

Coordination and Optimal Supply of Microgrid Clusters in Large-Scale Transportation Self-Consistent Energy Systems: A Review

Muhammad Adeel

School of Electronics and Control Engineering, Chang'an University, Xi'an 710064, China

Biao Wang

Corresponding Author

School of Energy and Electrical Engineering, Chang'an University, Xi'an 710064, China

Assad Ali

School of Architectural Engineering | 081402, Chang'an University, Xi'an 710064, China

Ananna Zaman

School of Economics and Management, Department of Logistics Engineering and Management, Chang'an University, Xi'an 710064, China

Amin Ullah Khan

School of Economics and Management, Department of Logistics Engineering and Management, Chang'an University, Xi'an 710064, China

Misbah Fida

School of Water and Environment, Chang'an University, Xi'an 710064, China

Israel Muaka MVITU

School of electronics and control engineering, Chang'an University, Xi'an 710064, China

Rabbi Binda MVITU

(UdeM) University of Montréal, School of Computer Science and Operational Research,

Selma Magano Shuuya

School of Economics and Management, Department of Logistics Engineering and Management, Chang'an University, Xi'an 710064, China

Abstract: The universe faces a huge challenge in fulfilling rising energy demand while lowering carbon emissions and boosting the RESs. This study addresses the problem that there has been no systematic research on the combined effects and benefits of using three coordination optimization methods in LSTSCESs. Due to a lack of mathematical and digital models, existing models may be limited in their ability to capture the complex interactions and dynamics of such systems. As the number of MGs and EVs grows, it is necessary to investigate scalable techniques for coordinating and optimizing energy supply within these systems. Considering the economic viability and strategic consequences of coordinating and supplying energy in MGCs inside transportation systems, research may be lacking. This paper presents an extensive review of the coordination and optimal supply of MGCs in LSTSCESs that has the potential to transform the energy sector. The aim of this study is to review new types of power transportation that have the potential to reduce GHG emissions, promote sustainability, and improve total transportation efficiency. To review the coordination and uncoordination, we found that coordination is more beneficial for the MGs and transportation systems. To study the hierarchical, centralized, and decentralized control structures and prove that hierarchical control in the fashion of decentralized control for large-scale systems is more beneficial and cost-effective. To discuss the optimization techniques and prove that metaheuristic algorithms are more economical. Moreover, to study the economic

model, RESs is more economical than traditional sources with ESSs for MGCs. Renewable energy generation in transportation systems has become a fascinating trend, with advanced control algorithms and demand response strategies ensuring optimal energy supply in MGCs. With the rise of EVs, V2G technology is being increasingly used. The resulting energy from MGs can be harnessed through advanced techniques, reducing traditional dependence on energy sources and promoting renewable energy usage.

Keywords: Coordination, Optimization techniques, Control strategies, Microgrid clusters, Large-scale transportation system, Self-consistent energy system.

1. Introduction

The globe faces a huge challenge in fulfilling rising energy demand while lowering carbon emissions and boosting sustainable energy sources. One answer to this problem is to integrate microgrid clusters (MGCs) into large-scale transportation self-consistent energy systems (LSTSCESs). By integrating diverse renewable energy sources (RESs), energy storage systems (ESS), and smart grid technologies, these systems strive to provide efficient and cost-effective energy solutions^[1, 2]. MGCs are groups of interconnected microgrids that can function separately or collaboratively. They can be used to power a small town or a major industrial complex. The use of MGCs in LSTSCES scan aid in reducing dependency on traditional energy sources and encouraging the use of RESs^[3, 4].

Moreover, the optimal supply and coordination of these MGCs, however, remain key challenges. MGC coordination entails managing different energy sources, energy storage devices, and loads to maintain a stable and sustainable energy supply. MGC optimal supply entails the efficient use of energy resources to meet energy demand while minimizing costs and lowering carbon emissions^[5, 6]. Various methodologies and techniques have been developed to achieve optimal supply and coordination of MGCs in LSTSCESs. Advanced control algorithms, energy management systems, and optimization approaches are examples of these. The goal is to maintain a stable and sustainable energy supply while reducing costs and carbon emissions^[7, 8].

Additionally, there are various advantages to integrating MGCs into LSTSCESs. Initially, it can aid in the reduction of dependency on traditional energy sources, which are frequently connected with high costs and carbon emissions. Second, it can encourage the use of RESs, which are often more environmentally friendly and economical. Finally, it can increase the energy system's stability and resilience by supplying backup power in the event of a power loss^[9, 10]. Coordination and optimal supply MGCs in LSTSCESs necessitate collaboration from a variety of participants, including energy providers, legislators, and consumers. To guarantee the success of these systems, laws and regulations that promote the integration of microgrid clusters must be developed^[11].

Similarly, the fluctuation of RESs is one of the issues in the coordination and optimal supply of MGCs. Hydro, solar and wind power, for example, are intermittent and weather-dependent. This variability can cause changes in energy supply and demand, threatening the energy system's stability. As a result, improved forecasting methodologies and energy management systems must be developed to enable the reliable and efficient operation of MGCs^[12]. Integration of ESSs is another problem in the coordination and optimal supply of MGCs. Batteries, for example, can serve to store extra energy created by RESs and release it when needed. However, the proper sizing and placement of ESSs necessitates careful consideration of a variety of parameters, such as energy demand, energy supply, and cost^[13, 14].

In related vein, smart grid technologies can also aid in the coordination and optimal supply of MGCs. Smart grid technologies, such as enhanced metering infrastructure and demand response systems, can assist in real-time monitoring and management of energy consumption. This can help reduce energy waste and increase energy system efficiency^[15, 16]. MGC coordination and optimal supply in LSTSCESs has substantial ramifications for the energy sector. These technologies can help minimize carbon emissions, boost sustainable energy sources, and increase the energy system's stability and resilience. Furthermore, the development of these systems may open up new avenues for advancement and investment in the energy sector^[10].

Furthermore, integration of MGCs in LSTSCESs can also significantly assist the transportation sector. Electric vehicles (EVs), for example, can be charged using renewable energy sources from MGCs, lowering dependency on fossil fuels and boosting environmentally friendly transportation^[17-19]. The appropriate supply and coordination of MGCs can also help developing countries solve the problem of energy poverty. MGCs can provide communities that are not connected to the main power grid with dependable and economical energy alternatives^[20]. The advancement of MGCs in LSTSCESs necessitates significant infrastructural and technological investment. The long-term benefits of these systems, on the other hand, can outweigh the initial expenses, resulting in significant cost savings and environmental benefits^[21].

Moreover, in this study, the contribution is towards the problems, gaps, and objectives that there has been no systematic research on the combined effects and benefits of using three coordination optimization methods in LSTSCESs. More advanced mathematical and digital models that accurately depict and optimize the

coordination and supply of MGCs in transportation systems may be required. As the number of MGs and EVs grows, it is necessary to investigate scalable techniques for coordinating and optimizing energy supply within these systems. Considering the economic viability and strategic consequences of coordinating and supplying energy in MGCs inside transportation systems, research may be lacking. The aim of this study is to review new types of power transportation that have the potential to reduce GHG emissions, promote sustainability, and improve total transportation efficiency. To review the coordination and uncoordination, we found that coordination is more beneficial for the MGs and transportation systems. To study the hierarchical, centralized, and decentralized control structures and prove that hierarchical control in the fashion of decentralized systems for large-scale systems is more beneficial and cost-effective. To discuss the optimization techniques and prove that metaheuristic algorithms are more economical. Moreover, to study the economic model, RESs is more economical than traditional sources with ESSs for MGCs.

This paper affords a systematic literature review of the coordination and optimal supply of MGCs in LSTSCESs and organized as follows: Section 2.2 reviewed the new types of transportation power systems, such as EVs, solar-powered vehicles, hydrogen fuel cells, sustainable biofuels, and Maglev trains. Section 2.3 explained the coordination and uncoordination of MGs and their integration with large-scale transportation systems, as well as the merits and demerits of each and how coordination is more beneficial than uncoordination. Section 2.4 briefly discussed hierarchical control structures and centralized and decentralized control techniques of MGs and integration with large-scale transportation systems from an economical perspective and also provided their features, merits and demerits. How hierarchical control in the fashion of decentralized systems for large-scale systems is more economical. Section 2.5 reviewed optimal supply and energy management of MGs and transportation systems and discussed different optimization techniques like mathematical programming and algorithms, for example, metaheuristics and heuristics. From an economical point of view, metaheuristic algorithms are more suitable. Section 2.6 explained the economic model and DERs of MGs and transportation systems, examined energy prices, fossil fuel prices, and impacts from an economic and environmental perspective, and also discussed DERs such as solar, wind, and hydro and the benefits of ESSs for MGs. Section 2.7 summarizes the latest research trends in the field of energy integration with transportation systems. Section 2.8 presents the conclusion.

2. New Types of Transportation Power System

As stated by Goel et al. (2021) numerous developing power systems for transportation are being established, including: Electric vehicles (EVs), such as electric cars, buses, and motorcycles, are powered by rechargeable battery banks. When compared to regular gasoline-powered automobiles, these vehicles emit no exhaust emissions and have reduced operating costs^[22]. Camacho et al. (2022) explained that some vehicles, such as cars and buses, are powered by hydrogen fuel cells. A chemical process involving oxygen converts hydrogen gas into energy, with water as the only waste. In comparison to EVs, fuel cell vehicles have larger traveling ranges and quicker refueling periods^[23]. Afolalu et al. (2021) described sustainable biofuels as organic-based renewable fuels such as plant-based ethanol or biodiesel generated from vegetable oils. Biofuels can be utilized in conventional combustion engines, lowering greenhouse gas emissions and reliance on fossil fuels^[24].

Moreover, Li & Taghizadeh-Hesary(2022) created quantitative models to examine the economic viability of hydrogen energy generated from renewable energy and then implemented in China's road transport system. A well-to-wheel model is being created to assess the carbon emissions of both the hydrogen supply chain and fuel cell EVs. Meanwhile, a levelized cost of hydrogen model is being used to assess the cost of hydrogen as a sustainable energy storage medium. It is examined how energy policy affects the competitive edge of hydrogen produced from renewable energy and the fuel cell EVs^[25]. Ahmadi & Khoshnevisan(2022) simulated a hydrogen fuel cell car using Simcenter Amesim, analyzing its impact on reducing air emissions and comparing it to gasoline vehicles using natural gas reforming, electrolysis, and thermochemical water splitting techniques. Because the provider of electricity used for electrolysis has an important effect on a hydrogen vehicle's life cycle emissions, three distinct power sources were investigated. Ultimately, despite the fact that a hydrogen vehicle with a deteriorated fuel cell releases less carbon dioxide(CO₂) than a gasoline vehicle, the CO₂ released by this vehicle using hydrogen from electrolysis is about 25% greater than that of a fresh hydrogen vehicle^[26].

In a related vein, according to Khan et al. (2018),Zhang et al. (2021), Sierra & Reinders (2021), and Shariff et al. (2020) solar energy can be utilized to directly power vehicles via photovoltaic (PV) cells mounted on the vehicle's surface. This energy source is used by solar-powered cars and bicycles to charge batteries or supply immediate propulsion^[27-30].Li et al. (2022) stated that the magnetic levitation (maglev) trains suspend themselves above the tracks, removing friction and permitting high-speed movement. When compared to traditional railway systems, these trains are powered by electricity and provide quicker speeds and better journeys^[31].It's worth noting that some of these technologies are still in the initial phases of research or

acceptance and may not be readily available just yet. They nevertheless have the potential to reduce greenhouse gas emissions, promote sustainability, and improve total transportation efficiency.

