated the superiority of the utilized methodology compared to traditional and stochastic cross-linked neural networks.

IV. Photovoltaic System in Energy Management

A photovoltaic system is a type of renewable energy source that converts sunlight into electrical energy. This sort of energy generation has grown significantly in the past few decades and is currently one of the world's most important sources of renewable energy. Photovoltaic systems are significant in energy management because they offer a sustainable and cost-effective energy source. The monitoring and control of the energy produced by a solar system is referred to as energy management. It is critical to monitor the system's energy output and guarantee that it is utilised appropriately [91].

The implementation of energy management systems (EMS) to optimise energy use is an essential part of energy management. Energy management may also assist optimise solar system operation by monitoring system performance in real time and making modifications as needed. For example, to optimise functioning, the EMS can manage the inverter to modify the voltage or current based on the demands of the power grid. Integration of energy storage systems is another critical part of solar system energy management. Energy storage devices can store energy created when it is not directly utilised for later consumption. This allows for more flexible energy supply and increases power grid resilience. The energy management of a PV system has to accommodate for the greatest amount of power generated from the solar generator, protection of the battery against overcharge and deep discharge, and satisfaction of the user's energy demands by preventing energy deficit [92].

Photovoltaic power systems are classed broadly based on their functional and operational needs, component configurations, and how the equipment is coupled to other power sources and electrical loads. Grid-connected or utility-interactive systems and stand-alone systems are the two main types which is depicted in Figure 3.

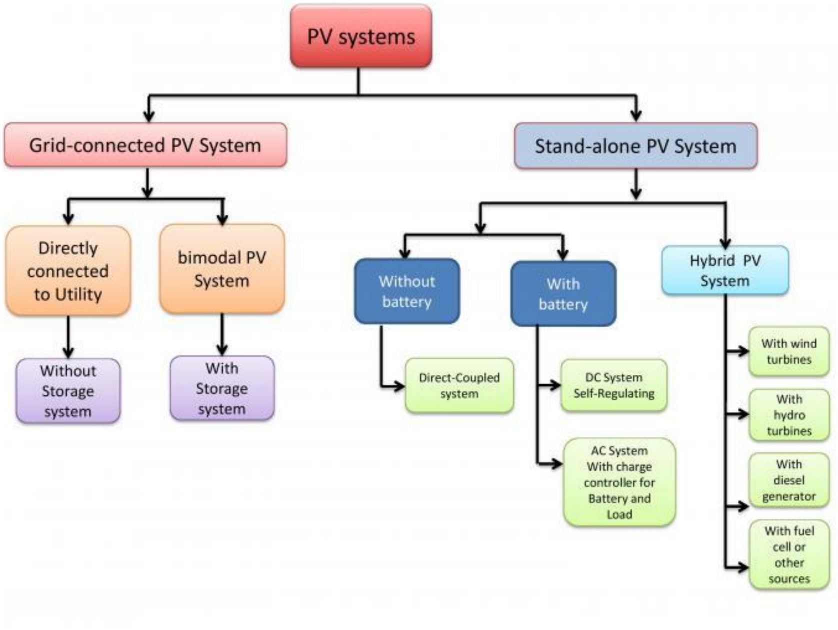

Figure 3: Types of PV Systems [93]

i) Grid connected PV system

Photovoltaic (PV) power, recognized as both environmentally friendly and renewable, stands as a forefront technology in the renewable energy sector. Consequently, there has been a notable increase in research efforts dedicated to this field in recent years. The effective utilization of PV electricity necessitates the integration of PV systems with the grid. PV power production connected to the utility grid has witnessed significant expansion, drawing considerable attention from policymakers [94]. Grid-connected photovoltaic systems comprise PV panels linked to the grid via a DC-AC inverter equipped with a maximum power tracker (MPPT) and a permanent power pump controller. These systems establish bidirectional communication between the AC output circuits of the PV system and the grid, as well as among the primary electricity grid and the DC and AC loads. Additionally, they integrate a control system crucial for ensuring the safe operation of the system.

When integrating PV energy into the grid, various factors and specific conditions are considered to regulate power flow efficiently. PV modules play a crucial role in electrical systems and should not be overlooked. Grid-connected PV systems can pose challenges regarding grid flow control and stability. Grid-adjustable PV systems enable the effective use of generated power. These systems have been extensively studied globally. Adaramola [95] investigated the feasibility, reliability, and economic performance of an 80 kW solar PV-grid linked system using HOMER. Results showed economic viability with reduced reliance on diesel generators, leading to decreased greenhouse gas emissions. Kaundinya et al. [96] conducted a literature review, revealing a generation cost of 8.50 INR ($0.129) per kWh without subsidies, with a performance ratio of 63.68% and a capacity factor of 8.77%, and a payback period of 7.5 years. Peerapong and Limmeechokchai [97] compared different grid-connected PV power plant categories, with utility-scale systems exhibiting the lowest electricity cost at $0.27 per kWh. Residential and ground-mounted systems showed different financial implications.