Similarly, Fakour et al. (2023) discovered that, while sustainable mobility and transportation sector carbon reduction are among the most complete solutions to the issue of global warming, EVs are growing more popular as the future way of transportation. The integration of a solar carport canopy into a possible EV charging station is discussed by the authors using various operational scenarios. According to the findings of a case study, there is a possibility for 140 MWh/year of solar energy production, which could offer solar electricity to more than 3000 automobiles per month with one hour of parking time while emitting 94% less total CO₂ than standard grid techniques. The findings can be applied on a larger scale, providing instructions and tools for building a solar-powered EV charging station network^[32]. Obaideen et al. (2023) covered the various types and generations of solar PV technology, as well as various major uses of solar PV systems, including “Large-scale solar PV”, “Residential solar PV”, “Green hydrogen”, “Water desalination” and “Transportation”^[33].

Likewise, Prasad et al. (2019) investigated maglev technology as a feasible, speedier, and cleaner option in light of rising transportation, its energy demands, and its influence on the global climate. The study provided an overview of maglev technology, with a particular emphasis on electrical system elements. Integrated design of levitation, guiding, and propulsion with appropriate control algorithms gives tremendous cost, weight, and volume savings. The electrical system and its elements are critical to the long-term advancement of maglev systems. The holistic examination of the electrical system reveals that the current alterations and customization of its elements as a result of technical improvement enable maglev to compete with traditional rail transportation^[34]. According to García-Olivares et al. (2018) a 100% renewable economy would provide a long-term solution to the concerns of climate change, energy security, sustainability, and pollution. One of the hardest parts of such a renewable transition looks to be the alteration of the current transportation system. The energetic cost of transitioning from the current transportation system to global 100% renewable transportation, as well as the electrical energy needed for running the new renewable transportation system, are estimated^[35]. The following section discusses the coordination of MGs and their integration with transportation systems.

3. Coordination of MGs and integration with Large-Scale Transportation System

3.1 Concept and Importance of Coordination

Coordination, being a complex choice issue, includes two aspects: self-regulation (adapting the structure) and control (choosing the coordination input for the static structure). Mesarovic assumed that there is already a coordination method, and self-regulation implies adaptations in the tasks and interactions utilized during the coordination process. These changes are referred to as adaptations by the authors. Any choice problem is defined in a broad sense by an objective and an image of the choice-making scenario; in this regard, there are two categories of adaptations: *aim adaptation* and *image adaptation* (for a certain coordination mode). For instance, the interaction unbinding method (IUB-M) (the control-in-the-large choice) might be specified^[36]. The section that follows discusses coordination in microgrid clusters and transportation systems, as well as the benefits and importance of coordination.

3.2 Coordination and Uncoordination of MGs and Transportation System

Jiang et al. (2017), and Chang et al. (2021) provided an optimization model for coordinating renewable energy sources with EVs. The optimization model calculates the charging and discharging power of electric vehicles in each schedule period by utilizing the minimum variance of equivalent load as the target function and taking into account EV driving behavior and capacity restrictions. The simulation outcome proves the model's utility. The findings show that EV charging and discharging can be planned to reduce equivalent loads while increasing renewable energy absorption capacity^[37, 38].

Similarly, Li et al. (2018) and Wang et al. (2019) created a temporal-spatial electric car charging need model comprised of three components: trip plans, span of stay, and a Dijkstra algorithm-based search for the quickest path. Then, they provide a coordinated scheduling strategy for a grid-connected gas, electricity, and heat microgrid. A day-ahead planning method is used to determine the function of the microgrid (i.e., whether it should operate as a load or as a generator from the utility's perspective), and a real-time rolling-horizon dispatching algorithm is utilized to deal with errors in forecasting while also implementing real-time actual power trade between the MG and the main grid. The problem is expressed as a linear mixed integer programming (LMIP) problem. The temporal-spatial electric car charging demand model is centered on an 81-node transportation network, and the power supply network is a mixture of IEEE-30, gas-20, and heat-14 networks. Simulation findings demonstrate the efficacy of this coordinated scheduling strategy^[39, 40].

In addition, Hao et al. (2020) and Shi et al. (2019) presented an extensive power forecasting-based coordination dispatch approach for solar power generation MGs with plug-in EVs to increase local renewable energy usage in the MG by directing EV regular charging. In this method, they employ a clustering technique and a neural network to develop a power forecasting model (PFM) using actual information that can accurately define the ambiguity of solar power production and EV charging loads. A one-leader, multiple-follower Stackelberg game is created based on the interaction between the solar power generation MGs with plug-in EVs energy control center (ECC) and the EV users, and the Stackelberg solution is obtained using a power forecasting-based genetic algorithm (GA). Solar power generation and EV charging load output from the PFM are utilized to build a higher-quality starting population of the GA, which improves its efficiency. An investigation utilizing actual information taken from the Aifeisheng solar power plant in China and EV charging stations in the United Kingdom (UK) proves the enhanced coordination dispatch algorithm's good performance^[41, 42].

Likewise, Niu et al. (2023) and Li & Xu. (2018) replaced standard centralized power scheduling, a more advanced coordinated energy planning strategy is presented for common highway demand situations that utilizes the deployment of vehicular power storage systems. It has the potential to uphold the balance between power supply and consumer demand while lowering the cost of power system dispatch procedures. The cost and appropriateness of the transportable energy storage system (ESS) are researched and examined. The efficiency of the suggested versatile dispatching strategy is validated using data from the specified 30% green energy highway service facility development project in Xinjiang, China. The strategy offers an efficient approach as well as forward-thinking guidelines regarding the incorporation of the highway transportation energy network^[43, 44]. Many researchers discussed about uncoordination in the field of MG and transportation system.

In related vein, Wafa et al. (2017) and Habib et al. (2015) examined the effects of EV integration into supply networks and emphasizes potential managerial problems like feeder and transformer overloading, smaller voltage identities, larger system losses, and operating expenses. EV integration is achieved by the use of two charging schemes: coordinated and uncoordinated, at two stages of EV penetration: 30% and 100%. A standard RBTS test system and an actual Egyptian supply chain ShC-D8 are developed. Every system of testing has a distinct model for daily load and cost fluctuations. The impact of EV adoption and coordination on voltage description, feeder and transformer loads, losses to the system, cost of operation, voltage description, and everyday load curves is investigated using experiments. According to simulation studies, EV adoption rates have a major effect on system efficiency, uncoordinated charging has a negative impact on system efficiency, and coordinated charging eliminates those negative consequences^[45, 46].

Similarly, according to Zhou et al. (2020) and Zheng et al. (2018) the uncoordinated charging of a large number of EVs may result in a significant spike in peak loads, influencing the performance of the power grid. As a result, this research developed a coordinated charging scheduling strategy for EVs in MGs in order to move load demand from peak to valley periods. The technique selects the charging method for EVs according to an urgent charging indication, which can reflect varying charging needs. Then, to minimize the overall peak-valley load difference, a coordinated charging schedule optimization model was developed. Many restrictions for slow-charging EVs, fast-charging EVs, and microgrid function were investigated. Monte Carlo Simulation (MCS) was also utilized to model the inconsistency of EVs. As a consequence, this model can allow friendly power supply-demand interactions to handle EV penetration and the quick growth of dynamic MGs^[47, 48]. It is possible to see that Shi et al. (2019), Savari et al. (2023), Gong et al. (2020), Marinenas et al. (2017), Crozier et al. (2021), Jian et al. (2017), and Liu & Zhou (2022) discussed merits and demerits of coordination and uncoordination of MG and the transportation system [Table 1](#) shows the comparison. As per the literature, many scientists have suggested coordination over uncoordination. Because coordination is more beneficial for the MGs and transportation systems. In the literature, I found that no one discussed the methods of coordination in the fields of MG and transportation systems.

Table: 1 Merits and demerits comparison of Coordination and Un-coordination

	Merits	Demerits
Coordination <small>[41, 49-54]</small>	<ul style="list-style-type: none"> It is beneficial for the operation of grid. It decreases total cost of charging and consumption of power. It decreases power loss, voltage variability and frequency distinction of the system, which may increase the overall performance of the system. The grid system is very stable. 	<ul style="list-style-type: none"> It is time consuming to produce a globally optimal solution.

<p>Uncoordination [41, 49, 52–54]</p>	<p>It has not risk of privacy.</p>	<p>It is really harmful for the operation of grid. It increases total cost of charging and consumption of power. It increases power loss, voltage instability and frequency variation, which may collapse the power system. It increases the stability problems for grid.</p>
--	------------------------------------	---

As per literature many scientist’s suggested coordination over un-coordination. Because coordination is more beneficial in MG and transportation system. In the literature, I found that no one discussed the methods of coordination in the field of MG and transportation system.

4. Hierarchica Control Structure of MGs and integration with large-scale transportation systems

According to Mahmoud et al. (2015), and Yamashita et al. (2020) in large-scale systems, hierarchical control refers to a control architecture that arranges control tasks into numerous tiers or layers, each of which is responsible for a certain component of system operation. It's ubiquitous in complex systems like power grids, manufacturing plants, transportation networks, and smart cities^[55, 56]. Many researcher’s discussed hierarchical control structure in transportation system. Moreover, the impact of plug-in electric vehicles (PEVs) is growing exponentially, which could enhance a considerable quantity of load on the power grid since charging one PEV is closely equivalent to adding three houses to the grid. Wu et al. (2019) presented a hierarchical charging scheduling and control system to allow PEVs to provide grid services while also meeting the travel requirements of vehicle owners. Coordination and vehicle tiers comprise the control framework. When contrasted to existing approaches, the charge coordination strategy can help decrease computing complexity and communication requirements. It is also adaptable to the growing PEV network and resistant to uncertainties in future vehicle travel and system situations^[57].

Likewise, Wu et al. (2019), Sarabi et al. (2016), Xu et al. (2016) and Luo et al. (2018) presented, a unique hierarchical charging control structure in Fig. 1. When a PEV is plugged in, a local controller located at each EV supply equipment (EVSE) activates the suggested charging control structure. The consumer can then enter how many miles of charge they need or demand a percentage of the energy level necessary by a specific time. The data is gathered and dealt with on a regular basis to create a set of four parameters that are representative of each vehicle's charging adaptability and needs. The central coordinator obtains revised adaptability structures from all EVSE controllers and resolves a charging coordination issue that is optimal. As a result, the central coordinator is spared the burden of incorporating precise PEV mobility models. The procedure is repeated in model predictive control (MPC) manner and can adjust to any changes in the travel requirements and power grid conditions of PEV owners^[57-60].

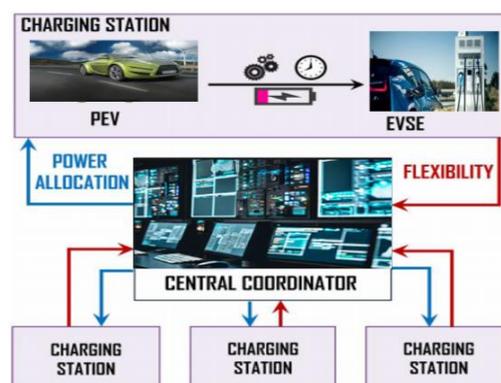


Fig. 1. Hierarchical charging control structure

Similarly, Yamashita et al. (2021) conducted research and offer a two-level hierarchical model predictive controller (HMPC) improved by two data-driven modules to continually and automatically improve the performance of building microgrids equipped with hybrid energy storage. The two data-driven methods increase the accuracy of Li-ion battery and hydrogen storage models and determine appropriate parameters for the

HMPC cost function with minimal pre-design processes. The controller lowers annual expenditures in residential buildings by up to 5% and in non-residential buildings by up to 9%. Conversely, the annual cost of both types of buildings is lowered from 1% to 7% when compared to a standard HMPC^[61]. Tavakoli et al. (2018) addressed a two-stage hierarchical control approach to energy management techniques for the contribution of PEVs to commercial building MG demand response (DR) programs. The main benefit of this work is the inclusion of price uncertainty in an energy management optimization strategy centered around MPC. Firstly, the optimization issue addresses the functioning of PEVs and wind power to be able to optimize commercial building energy management. Secondly, the entire charged power level computed for PEVs in this phase is passed to the PEV control portion to be assigned to every PEV. The findings show that PEVs can efficiently aid in DR programs for the MG paradigm^[62]. Furthermore, according to Wu et al. (2022) certain EU-funded H2020 works have investigated various kinds of control hierarchy, including two-level, three-level, and multi-level control hierarchy^[63].

Likewise, Abhishek et al. (2020), Tavakoli et al. (2016), Olivares et al. (2014), Gao et al. (2019) and Islam et al. (2018) considered the coordinated control of various sources of energy, loads, and direct current (DC)MG energy storage, the need for a communication connection, and mathematical modeling on local variables; Fig. 2 depicts a three-level control system, i.e., a functionality-based general structure of hierarchical control. Hierarchical control is classified into three levels depending on response time, control frame, and operation area: first level, second level, and third level. The first control level, also referred to as the local controller, aims at recovering the DC bus voltage in both constant and dynamic settings by utilizing local data. It also attempts to ensure adequate current share in order to minimize imbalances in power at the microgrid's lowest level. To compensate for voltage deviation induced by the first level, the second highest level controller, i.e., the second level controller with a slower response time than the first level control, is employed. As a result, the second level controller concentrates on recovering voltage in the DC bus and ensuring appropriate current sharing amongst distributed energy resources (DERs). The third level controller, on the other hand, is the top-level control that is used to ensure optimal operation in the context of cost and efficiency within microgrids, between microgrids and utility grids, and vice versa^[64-68]. Papadimitriou et al. (2015) and Souza et al. (2015) said it is also accountable for managing power flow and scheduling energy^[69, 70].

Similarly, Wu et al. (2018) said that depending on the level of control and microgrid structure, these various levels of control can be centralized or decentralized. Apart from the aforementioned purposes, it also has many additional functions, such as getting optimal DER dispatch in terms of economic, technical, and environmental factors^[71]. Various hierarchical control techniques are given in the literature, including the typical PI-hierarchical control^[72], hierarchical multi-agent systems^[73], hierarchical predictive control^[74, 75], and stochastic hierarchical control [55, 76, 77]. It is possible to see that Bandejas et al. (2020), Mao et al. (2017), Abhishek et al. (2020), Wu et al. (2022), Chen et al. (2022), Yamashita et al. (2020), Yamashita et al. (2021) and Xu et al. (2016) asserted the merits and demerits of hierarchical control structure in the microgrid and transportation system. Its depicted in Table 2. Anterior studies suggested that hierarchical control structures are more economical for the MG's integration with transportation systems. The following section discusses the centralized and decentralized control structures of MG's integration with the transportation system.

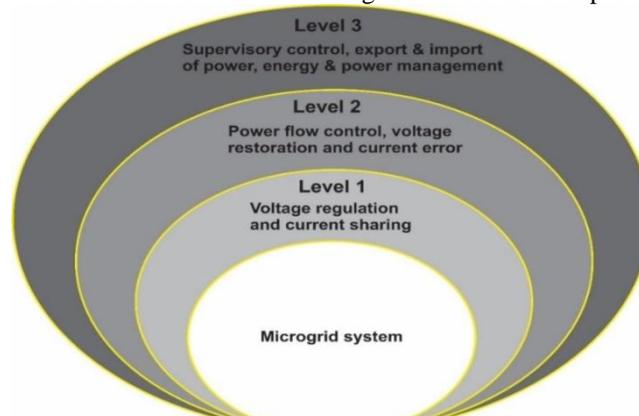


Fig. 2. Hierarchical control structure

Table 2. Merits and Demerits of hierarchical control structure

Merits	Demerits
--------	----------

<p>Hierarchical [55, 59, 61, 63, 64, 78–80]</p>	<p>Provides flexible layered control of networks with multiple systems. Offers a cost-effective solution with easy implementation and low operation costs. It's better for scheduling energy. Improves the system stability. It helps to divide a complex problem into different time-based chunks. Beneficial for electric grid demonstration.</p>	<p>Susceptibility to failure due to the strong dependency between lower and upper control levels.</p>
--	---	---

4.1 Centralized control structure

An ephemeral explanation of the centralized control structure is revealed in Fig. 3(a). (Li et al. (2019) stated that centralized controls make use of a central controller that is connected to supplies and loads via networks of communication. A centralized control employs an MG central controller, which gathers and then evaluates information from all controllers in order to get the optimum results without repetition^[81]. (Dragicevic et al. (2016) described a centralized controller as easier to use because it regulates the supply of power from a single location. Larger MGs use a hierarchical control arrangement, as opposed to smaller MGs, which use a master-slave scheme to connect the units to the central controller^[82]. Zaheeruddin & Manas (2015) studied the many levels of control in centralized control, which are explored in detail later. A central controller makes choices based on the state of generation and load^[83]. Yamashita et al. (2020) and Ishaq et al. (2022) said that centralized control needed communication links^[55, 84]. However, Kou et al. (2017) studied huge amounts of data are handled and restricted in one area, leading to one point of collapse that threatens the stability of the entire cluster^[85]. Another study Mao et al. (2017) Bandejas et al. (2020) and Kou et al. (2017) noted the disadvantage of these systems with centralized control structures: they are frequently unable to scale into larger and more complicated networks. Furthermore, because the central controller must receive data from and send control signals to all local units, two-way communication between the central controller and each local unit is required^[78, 79, 85].

Similarly, Nimalsiri et al. (2020) stated that while the centralized approach is still studied in the literature on occasion, its use is becoming more and more restricted due to issues linked to the growing number of EVs, enhanced distribution system scale, growing utilization of renewable and non-renewable distributed generation, and other factors that make optimization and its search space incredibly impossible to solve. Another issue with the centralized method is the requirement for extensive data exchange in the case of significant EV deployment^[86]. Wang et al. (2016), Mohan et al. (2015), Chen et al. (2015) and L. Wang et al. (2018) concentrated on centralized power network dispatch. When dealing with a large network, it gathers and evaluates data from every network element at a central control center, which could be challenging. Because it is linked to a large number of unknown factors, such as EVs and renewable generations (RGs), and their behaviors are subject to change at any moment, the frequency and volume of data gathering are expected to be significant. Furthermore, the amount of restrictions grows significantly with the size of the network when posing the optimization issue for centralized dispatch^[87-90].

4.2 Decentralized control structure

Fig.3(b) shows an impressionistic depiction of the centralized control structure. A central controller is not present in this structure, according to Wu et al. (2018) as a consequence, various control instructions are used by various control units^[91]. (Dragicevic et al., 2016) described a decentralized control system that employs only local knowledge to iteratively discover optimal solutions. Local controllers use coordination mechanisms^[82]. Local micro source controllers were examined by Mao et al. (2017), Bandejas et al. (2020) and Ishaq et al., (2022). Local controllers act autonomously and coordinate their optimal operation without depending on communication among themselves. As a consequence, each MG system in the cluster is responsible for collecting local information in order to coordinate its optimal function. This technique gives each unit autonomy and enhanced stability while also providing robustness against communication failures^[78, 79, 84]. According to Bandejas et al. (2020) and Bian et al. (2015) a decentralized control structure permits system to simply scale up in size and complexity^[78, 92].

Similarly, Mohiti et al. (2019) and Shamshir band et al. (2018) developed a decentralized, robust approach to reduce total system costs by coordinating the smart distribution network (SDN) and electric vehicle aggregators (EVAs). An adaptive robust optimization (RO) approach is used to address the enforced operating

constraints associated with wind generation and wholesale prices at the market, allowing distribution network operating (DNO) to modify different conservation levels across the operating span. To maintain EVA independence and reduce computing overhead, the RO-based model is solved using a decentralized algorithm based on the alternating direction method of multipliers (ADMM). The suggested model's effectiveness is illustrated by employing an adapted 33-bus smart distribution network with several EVAs^[93, 94].

In related vein, Lemeski et al. (2022) presented an innovative decentralized system for coordinating the activities of separate, independently operated EV aggregators and distributed generators. The aim functions, representing the purposes of the aggregators and generators, seek greater profit or fewer costs. The targets also take into account the demands of the distribution system operator (DSO), which include technical metrics such as losses and bus voltages. Many EV-related issues, such as plug-in and plug-out times, initial state of charge, and deviations in the number of aggregators and distributed generators, along with grid techno-economic factors such as cost and load variations and disputes of interest among the three parties, all add to the complexity of the model. To solve the model, a decentralized method based on the fast alternating direction method of multipliers (FADMM) is used. Through various scenarios, the suggested technique is evaluated on two 33-bus and 69-bus distribution test networks consisting of aggregators and distributed generations (DGs). Findings show that, while protecting various agents' secrecy, the recommended approach satisfies the aims both of aggregators and DGs via better revenues while also ensuring the technical satisfaction of the grid operator^[95].

Likewise, Yu et al. (2022) introduced a scalable and flexible hybrid microgrid clustering design as well as a decentralized control technique. In the beginning, the energy networking unit (ENU) was a new, interacting converter. The ENU is utilized to link the alternating current (AC) and DC sub grids in a single hybrid microgrid as well as to communicate with the external power grid. Finally, the recommended decentralized control technique for this design could enable autonomous power exchange between sub grids in a single microgrid while taking energy storage constraints and continuous phase switching into account. Furthermore, an adaptive and autonomous power interaction among surrounding MGs is realized with full exploitation of cluster adjustment ability, enhancing system dependability as well as RES usage and consumption at the local level. Comprehensive instances are used to demonstrate the usefulness of the clustering architecture and decentralized control technique^[96]. Zou et al. (2019) and Yang & Hu (2021) provided a decentralized method for the underlying optimization issue and demonstrated the system's logarithmic rate of convergence to the optimal approach. Additionally, the authors take into account the power exchange capacity between the multi-microgrid (MMG) system and the main grid and provide a decentralized algorithm to find an optimal approach that reduces system cost underneath this ability limitation^[97, 98].

Similarly, Ma et al. (2023) promoted a virtual energy storage-based decentralized and coordinated scheduling solution for interconnected MMGs. Research aims to reduce the dangers of renewable energy installations as well as the operating costs. Case examples illustrate the recommended schedule method's accuracy and economy^[99]. According to Bandejas et al. (2020), Yamashita et al. (2020), Ishaq et al. (2022), Yu et al. (2022), Fiorini & Aiello (2019), Mao et al. (2017) and J. Edward et al. (2019) Table 3 compares centralized and decentralized structures and presents an economic analysis of centralized and decentralized controls. Previous studies proved that the decentralized control structure is more beneficial, cost-effective, and suitable for system stability than the centralized control structure. Many researchers suggested hierarchical control in the fashion of decentralized systems for large-scale systems.