Nurunnabi and Roy [98] found that the grid-connected hybrid PV/wind power system was the most appropriate and economically viable option for their location. Deepthisree et al. [99] introduced a hybrid power system connected to the grid, aiming to minimize electrical energy expenses by scheduling appliances effectively during low-demand periods when tariffs are more affordable. In their investigation, Etawil and Jhao [100] comprehensively assess challenges associated with grid-connected PV systems, noting inverter failure as a predominant issue. Additionally, a study [101] underscores the role of energy storage systems in microgrid power balance attainment, introducing a fuzzy logic controller-based power management technique. Switching signals generation is based on the controller's input-output functions, enabling decisions considering PV power supply, Battery State of Charge (SoC), and Load, ensuring synchronized operation.

ii) Stand-Alone Photovoltaic Systems

Stand-alone photovoltaic (PV) systems function independently from the electric utility grid, tailored to meet specific DC and/or AC electrical requirements. These systems can solely rely on a PV array or integrate supplementary power sources like wind energy, an engine-generator, or utility electricity, forming a PV-hybrid system. Direct-coupled systems, illustrated in Figure 4, represent a basic type of independent PV system where the DC output of a PV module or array directly serves a DC demand, ideal for applications like ventilation fans and water pumps. These systems rely on electrical energy storage, typically batteries, and operate solely during daylight hours. Ensuring the impedance alignment of the electrical load with the PV array's maximum power output is crucial for optimal performance. A maximum power point tracker (MPPT) is utilized across the array and the load to maximize power utilization, especially for specific loads like positive-displacement water pumps.

Barsoum et al. [102] conducted independent study on solar and biomass systems. The research proposed the implementation of a biomass energy system in rural regions, citing its advantageous characteristics of low cost of energy (LCOE) and high efficiency. Based on their HOMER cost optimization research, it has been demonstrated that a stand-alone biomass system offers greater cost-effectiveness compared to a stand-alone PV system. Ibrahim et al. [104] employed a numerical approach to investigate the most efficient modeling and design of a PV/Battery system operating independently in the Klang Valley region of Malaysia. Their study revealed that the optimal ratio for PV array size is 1.184, the optimal battery size is 0.613,

In their research, Ma et al. [104] explored the performance of a stand-alone photovoltaic system on a remote island in Hong Kong. They observed a notable decrease in the PV system's output as the temperature of the cells increased. Despite an anticipated value of 4.94 kW h/kWp/day, the actual production of the array amounted to 3.08 kW h/kWp/day. Akikur et al. [105] conducted an extensive assessment of standalone solar photovoltaic (PV) and hybrid energy systems utilized for powering off-grid locations globally over a span of 12 years. Solar energy emerged as a cost-effective and environmentally sustainable power solution for various load conditions in remote regions lacking grid connectivity. They suggested incorporating alternative power sources to enhance the reliability and cost-effectiveness of solar PV systems. Similarly, Aswin et al. [106] developed a self-contained three-phase four-wire power supply system integrating a solar photovoltaic system (PV), a battery energy storage system (BESS), and a four-leg voltage source inverter (VSI). The control of the inverter is achieved through the integration of near-state pulse width modulation (PWM) and zero sequence injected PWM (PWM).

The system that is suggested undergoes testing under both balanced and unbalanced load conditions. The modulating signal reduces switching losses by causing one switch to remain fully on or off for one-third of the time. As a result, it aids in reducing the overall losses inside the framework.

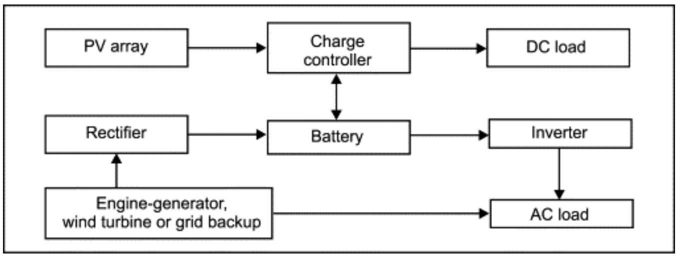

Figure 4: Standalone PV system

V. Conclusion

To accomplish the economical, sustainable, and reliable operation of the smart grid, EMS ensures that distributed energy sources are used appropriately. This study provides a thorough and critical analysis of the concept, objectives, control structures, types, benefits, and issues of the EMS in addition to a thorough examination of all of the various participants and stakeholders in the EMS. The three control architectures—hierarchical, decentralized, and centralised EMSs—are examined. The paper carefully examines the several optimization techniques used in EMS to get the desired results while accounting for all constraints. The PV system and its many approaches are also covered in the study. Even though the solar PV industry has experienced rapid expansion and cost reductions recently, DG resources like GCPVS still need to overcome a number of technological challenges and financial realities to reach parity with conventional production. The broad usage of GCPVs necessitates the development of novel technologies that extend the capabilities of the inverter beyond its current function of converting DC to AC. Contemporary grid-interactive inverters necessitate affordability, provision of Volt/VAR control (power factor and voltage stabilization), frequency regulation, storage capabilities, and utilization of modern communication protocols. From the analysis of the analysed papers, it can be deduced that solar energy is currently the most widely utilized energy source worldwide, characterized by its quiet and environmentally friendly nature. Photovoltaic technology is highly desirable due to the aforementioned characteristics.

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