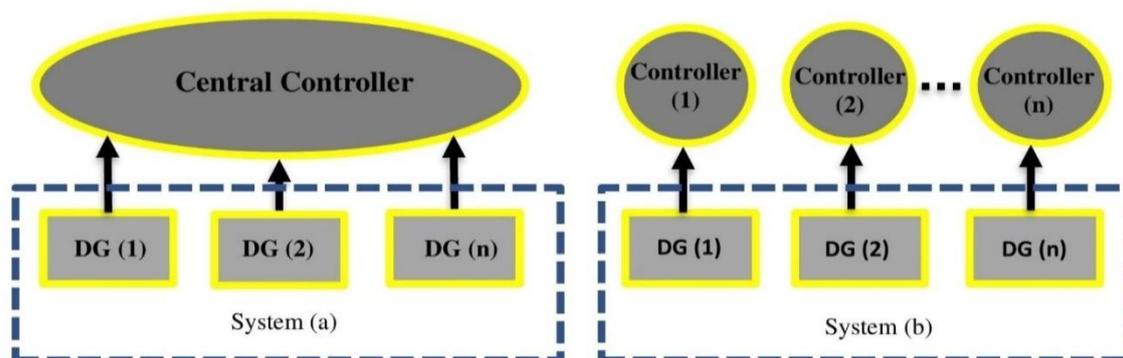


Fig.3. Control structure categories Centralized (a) and Decentralized (b)

Table 3. Inclusive comparison of centralized and decentralized control

Features	Merits	Demerits
The central controller makes	Suitable for small scale	Inability to scale to a

<p style="text-align: center;">Centralized [55, 78, 79, 84, 96, 100]</p>	<p>decisions in an organized way.</p>	<p>systems. More optimized solutions deliver. Simple to put into operation.</p>	<p>larger and more complex system. A point-to-point communication link is needed. Less trustworthy. Costly computationally. It consumes more time. Single point of failure caused system collapse.</p>
<p style="text-align: center;">Decentralized [55, 78, 79, 84, 96, 100, 101]</p>	<p>The local controller makes control decisions based on local facts.</p>	<p>Beneficial for large scale systems Appropriate for coordinating several autonomous systems. Allows every single system to operate independently, with no connection between systems. It does not rely on a single central unit. Highly trustworthy. The capacity to plug and play. This is beneficial for the charging infrastructure. It eliminates the possibility of a single point of failure. Cost effective.</p>	<p>Hard to accomplish complicated control tasks due to limited global information.</p>

5. Optimal supply and energy management of MGs and integration with large-scale transportation systems

5.1 Optimization of MGs and integration with transportation systems

According to Ahmed et al. (2020) and (2021), optimization approaches can be employed at every level in a MG system to produce the best conditions for operation. Several decision-making tasks require optimization strategies, including production planning, MG operating, and preservation. Optimization algorithms aim to identify the optimal solution in an environment of essential restrictions given numerous acceptable options. Depending on the distribution, generation, or management of MGs, optimization of MGs can be separated into three divisions. Designing a mix of production assets in an MG necessitates substantial study to determine the best ESS and production assets^[102, 103].

Similarly, Eldeeb et al. (2018) suggested a multi-objective optimization (MOO) procedure that strives to maximize the profits of the PV-EV station while concurrently decreasing the battery energy storage system (BESS) capacity. The goals must be realized within the power variation constraints enforced by the hosting grid at the point of common coupling (PCC). The procedure includes extensive modeling of the dynamics of the BESS along with the actions of the EV parking garage. The augmented-constrained (AUGMECON2) solution solves the MOO issue. The findings demonstrated the efficacy of the procedure in accomplishing the aforementioned goals. Furthermore, the outcomes demonstrated the negative impact of ignoring the battery's comprehensive modeling on the battery's duration^[104].

Likewise, Fu et al. (2018) and Solanke et al. (2020) provided a new hierarchical optimum control architecture based on MPC approach to perform real-time optimization. The control structure calls for a two-layer control that is exposed to relevant restrictions based on the changing rate of various parameters. It is demonstrated via experimentation and simulation outcomes that predictive control may successfully minimize the use of fuel and fatigue pollutants^[105, 106]. (Ji et al., 2016) suggested a scenario-based MPC method that combines both robust and stochastic models to reduce overall operating expenses in energy management. The outcomes of simulations on a combined power and heat microgrid show that the scenario-based MPC method outperforms an outdated deterministic model predictive control (DMPC) approach in terms of financial

outcomes while guaranteeing EV charging needs and reducing the trade-off between optimal outcomes and computing times^[107].

In addition, Huang et al. (2023) provided a real-time voltage optimization strategy based on model MPC for soft open points (SOPs) in highway transportation power supply networks (HTPSNs). The technology may considerably improve the voltage continuity of HTPSNs and reduce losses of power when the system's voltage fluctuates rapidly. The optimization framework is changed via response adjustment to increase the efficacy of voltage regulation substantially. The case studies demonstrate the efficacy of the strategy in various settings^[108]. Abdelghany et al. (2023) created a comprehensive MPC technique for a grid-dependent wind and solar MG that incorporates a hydrogen-ESS, a battery-ESS, and interactions with outside users such as battery or fuel cell EVs. The whole system necessitates the control of its output of energy of multiple kinds, namely electric and hydrogen. The technique considers the economic and operational expenses of hybrid-ESSs, degrading difficulties, and the structure's tangible and dynamic restrictions. Such evaluations show that the technique runs the plant effectively by meeting limitations and energy demands while lowering device prices and boosting the lifespan of batteries^[109].

Moreover, Antony et al. (2023) studied the problem of frequency regulation in standalone MG, MPC, and dynamical droop control (D2C), which is related to the impact on the framework of ESS and EVs following considerable RES insertion or a large shift in load requirement. The D2C safeguards EV energy in accordance with requirements for the system by retaining a minimum quantity of power for predicted EV usage. To boost efficiency, both the MPC and D2C settings are modified using a complicated evolutionary approach. A single MG is demonstrated and assessed in MATLAB Simulink, utilizing the controlling methodologies. Furthermore, regarding the level of performance, the MPC beats both fuzzy-based proportional-integral (FPI) and proportional integral (PI) controllers^[110]. According to Minchala-Avila et al. (2015) and Gavilema et al. (2021) Optimization strategies are further categorized based on their major goal in terms of specifications or the technique utilized to achieve the optimum level^[111, 112]. Fig. 4 depicts the optimization categories^[100, 113].

5.2 Mathematical programming

According to Dini et al. (2020) linear programming (LP) is the most basic mathematical optimization method, in which goals and restrictions are defined as linear variables^[114]. Sirinivas & Swarup (2017) presented a new approach that combines interval linear programming (ILP) with modified particle swarm optimization (MPSO). The main concept is to use the ILP concept to transform the constraints on inequality of a typical LP problem into interval obstacles, then describe the ILP issue as a typical LP problem. When compared to traditional optimization, this technique decreases the amount of coordination restrictions significantly and yields an improved sub-optimal solution. In a microgrid context, the approach is examined on an IEEE 14 bus test network^[115]. Yao et al. (2019) proposed restoration problem is required as a mixed-integer linear programming problem that takes into consideration different network and transportable energy storage system (TESS) limitations. The framework and method are tested in an adapted 33-bus test system made up of three MGs and four TESSs. The findings indicate that a distribution system with TESS is more durable than a normal ESS due to the advantage of overall cost minimization^[116].

Likewise, Ouramdane et al. (2021) and Diaz et al. (2017) stated that the problem is called an integer programming (IP) problem when all decision variables are integers; a mixed-integer programming (MIP) problem when some but not all variables are restricted to being integers^[117, 118]. Vita et al. (2023) employed a mixed-integer linear program (MILP) to mimic the problem and an improved IEEE 39-bus system for testing to validate the effectiveness of the restoration technique in MG after a blackout^[119]. Luna et al. (2017) demonstrated the mathematical representation and development of a flexible energy management system (EMS), as well as its integration with a grid-connected battery-based MG. The organizing model is a power generation-side method described as general MILP with two phases for adequate storage entity charging. In accordance with 24-hour prediction data, this framework is regarded as an eternal issue that tries to reduce the cost of operation and encourage self-consumption^[120].

Similarly, according to Raya-Armenta et al. (2021) non-linear programming (NLP) describes an optimization issues with non-linear objective functions and/or restrictions, such as the specified minimizing cost issues^[121]. Shawon et al. (2023) developed a DG optimum deployment strategy based on reducing overall energy losses, with the scheduling expressed as NLP issue. In comparison to existing approaches, the method outperforms them^[122]. Kumar et al. (2023) took into account unpredictable parameters such as renewable power generation, load demand, and power loss, as well as voltage limit restrictions, and the resulting challenge is framed as a stochastic mixed-integer non-linear programming (MINLP) problem to improve MG load efficiency and optimize the regular cost of operation. To address the optimization problem, the newly discovered whale optimization algorithm (WOA) is used, and the computational findings are verified by contrasting them to

prominent metaheuristic methods. By preserving system voltage description, the power company's computational overhead is minimized for the optimum planning of a grid-integrated MG to obtain the greatest electricity^[123].

Moreover, as reported by Li et al. (2023) quadratic programming (QP) expresses the optimization target as a quadratic function^[124]. Hosseini et al. (2023) indicated a model for the hierarchical coupling of deep reinforcement learning (DRL) and QP for the restoration of distribution systems after large failures. A DRL-trained controller determines optimal power delivery of an assortment of distributed energy resources dubbed integrated hybrid resources (IHRs) in the mathematical framework, while a grid-level QP task checks grid restriction and executes key restoration operations. DRL is carried out utilizing the Soft Actor-Critical (SAC) algorithm, which outperforms the commonly used deep deterministic procedure gradient in ongoing action fields. The mathematical investigations on the 123-bus test distribution system show that the hierarchical combination of DRL and QP not only accelerates the local operation of multiple IHRs but also guarantees that network constraints are met throughout the restoration work^[125].

In addition, dynamic programming (DP), as defined by Bahlwan et al. (2021) splits a large problem into multiple manageable sub-problems that are solved iteratively by recording their solutions. DP is employed to reduce the cost of energy^[126]. Hu et al. (2023) established an adaptive dynamic programming (ADP)-based data-driven signal assessment approach. Operators would use emergency procedures to resolve a leak incident in the energy transportation system based on the aberrant signal assessment outcome. Lastly, various case findings show that the method may be applied to the signal assessment difficulty^[127]. Li et al. (2020) concentrated on optimal MG energy transmission management. It is written as a nonlinear quadratic programming (NQP) challenge with quadratic constraints, and it is also an unlimited-stage optimization task due to an unlimited MG operating cycle. Typical optimal scheduling algorithms are challenging to work with. As a result, the researchers indicated an ADP approach for solving an unlimited-stage optimization task. Ultimately, mathematical calculations reveal that, compared to the simulated annealing (SA) technique, the ADP algorithm has lower costs of operation and a superior control mechanism^[128].

5.3 Optimization Algorithms

As reported by Islam et al. (2020), Hamann et al. (2017), Nazari-Heris et al. (2017), Saadatpour et al. (2020) and Yang et al. (2015) there is an increasing interest in conducting research to invent unique techniques for solving complicated optimization issues, such as artificial neural networks (ANN)^[129], real time optimization algorithms^[130], heuristic^[131], and meta heuristic methods^[132, 133]. Fioriti et al. (2020) and Tsao & Thanh (2021) declared heuristic algorithms handle complex problems by employing trial-and-error tactics. Metaheuristic approaches, on the other hand, employ algorithms influenced by nature^[134, 135]. According to Dokeroglu et al. (2019) the metaheuristic technique is gaining popularity in this field due to its low cost and time requirements^[136]. The advantage of metaheuristic approaches over traditional methods, as dictated by Lai et al. (2022) is the extraneity of developing a unique beginning condition, convexity, stability, and differentiability^[137]. Meta-heuristic algorithms are classified into many classes, as shown in Fig. 4, that are found in the literature^[100, 113].

Moreover, in recent years many researchers have carried out various studies on several themes for example De & Mandal. (2022) concentrated their efforts on multi-layer energy management systems for MMG smart distribution networks. Metaheuristic optimization, or multi-objective modified personal best particle swarm optimization (PSO), is used to effectively describe uncertainty in renewable energy. The experiments are carried out using a modified IEEE-33 bus system. The outcomes resulted in cost savings^[138]. Abdolrasol et al. (2021) demonstrated an ANN improvement utilizing PSO to control RESs in a virtual power plant (VPP) system. The study compares the ANN-based binary particle swarm optimization (BPSO) algorithm to the original BPSO algorithm. The comparison was conducted after determining the best value for the number of nodes in the hidden layers and the rate of learning. These parameter values are utilized in ANN training for optimal energy management in MGs. The findings reveal that ANN-PSO offers more exact decisions than the BPSO algorithm, proving that the neural net improvement achieves the optimal level of energy management^[139].

Similarly, Jefimowski et al. (2020) investigated the idea of vanadium redox flow batteries as stationary energy storage for optimizing energy and profitability characteristics in transportation MGs. The major goal of such energy storage is to use the energy saved from brake trains to reduce power peaks. The fundamental driver of steps to optimize battery parameters, especially joint energy and power ability, as well as energy management plan factors, is economic viability. The outcomes of optimization from the GA and PSO were compared, and the comparison shows that the second method performs better^[140]. As a universal tool, Nemati et al. (2018) presented two dispatch optimizers for a centralized EMS (CEMS). To set up the unit promise and economic

dispatch of MG units, an upgraded real-coded GA and an upgraded MILP-based technique have been established. The approaches take into account network constraints such as voltages, equipment loadings, and unit restrictions. For identifying the global optimal zone in high-constrained issues, the method appears to be more resilient and rapid^[141].

In related vein, Zamee et al. (2023) developed a novel Monte Carlo artificial bee colony (ABC) optimized fractional-order PI controller that was applied to construct a single inverter that could perform optimally under both grid-connected and islanding scenarios. An MCS was used to determine the optimizer's first optimal search space. The controller's execution was compared to two other optimization techniques, PSO and Gray Wolf Optimization (GWO). The ABC algorithm is more efficient and beneficial^[142]. Habib et al. (2020) explored entails using vehicle-to-grid (V2G) technology to reduce the cost of all three aims, namely operation cost, pollution cost, and carbon emissions, with economic dispatch (ED). PSO and ABC algorithms are used in a variety of control and operation tactics. The frameworks are validated and assessed using various scenarios. The research findings verify the greater efficiency of the EV-based MG model in the coordinated charging and discharging phase in terms of operating costs. In regards to cost minimization for all purposes, the ABC algorithm outperforms the other methods^[143].

Additionally, Suresh et al. (2023) tackled the microgrid economic dispatch challenge. The algorithms investigated include three conventional algorithms, GA, PSO, and the mixed integer distributed ant colony optimization (ACO), as well as two newly established algorithms, the political optimizer and the Lichtenberg algorithm. All algorithms under consideration had their hyper parameters tuned. The outcomes demonstrate that the ACO-based algorithm is the best fit of all options. It is subsequently utilized for ED, which is directed by an objective function that reduces the MG leveled price of energy^[144]. The multi-objective optimization with uncertainty was developed by Kreishan & F. Zobaa. (2023) to reduce the net MG cost, maximum voltage error, frequency deviation, and total energy loss. For the first time in MGs, the mixed-integer distributed ACO was used in a huge synchronization framework to tackle the deconstructed probabilistic issue of the majority of likely cases. Finally, the outcomes obtained indicate the critical function of dump load as a power control technique that minimizes costs and energy waste^[145].

Likewise, Li et al. (2023) have shown that cloud or fog computing can also help a MG with computing-intensive obligations. Integrating an ANN and an adapted GWO to economically handle a fog-driven energy management challenge, experiments are run to confirm the technique for reducing expenses and reducing energy imports, despite taking into consideration the electronic replica of intelligent houses^[146]. Ramadan et al. (2023) identified unique ways for eliminating unwanted catastrophic voltage fluctuations and limiting the entire cost of PVs deployment inside linked microgrids. A reasonable analysis of GWO, PSO, the arithmetic optimization method, and the chimp optimization algorithm is shown using MATLAB mathematical simulations. The coronavirus herd immunity optimizer (CHIO) tool outperforms the other algorithms in terms of target function fulfillment, integration, and large-scale processing time. The dynamic infiltration of structure-surface thermal photovoltaics (TPVs) greatly improves the voltage profile at all buses^[147].

Moreover, Suman et al. (2021) used a hybrid of solar, wind, and bio-generator energy generation devices, as well as diesel generation and a battery. The tradeoff between cost of energy (COE) and deficiency of power supply probability (DPSP) has been studied, and a goal function is defined as an amalgamation of the two with a renewable factor (RF) boundary. For optimization, a hybrid (PSO-GWO) approach is used. The findings were compared to those acquired through other previously utilized algorithms in the literature, and the efficacy of the developed algorithm was determined^[148]. The hybrid MG recommended by (Jasim et al., 2023) integrates renewable energies such as solar PVs, wind turbines (WTs), biomass gasifiers (biogasifiers), battery storage energies, and a supplementary diesel generator. A metaheuristic optimization approach (hybrid gray wolf with cuckoo search optimization (GWCSO)) is used to optimize the sizing of the MG elements. To determine the optimal sizing outcomes with the lowest costs, the computational outcomes are contrasted to those obtained using PSO, GA, GWO, Cuckoo Search Optimization (CSO), and Antlion Optimization (ALO). The GWCSO seems more reliable than the other algorithms since it has a smaller variance, and its optimal number of element units, annual cost, and leveled cost of energy (LCOE) are superior to the others^[149].

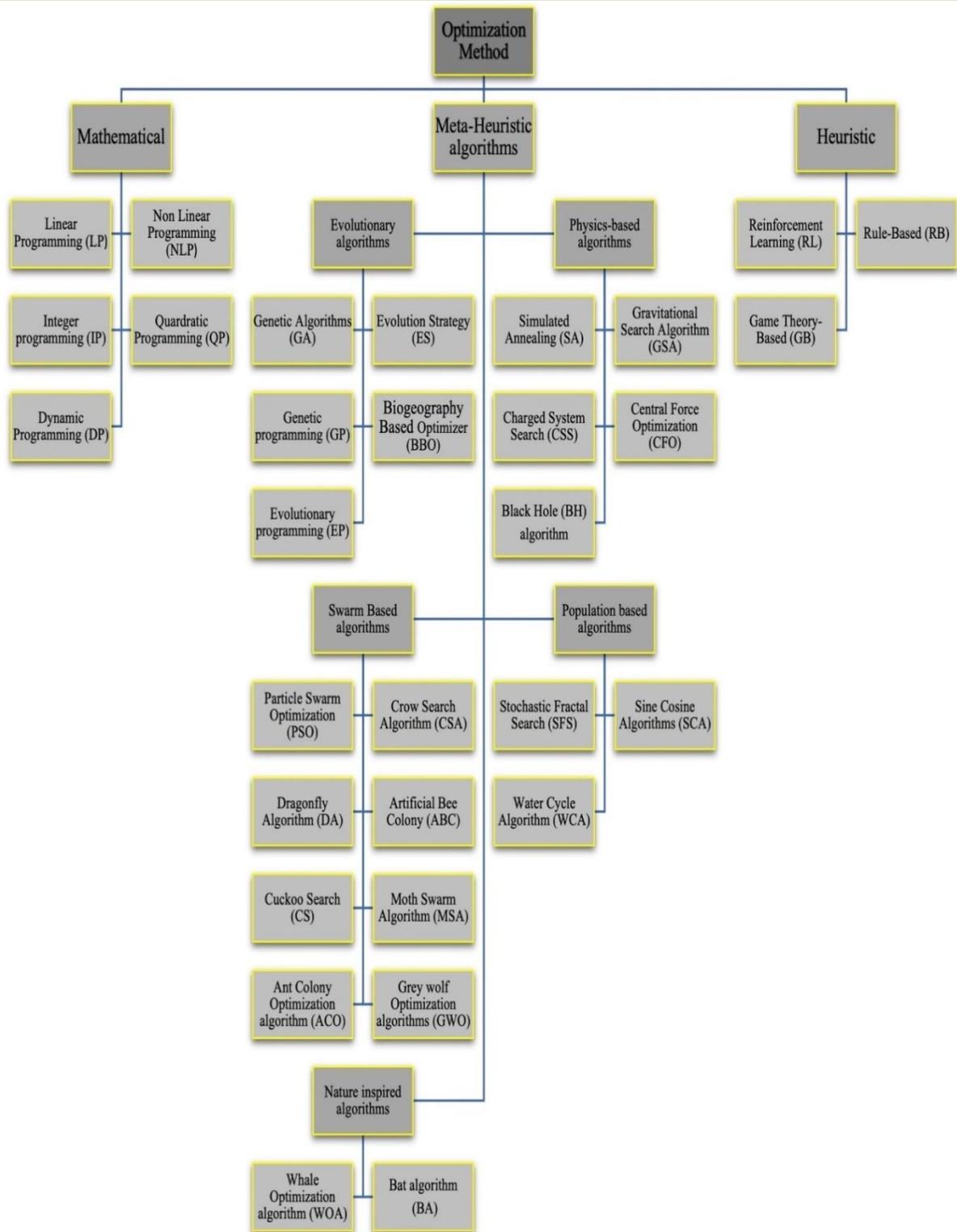


Fig. 4. Categories of optimization methods

6. Economic model and distributed energy resources of MGs and integration with large-scale transportation system

Key elements in optimizing MGC in a transportation energy system include incorporating all available energy sources, calculating transportation sector needs, and taking economic consequences into account. This involves reducing costs through efficient hydro, solar and wind power distribution, establishing methods to fulfill transportation energy demands, and taking grid interaction, pricing structures, and possible profits from energy trading into account. Taking these elements into account, supply perspectives for the cluster's economical and long-term operation within the large energy system.

6.1 Energy price

According to Amin et al. (2020), Abdullah et al. (2016), Zhang et al. (2019), Najafzad et al. (2019) and Zheng et al. (2021) several studies separate two or more price levels based on the time of usage of power, including off-peak, mid-peak, and on-peak hours, adhering to a standard tariff structure. Few authors, on the other hand, advocate for setting consistent pricing for both buying and selling electricity^[150-154]. Dey et al. (2022), Seyedian et al. (2022) and Tsao & Linh (2022) considered the prospect of buy-back, or selling regionally generated electricity to the core distribution network. The selling price can be less than the acquiring price or equal, depending on overhead expenses such as taxes and distribution grid contingents^[155-157]. An et al. (2022) and Pan et al. (2022) stated that the cost of selling solar electricity is bigger or smaller than the cost of buying it, depending on the present weather or the tariff policy in place. The cost of exporting is much greater than the import cost^[158, 159]. Sahebi et al. (2023) stated that all locally generated renewable energy is sold to the main grid^[160].

Similarly, the study by Taghvaei et al. (2017) examined the impact of pricing and the use of energy on renewable energy development under Iran's various economic expansion zones. Throughout periods of great economic expansion, the data demonstrate a negative and significant link between the energy price index and the share of renewable energy in Iran. This is owing to the economy's uneven and inconsistent growth, unethical resource management as a result of greater earnings from rising energy costs, energy incentives, and the private industry's inability to invest in cheap renewable energy from fossil fuels^[161]. Belaid (2022) according to recent research, 80 million European households are battling to stay warm, and the recent increase in energy expenses is projected to exacerbate the issue. The influence of the energy price rise on the situation of energy poverty in Europe is examined here. This study examined how rising energy prices and the green transition may increase Europe's energy poverty^[162].

In addition, Wang et al. (2015) developed a new holistic energy poverty assessment index, which is used to assess regional energy poverty in China. China's energy supply accessibility increased somewhat; the use of energy hygiene did not change significantly; energy management completion fell with variations; and household energy affordability and effectiveness improved steadily. Furthermore, various regions of China exhibit various indicators of energy poverty. Such as the Middle Yangtze River region, which had the lowest energy availability, and the Eastern Coast region, which had the lowest control over energy adequacy^[163]. (Mulder et al., 2023) studied that the sharp rise in energy prices since 2021 has marked a watershed moment in contemplating energy poverty in the Netherlands, where the notion had hitherto been ignored in national policy formulation. In terms of energy poverty geography, the authors discovered that severe energy poverty is more spatially focused than income poverty, occurring mostly in outlying regions of the Netherlands as well as several highly populated urban areas. Energy poverty is a sign of the delayed dissemination of energy-saving technology as a consequence of a mixture of funding hurdles that should be tackled with a balanced mix of extra funding, pricing incentives, and house insulation regulations^[164].

Furthermore, Brown et al. (2020) studied that in an era of abundant energy in the United States, the continually high energy costs paid by low-income households are alarming. Despite centuries of weatherization and bill-payment programs, low-income households continue to spend the highest percentage of their income on energy and gas bills of any income category. Their energy load is not decreasing, and it is particularly high in certain geographies such as the South, rural America, and minority populations. Many programs that encourage energy efficiency, rooftop solar, EVs, and home batteries are mostly inaccessible to low-income households due to accessibility constraints as public organizations and utilities strive to move to a clean energy future^[165].

6.2 Fossil fuels price and impacts

According to Azni et al. (2023) for an extended period of time, the world has depended on fossil fuel energy, which has had many negative consequences. Continued reliance on fossil fuels has boosted carbon emissions and exacerbated climate change. Furthermore, fossil fuels are dwindling and will eventually become prohibitively expensive. Also, the costly national power grid has yet to reach rural communities and will be cut

off in flood zones^[166]. N. Abas et al. (2015) stated that the cost of producing oil ranges from \$20 to \$25 per barrel, but the price at the pump reaches 159 dollars per barrel due to processing and transportation costs. Oil prices are expected to be at the \$200 per barrel level by 2050, based on energy scientists^[167]. Coal and natural gas prices are expected to be \$300 per tonne and \$20 per thousand cubic feet, respectively, by 2050^[167].

Similarly, Curtin et al. (2019) identified that a high emphasis has been placed on analyzing abandoning hazards for liquid assets at the earliest stages of the funding chain: fossil fuel reserves and the energy production industry. These analyses highlight the hazards of abandoning high-cost or polluting deposits as well as energy generation systems that rely on these resources, particularly coal. There is also proof that financial asset owners may be vulnerable to abandoning hazards because coal, oil, and gas company assessments may be exaggerated, especially for undiversified corporations with big financial exposure to carbon-intensive resources^[168]. Sharvini et al. (2018) stated that global warming is one of today's biggest environmental challenges, owing mostly to the release of warming gases such as carbon dioxide from the use of fossil fuels. Surprisingly, fossil energy remains the biggest energy source in all countries, with coal dominating in China (77%) and Indonesia (70%), oil dominating in Japan (28%), and natural gas dominating in Malaysia (61%)^[169].

In addition, according to Maamoun et al. (2020) and Osman et al. (2023) because of their tremendous density of energy, fossil fuels are the dominant energy source globally, yet burning fossil fuels generates greenhouse gases (GHGs); current power plants generate around 35% of GHGs^[170, 171]. Yang et al. (2020) studied that China's coal-fired power plants release 42% of nitrous oxide and 38% of sulfur dioxide, accounting for 40% of the heat-trapping GHGs that contribute to global warming^[172]. Farghali et al. (2022) and Fawzy et al. (2020) described that climate change impacted over 300 natural catastrophes in 2018, harming over 68 million people and incurring over \$131.7 billion in economic losses, with storms, floods, wildfires, and droughts taking up 93% of the total. The reality that the wildfire's economic damages in 2018 were roughly equal to the decade's overall losses is very concerning. Furthermore, climate change threatens food, crop production, water, health, the prevalence of infectious illnesses, human dwellings, infrastructure, and environments^[173, 174].

6.3 Distributed energy resources of MGs and integration with large-scale transportation systems

According to Ishaq et al. (2022) DGs units that rely on renewable energy systems are environmentally friendly as well as sustainable. Examples of RESs such as those shown in DGs are wind, solar, geothermal, tidal waves, hydro, biogas, biomass, and hydrogen fuel cells^[184]. Kang et al. (2016) stated that EVs gained significant development in the past. Their large-scale utilization has the potential to reduce GHG emission, save fuel costs for EV drivers, and increase the use of renewable energy^[175].

6.3.1 Solar PV System

According to Akil et al. (2020) integration of renewable energy generation with EV is one of the new trends for optimizing the utilization of RESs, fulfilling energy demand, enhancing the stability of the grid, and ensuring durability. The energy management of EV charging using a PV system for an industrial microgrid (IMG) is discussed in order to supply EV load shaving utility while minimizing the cost of charging electrical energy. The findings of the analysis of simulations for 5000 EVs reveal that EV charging needs in various time frames may be satisfied by the solar power plant (SPP) in an industrial region. It is anticipated that employing a SPP in EV charging ahead of a MG in the event of extra electricity will lower EV customer charging prices and be suitable for eventual V2G solutions^[176]. Solar-powered, grid-connected systems are now frequently employed during load shedding. Singh et al. (2021) suggested a novel supervisory control strategy to enable optimal solar power use while effectively utilizing stored energy. To select whether to use electricity from the solar PV or the grid, the control action is contingent on battery voltage, solar irradiation, and grid supply. The MG system is achieved by modeling and analyzing experiments with efficient performance findings^[177].

Moreover, Tercan et al. (2022) demonstrated the techno-economic advantages of boosting PV self-consumption through pooled energy storage for a prosumer society at different adoption prices. The optimal energy storage distributions were performed in the first stage utilizing the new best algorithm and GA with MATLAB. In the second stage, the economic feasibility of growing PV self-consumption utilizing pooled energy storage at different adoption prices are assessed while remaining energy is taken into account. Incentives are evaluated using economic variables such as payback duration, net actual value, and an inner rate of return. As a result, pooled energy storage enhanced prosumer self-consumption by up to 11%. The approach has major economic benefits as well as enhanced electricity efficiency^[178]. Yuan & Xie. (2023) investigated an integrated scheme for home load planning or load commitment problems (LCP) using renewable energy resources, regardless of tariff type. Reinforcement learning (RL) is a successful approach for solving uncertainty-based decision-making difficulties. The RL-enabled LCP solution in smart MG. The arrangements are examined for

efficacy and adaptability in simulated experiments. The effectiveness of the algorithm was examined using a home user, schedulable and non-schedulable devices, and PV resources^[179].

Power output of a PV array is based on ambient temperature and solar irradiance. The power output is estimated by Bhandari et al. (2014), Singh & Bachawad. (2015), Janevska. (2017), Kumar et al. (2022), H. Nguyen & P. Nguyen (2015), Roy et al. (2022), Sawle et al. (2016), Niranjana & Pandey (2018), Bani-Hani et al. (2018) and Icaza et al. (2020) as follows:

$$P_{pv} = \eta_{pv} A_{pv} G_t(1)$$

Where η_{pv} is PV generation efficiency, A_{pv} is PV generator area (m^2), and G_t is solar irradiation in tilted module plane (W/m^2)^[180-189].

6.3.2 Wind Power System

According to Qi et al. (2020) one of the significant issues with prosumer MGs is the uncertainty of RESs such as wind power. The authors evaluate the impact of a static synchronous compensator (STATCOM) and a static VAR compensator (SVC) on transitory voltage stability at a doubly fed induction generator (DFIG)-based wind farm's point of common coupling (PCC). The coordinated control strategy can not only increase transitory voltage stability but also help minimize STATCOM capacity, lowering the cost of wind farm spending^[190]. Tan et al. (2021) suggested a method for assessing wind power accommodation capability (WPAC) in multi-energy microgrids (MEMG). The volatility of wind power has created significant issues for wind power accommodation as installed capacity has increased. The accurate evaluation result of WPAC has significant guiding value in the construction of the MEMG day-ahead wind power trading plan. Experiments on a MEMG comprised of an IEEE 33-bus power system and a 23-node district heating network (DHN) validate the method's effectiveness^[191].

In a similar vein, Msigwa et al. (2022) discovered that the energy sector contributes greatly to GHG emissions because of the burning of fossil fuels, which causes environmental difficulties. There is a global shift away from fossil fuel-based energy and toward RESs such as solar, wind, geothermal, and biomass. Wind energy is a promising RES since it is both viable and cost-effective. The authors intend to examine the effects of wind energy generation on environmental, economic, and social elements of long-term viability as well as mitigating techniques. Finally, suggestions and future views on the long-term viability of wind energy generation are presented^[192]. Jacob Knauf (2022) stated that according to a choice-based combined study of 811 German individuals, financial rewards improve citizens' approval of a hypothetical wind energy installation near their houses. All evaluated benefits are valued by enthusiasts and a substantial proportion of residents who have very weak inclinations toward local wind energy plants. The results help to influence present regulations that implement reward schemes for wind energy projects in order to enhance community acceptability and secure broad approval for projects^[193].

In addition, Maitre et al. (2023) varied between shared community benefit funds, near-neighbor compensation, and citizen investment in relation to the problems of ownership, forms of interaction, and economic benefit management during wind farm siting, building, and employment. Strong advocates are swayed more by the economic benefits to the community as a whole and local ownership of wind farms, especially joint partnerships between the developer and the community^[194]. The core equation determining wind turbine mechanical power is provided by Bhandari et al. (2014), Singh & Bachawad (2015), Janevska. (2017), Kumar et al. (2022), H. Nguyen & P. Nguyen (2015), Roy et al. (2022), Sawle et al. (2016), Niranjana & Pandey (2018), Bani-Hani et al. (2018), Icaza et al. (2020) and Acakpovi et al. (2020) as follows:

$$P_W = \frac{1}{2} C_p \rho A V^3 (\lambda, \beta) (2)$$

where, C_p is power coefficient of the turbine, ρ is air density (kg/m^3), A is intercepting area of the rotor blades (m^2), V is average wind speed (m/s), λ is tip speed ratio of the rotor blade tip speed to wind speed and β is blade pitch angle (degree). The theoretical maximum value of the power coefficient C_p is 0.593, also known as Betz's coefficient^[180, 181, 195, 182-189].

6.3.3 Hydro Power System

Baurzhan et al. (2021) examined the economic impacts of 57 World Bank Group-sponsored hydropower dam plant investments. Hydropower dams are one of the primary forms of energy generation and the entire globe's largest renewable source of energy production. In the Clean Energy Revolution to address global climate change, hydropower dams are frequently a lower-cost choice for energy production. According to the outcomes, the examined hydropower inventory helped prevent over a billion metric tons of CO₂ for a global environmental benefit predicted to be worth almost USD 350 billion. The net economic benefits of hydropower can be higher if more effort is made to control costs and time overruns^[196]. As per Sibtain et al. (2021) hydropower remains a

key source of secure, low-cost, and clean energy for the country due to the substantial availability of resources and well-managed technology^[197]. Adomavičius et al. (2023) presented a brief outline of the infrastructure required to establish a MG employing a small-scale hydro power plants (HPPs) supplemented by a floating solar power plant (SPP) and wind power plants (WPP). Solar, wind, and hydropower plants now have the lowest electricity costs, while fossil-fuel power plants are significantly below them^[198].

In a related vein, Shukla & Raju (2021) investigated studies on two-area microgrid systems, one with modest hydro and the other with DG. EVs are now available in both places. The EV can be performed in either V2G (source) or grid-to-vehicle (G2V)(load) mode. The outcomes are obtained using the MATLAB/Simulink platform, which produces outstanding results^[199]. (Bhatti et al., 2023) developed a hybridization technique in which HPP is coupled with an ESS to boost operational flexibility and decrease HPP harm. Models are created to describe the hybrid system's function, evaluate deterioration, and evaluate economic advantages. Furthermore, a novel controller separates the market allocation signal into control set points for the ESS and HPPs. According to case studies conducted on a real-world hydropower facility, ESS-based hybridization can increase the life of the HPP by 5% in aggregate. The projected economic benefits of decreased upkeep and delayed spending are \$3.6 million^[200]. The turbine's mechanical power is specified by Bhandari et al. (2014), Singh & Bachawad (2015) and Janevska (2017) as follows:

$$P_H = \eta_{total} \rho g Q H \quad (2.3)$$

where P_H is mechanical power output produced at the turbine, η_{total} hydraulic efficiency of the turbine, ρ is density of water (1000 kg/m^3), g is acceleration due to gravity (9.81 m/s^2), Q is flow rate in the pipe (m^3/s) and H is effective pressure head (m)^{[187]-[189]}. Osman et al. (2023) and Rahman et al. (2022) shown in Fig.5 renewable energy sources in electricity generation in giga watt% from a total of 2587.6 giga watts. Hydropower is the major contributor to the production of energy. Solar and wind energy contribute 50% of overall electricity use. Power plants based on geothermal, oceanic, and biomass sources contribute little over 6%^[170, 201].

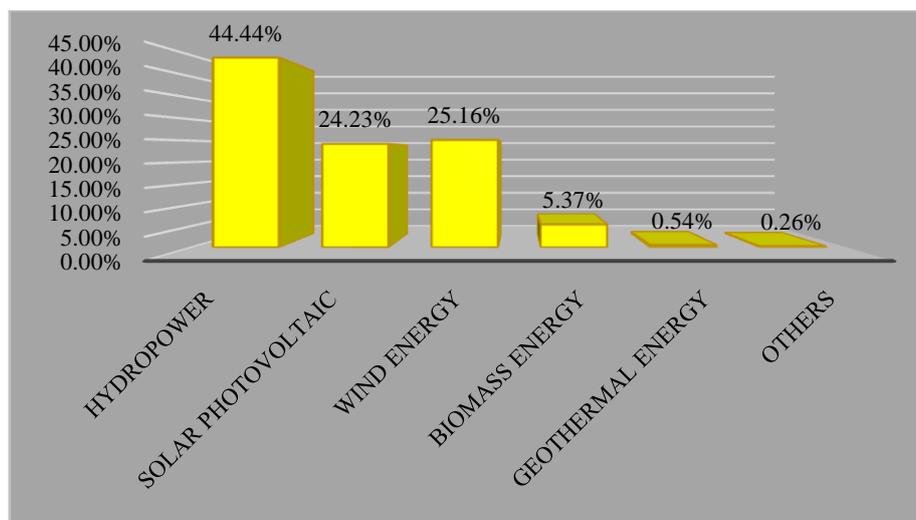


Fig.5. Electrical power generation by RES based power plants

6.3.4 Energy Storage Systems

Hannan et al. (2021) stated that each type of storage has unique characteristics, including capacity, energy and power output, charging and discharging rates, efficiency, life cycle, and cost, which must be considered for potential uses. The various ESS technologies exhibit varying incarceration based on the materials and power electronic interactions^[202]. Many researchers used the storage system technologies in MGs like, Luo et al. (2015) and Yi et al. (2021) Lithium-ion batteries^[203, 204], Chen et al. (2018) and Cruz et al. (2018) Lead acid batteries^[205, 206], Lourenssen et al. (2019) Vanadium redox flow batteries^[207], Luo et al. (2015) and Wang et al. (2020) Sodium sulfur batteries^[204, 208], Torres et al. (2022) Sodium nickel chloride batteries^[209], Edalati et al. (2022) Nickel metal hybrid batteries^[210], Edalati et al. (2022) and Blumbergs et al. (2021) Nickel cadmium batteries^[210, 211], Edalati et al. (2022) and Popat et al. (2022) Polysulphide bromine redox flow batteries^[210, 212], and Xu et al. (2020) Zinc bromine redox flow battery^[213]. According to Zarate-Perez et al. (2022) the most prevalent barriers to building a battery energy storage system are economic considerations, since academics have concentrated on the analysis of costs and benefits^[214].

Likewise, Rahmani et al. (2023) studied that ESSs are beneficial technologies for ensuring the steady functioning of microgrids, particularly those with high renewable energy consumption. The functioning of a microgrid is closely linked to the planning of ESS units. In order to control MG in an effective way, a novel method for ESS planning has been proposed. As ensuring dependability and cost minimization are opposing objectives in ESS planning, the issue of multi-objective optimization should be solved for efficient ESS scheduling. The findings of implementing this strategy on a modified 33-bus IEEE test system support the usefulness of the scheme for improving MG dependability^[215]. X. Liu et al. (2023) offered photovoltaic and energy storage system (PVESS) integration in public transportation (PT) as a possible way to reduce transit companies' charges and carbon emission expenses. On the other hand, the quantifiable consequences of PVESS on operational costs, carbon emission costs, bus planning, and energy management in PT are unknown. To establish the best PVESS layout for battery electric bus (BEB) charging points, a surrogate-based optimization method is used. An investigation is conducted by implementing PVESS at BEB charging points in Beijing, China, utilizing archaeological climate and bus operational information. According to the findings, the recycling power price of PV generation is critical to impacting charging costs and carbon emissions. Battery capacities have a significant impact on PVESS planning patterns^[216].

In a related vein, Gonzalez et al. (2021) examined the energy characteristics of a BEB driving on commercial paths as well as the technical viability of replacing the present public transportation inventory in an Andean city with BEBs. As an addition to the PT's long-term viability, the study demonstrates a potential replacement for integrating renewable energy sources for BEB charging based on photovoltaic solar power and the utilization of energy storage devices^[217]. As per the literature, I found that the integration of renewable energy generation, such as hydro, solar, and wind power plants, with transportation systems is more economical, environmentally friendly, and has a lower operational cost as compared to traditional fossil fuel-based energy generation. Additionally, energy storage systems are more beneficial for MG reliability, sustainability, and increased efficiency.

7. Research Trends

According to Akil et al. (2020), Ishaq et al. (2022), Azad et al. (2020) and Engel et al. (2022) recent developments in MG and transportation systems include the following trends^[84, 113, 176, 218]:

- Renewable energy generation with transportation systems has become a fascinating trend, providing an unparalleled chance to capture the entire potential of RESs while also meeting our world's expanding energy needs. This easy integration not only encourages efficient RES consumption but also acts as a catalyst to increase grid stability and sustainable energy management. By adopting this enthralling cooperation, we unlock a future of limitless possibilities in which our reliance on traditional energy sources fades into oblivion, paving the way for a new era of clean, green, and sustainable energy.
- Advanced control and development of optimization algorithms have become great trend in coordinating and managing the optimal supply of energy in MGCs. These algorithms will use real-time data analytics, mathematical models, machine learning, and predictive modeling to optimize energy usage, reduce waste, and guarantee the transportation system has a consistent energy supply.
- There is a trend toward implementing demand response and load management strategies to assure the optimal supply of energy in a large-scale system. This entails modifying consumption of energy and generation in response to real-time demand and price signals in order to maximize efficiency and lower costs.
- There is a trend towards implementing energy storage solutions within MGCs to overcome the intermittency and unpredictable nature of RESs. This entails using batteries, pumped hydro storage, and other technologies to save excess energy during times of low demand and release it when needed.
- As EVs become more popular, there is an increasing trend toward employing V2G technology to allow bidirectional energy transfer between the grid and EVs. This enables EVs to not only use but also send energy returned to the grid during times of high demand, thereby improving the entire stability and durability of the transportation energy system.

8. Conclusion

To conclude, the coordination and optimal supply of MGCs and their integration with transportation systems have recently drawn a lot of attention due to the many benefits they hold. This paper presents an extensive review of the coordination and optimal supply of MGCs in LSTSCES. It is an important area of research that has the potential to transform the energy sector. MGC integration can help minimize dependence on traditional energy sources and boost the use of RESs. The purpose of this study is to review new types of power transportation that have the potential to reduce GHG emissions, promote sustainability, and improve total

transportation efficiency. To review the coordination and un-coordination, we found that coordination is more beneficial for the MGs and transportation systems. To study the hierarchical, centralized, and decentralized control structures and prove that hierarchical control in the fashion of decentralized systems for large-scale systems is more beneficial and cost-effective. To discuss the optimization techniques and prove that metaheuristic algorithms are more economical. Moreover, to study the economic model, RESs is more economical than traditional sources with ESSs for MGCs. The concentration of research could be on developing algorithms and strategies capable of handling large-scale applications while preserving efficiency and dependability. This could include doing a cost-benefit analysis, investigating regulatory frameworks, and assessing incentives or procedures to encourage the adoption of self-consistent energy systems. Renewable energy generation with transportation systems has become a fascinating trend. Advanced control and the development of optimization algorithms have become a great trend in coordinating and managing the optimal supply of energy in MGCs. These algorithms will use real-time data analytics, mathematical models, machine learning, and predictive modeling to optimize energy usage, reduce waste, and guarantee the transportation system has a consistent energy supply. There is a trend toward implementing demand response and load management strategies to assure the optimal supply of energy in a large-scale system. There is a trend towards implementing energy storage solutions within MGCs to overcome the intermittency and unpredictable nature of RESs. As EVs become more popular, there is an increasing trend toward employing V2G technology to allow bidirectional energy transfer between the grid and EVs. Advanced control algorithms, energy management systems, and optimization techniques can aid in the optimal supply and coordination of MGCs, resulting in a more sustainable and reliable energy future.

Future Work Suggestions:

- Investigate the use of advanced artificial intelligence (AI) approaches like machine learning and deep learning to improve the coordination and optimization of MGCs in transportation energy systems. AI can help with real-time decision-making, load forecasting, energy management, and problem identification.
- To solve the issues involved with coordinating and optimizing MGCs in a large-scale transportation system, develop and deploy novel optimization algorithms. These algorithms are capable of efficiently handling complex constraints, uncertainties, and multi-objective optimization problems.
- To explore the integration of advanced energy storage technologies like battery systems, super capacitors, and hydrogen storage in transportation MGCs, aiming to enhance system efficiency and reliability.
- The study explores demand-side management techniques for coordinating EV charging and discharging activities in MGCs and implementing smart charging infrastructure for efficient energy use.
- Analyze the economic and policy aspects of implementing MGCs in transportation self-consistent energy systems, considering pricing, regulatory frameworks, and market incentives.

Acknowledgement: This paper is supported by the Prof. Wang Biao, School of Energy and Electrical Engineering, Chang'an University, Xi'an City, Shaanxi Province, CHINA.

References

- [1] A. Yavuz, N. Celik, C. H. Chen, and J. Xu, "A Sequential Sampling-based Particle Swarm Optimization to Control Droop Coefficients of Distributed Generation Units in Microgrid Clusters," *Electr. Power Syst. Res.*, vol. 216, no. November 2022, p. 109074, 2023, doi: 10.1016/j.epsr.2022.109074.
- [2] A. A. Mohamed, A. T. Elsayed, T. A. Youssef, and O. A. Mohammed, "Hierarchical control for DC microgrid clusters with high penetration of distributed energy resources," *Electr. Power Syst. Res.*, vol. 148, pp. 210–219, 2017, doi: 10.1016/j.epsr.2017.04.003.
- [3] M. Yuan, J. Mai, X. Liu, H. Shen, and J. Wang, "Current Implementation and Development Countermeasures of Green Energy in China's Highway Transportation," 2023.
- [4] M. Mazidi, N. Rezaei, F. J. Ardakani, M. Mohiti, and J. M. Guerrero, "A hierarchical energy management system for islanded multi-microgrid clusters considering frequency security constraints," *Int. J. Electr. Power Energy Syst.*, vol. 121, no. January, p. 106134, 2020, doi: 10.1016/j.ijepes.2020.106134.
- [5] V. Nikam and V. Kalkhambkar, "A review on control strategies for microgrids with distributed energy resources, energy storage systems, and electric vehicles," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 1, pp. 1–26, 2021, doi: 10.1002/2050-7038.12607.
- [6] A. Nawaz, M. Zhou, J. Wu, and C. Long, "A comprehensive review on energy management, demand response, and coordination schemes utilization in multi-microgrids network," *Appl. Energy*, vol. 323, no.

-
- May, p. 119596, 2022, doi: 10.1016/j.apenergy.2022.119596.
- [7] B. An, Y. Li, J. M. Guerrero, W. J. Lee, L. Luo, and Z. Zhang, “Renewable Energy Integration in Intelligent Railway of China: Configurations, Applications and Issues,” *IEEE Intell. Transp. Syst. Mag.*, vol. 13, no. 3, pp. 13–33, 2021, doi: 10.1109/MITS.2019.2953482.
- [8] F. Ning, L. Ji, J. Ma, L. Jia, and Z. Yu, “Research and analysis of a flexible integrated development model of railway system and photovoltaic in China,” *Renew. Energy*, vol. 175, pp. 853–867, 2021, doi: 10.1016/j.renene.2021.04.119.
- [9] S. Xia *et al.*, “An energy scheduling method for clustering islands with shared power exchanging vessels,” *Int. J. Electr. Power Energy Syst.*, vol. 152, no. May, p. 109200, 2023, doi: 10.1016/j.ijepes.2023.109200.
- [10] X. Huang, W. Ji, X. Ye, and Z. Feng, “Configuration Planning of Expressway Self-Consistent Energy System Based on Multi-Objective Chance-Constrained Programming,” *Sustainability*, vol. 15, no. 6, p. 5605, 2023, doi: 10.3390/su15065605.
- [11] A. Ali, W. Li, R. Hussain, X. He, B. W. Williams, and A. H. Memon, “Overview of current microgrid policies, incentives and barriers in the European Union, United States and China,” *Sustain.*, vol. 9, no. 7, 2017, doi: 10.3390/su9071146.
- [12] F. Zhu *et al.*, “Short-term stochastic optimization of a hydro-wind-photovoltaic hybrid system under multiple uncertainties,” *Energy Convers. Manag.*, vol. 214, no. 1, p. 112902, 2020, doi: 10.1016/j.enconman.2020.112902.
- [13] Y. Xu, S. Ye, Z. Qin, X. Lin, J. Huangfu, and W. Zhou, “A coordinated optimal scheduling model with Nash bargaining for shared energy storage and Multi-microgrids based on Two-layer ADMM,” *Sustain. Energy Technol. Assessments*, vol. 56, no. May 2022, p. 102996, 2023, doi: 10.1016/j.seta.2022.102996.
- [14] R. Lalparmawii, S. Datta, S. Deb, and S. Das, “Load frequency control of a photovoltaic-pumped hydro power energy storagebased micro-grid System,” *Proc. - 2021 IEEE 10th Int. Conf. Commun. Syst. Netw. Technol. CSNT 2021*, pp. 312–317, 2021, doi: 10.1109/CSNT51715.2021.9509711.
- [15] S. R. Salkuti, “Emerging and Advanced Green Energy Technologies for Sustainable and Resilient Future Grid,” *Energies*, vol. 15, no. 18, 2022, doi: 10.3390/en15186667.
- [16] S. K. Rathor and D. Saxena, “Energy management system for smart grid: An overview and key issues,” *Int. J. Energy Res.*, vol. 44, no. 6, pp. 4067–4109, 2020, doi: 10.1002/er.4883.
- [17] H. Yu, S. Niu, Y. Shang, Z. Shao, Y. Jia, and L. Jian, “Electric vehicles integration and vehicle-to-grid operation in active distribution grids: A comprehensive review on power architectures, grid connection standards and typical applications,” *Renew. Sustain. Energy Rev.*, vol. 168, no. August, p. 112812, 2022, doi: 10.1016/j.rser.2022.112812.
- [18] K. Bhushan Sahay, M. A. S. Abourehab, A. Mehbodniya, J. L. Webber, R. Kumar, and U. Sakthi, “Computation of electrical vehicle charging station (evcs) with coordinate computation based on meta-heuristics optimization model with effective management strategy for optimal charging and energy saving,” *Sustain. Energy Technol. Assessments*, vol. 53, no. PB, p. 102439, 2022, doi: 10.1016/j.seta.2022.102439.
- [19] M. Longo, F. Foiaelli, and W. Yaïci, “Electric Vehicles Integrated with Renewable Energy Sources for Sustainable Mobility,” *New Trends Electr. Veh. Powertrains*, 2019, doi: 10.5772/intechopen.76788.
- [20] F. Valencia, M. Billi, and A. Urquiza, “Overcoming energy poverty through micro-grids: An integrated framework for resilient, participatory sociotechnical transitions,” *Energy Res. Soc. Sci.*, vol. 75, no. March, p. 102030, 2021, doi: 10.1016/j.erss.2021.102030.
- [21] B. Zhou, C. Xi, D. Yang, Q. Sun, and H. Zhang, “A Distributed Self-Consistent Control Method for Electric Vehicles to Coordinate Low-Carbon Transportation and Energy,” *IEEE/CAA J. Autom. Sin.*, vol. 10, no. 2, pp. 554–556, 2023, doi: 10.1109/JAS.2023.123240.
- [22] S. Goel, R. Sharma, and A. K. Rathore, “A review on barrier and challenges of electric vehicle in India and vehicle to grid optimisation,” *Transp. Eng.*, vol. 4, p. 100057, 2021, doi: 10.1016/j.treng.2021.100057.
- [23] M. de las N. Camacho, D. Jurburg, and M. Tanco, “Hydrogen fuel cell heavy-duty trucks: Review of main research topics,” *Int. J. Hydrogen Energy*, vol. 47, no. 68, pp. 29505–29525, 2022, doi: 10.1016/j.ijhydene.2022.06.271.
- [24] S. A. Afolalu, O. O. Yusuf, A. A. Abioye, M. E. Emeteri, S. O. Ongbali, and O. D. Samuel, “Biofuel; A Sustainable Renewable Source of Energy-A Review,” *IOP Conf. Ser. Earth Environ. Sci.*, vol. 665, no. 1, 2021, doi: 10.1088/1755-1315/665/1/012040.
- [25] Y. Li and F. Taghizadeh-Hesary, “The economic feasibility of green hydrogen and fuel cell electric vehicles for road transport in China,” *Energy Policy*, vol. 160, no. July 2021, p. 112703, 2022, doi:
-

- 10.1016/j.enpol.2021.112703.
- [26] P. Ahmadi and A. Khoshnevisan, “Dynamic simulation and lifecycle assessment of hydrogen fuel cell electric vehicles considering various hydrogen production methods,” *Int. J. Hydrogen Energy*, vol. 47, no. 62, pp. 26758–26769, 2022, doi: 10.1016/j.ijhydene.2022.06.215.
- [27] S. M. Shariff, M. S. Alam, F. Ahmad, Y. Rafat, M. S. J. Asghar, and S. Khan, “System Design and Realization of a Solar-Powered Electric Vehicle Charging Station,” *IEEE Syst. J.*, vol. 14, no. 2, pp. 2748–2758, 2020, doi: 10.1109/JSYST.2019.2931880.
- [28] A. Sierra and A. Reinders, “Designing innovative solutions for solar-powered electric mobility applications,” *Prog. Photovoltaics Res. Appl.*, vol. 29, no. 7, pp. 802–818, 2021, doi: 10.1002/pip.3385.
- [29] C. Zhang, C. Zhang, L. Li, and Q. Guo, “Parameter analysis of power system for solar-powered unmanned aerial vehicle,” *Appl. Energy*, vol. 295, no. April, p. 117031, 2021, doi: 10.1016/j.apenergy.2021.117031.
- [30] S. Khan, A. Ahmad, F. Ahmad, M. Shafaati Shemami, M. Saad Alam, and S. Khateeb, “A Comprehensive Review on Solar Powered Electric Vehicle Charging System,” *Smart Sci.*, vol. 6, no. 1, pp. 54–79, 2018, doi: 10.1080/23080477.2017.1419054.
- [31] M. Li, S. Luo, W. Ma, T. Li, D. Gao, and Z. Xu, “Experimental and numerical investigations of the dynamic responses of low and medium speed maglev train-track-bridge coupled system,” *Veh. Syst. Dyn.*, vol. 60, no. 5, pp. 1555–1578, 2022, doi: 10.1080/00423114.2020.1864417.
- [32] H. Fakour *et al.*, “Evaluation of solar photovoltaic carport canopy with electric vehicle charging potential,” *Sci. Rep.*, vol. 13, no. 1, pp. 1–14, 2023, doi: 10.1038/s41598-023-29223-6.
- [33] K. Obaideen *et al.*, “Solar Energy: Applications, Trends Analysis, Bibliometric Analysis and Research Contribution to Sustainable Development Goals (SDGs),” *Sustainability*, vol. 15, no. 2, p. 1418, 2023, doi: 10.3390/su15021418.
- [34] N. Prasad, S. Jain, and S. Gupta, “Electrical Components of Maglev Systems: Emerging Trends,” *Urban Rail Transit*, vol. 5, no. 2, pp. 67–79, 2019, doi: 10.1007/s40864-019-0104-1.
- [35] A. García-Olivares, J. Solé, and O. Osychenko, “Transportation in a 100% renewable energy system,” *Energy Convers. Manag.*, vol. 158, no. January, pp. 266–285, 2018, doi: 10.1016/j.enconman.2017.12.053.
- [36] “Theory of Hierarchical , Mu It i level , Systems”.
- [37] S. Chang, Y. Niu, and T. Jia, “Coordinate scheduling of electric vehicles in charging stations supported by microgrids,” *Electr. Power Syst. Res.*, vol. 199, no. October 2020, p. 107418, 2021, doi: 10.1016/j.epsr.2021.107418.
- [38] X. Jiang, J. Wang, Y. Han, and Q. Zhao, “Coordination Dispatch of Electric Vehicles Charging/Discharging and Renewable Energy Resources Power in Microgrid,” *Procedia Comput. Sci.*, vol. 107, no. Icict, pp. 157–163, 2017, doi: 10.1016/j.procs.2017.03.072.
- [39] X. Wang, M. Shahidepour, C. Jiang, and Z. Li, “Coordinated Planning Strategy for Electric Vehicle Charging Stations and Coupled Traffic-Electric Networks,” *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 268–279, 2019, doi: 10.1109/TPWRS.2018.2867176.
- [40] B. Li, R. Roche, D. Paire, and A. Miraoui, “Coordinated scheduling of a gas/electricity/heat supply network considering temporal-spatial electric vehicle demands,” *Electr. Power Syst. Res.*, vol. 163, no. July, pp. 382–395, 2018, doi: 10.1016/j.epsr.2018.07.014.
- [41] R. Shi, L. Xu, and Y. Xue, “Research on Coordinated Charging Strategy of Electric Vehicles Based on PSO Algorithm,” *Proc. 2018 Chinese Autom. Congr. CAC 2018*, pp. 1269–1273, 2019, doi: 10.1109/CAC.2018.8623731.
- [42] Y. Hao, L. Dong, J. Liang, X. Liao, L. Wang, and L. Shi, “Power forecasting-based coordination dispatch of PV power generation and electric vehicles charging in microgrid,” *Renew. Energy*, vol. 155, pp. 1191–1210, 2020, doi: 10.1016/j.renene.2020.03.169.
- [43] M. B. Niu, H. C. Wang, J. Li, H. Liu, and R. Yin, “Coordinated energy dispatch of highway microgrids with mobile storage system based on DMPC optimization,” *Electr. Power Syst. Res.*, vol. 217, no. November 2022, p. 109119, 2023, doi: 10.1016/j.epsr.2023.109119.
- [44] Z. Li and Y. Xu, “Optimal coordinated energy dispatch of a multi-energy microgrid in grid-connected and islanded modes,” *Appl. Energy*, vol. 210, no. May, pp. 974–986, 2018, doi: 10.1016/j.apenergy.2017.08.197.
- [45] S. Habib, M. Kamran, and U. Rashid, “Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks - A review,” *J. Power Sources*, vol. 277, pp. 205–214, 2015, doi: 10.1016/j.jpowsour.2014.12.020.
- [46] A. R. Abul’Wafa, A. El’Garably, and W. Abdelfattah, “Electric Vehicles Coordinated vs Uncoordinated

-
- Charging Impacts on Distribution Systems Performance,” *Int. J. New Technol. Sci. Eng.*, vol. 4, no. 6, pp. 1–11, 2017, [Online]. Available: [https://www.ijntse.com/upload/1502423799IJNTSE-Electric Vehicles Coordinated vs Uncoordinated Charging Impacts on Distribution Systems Performance.pdf](https://www.ijntse.com/upload/1502423799IJNTSE-Electric_Vehicles_Coordinated_vs_Uncoordinated_Charging_Impacts_on_Distribution_Systems_Performance.pdf)
- [47] Y. Zheng, Y. Shang, Z. Shao, and L. Jian, “A novel real-time scheduling strategy with near-linear complexity for integrating large-scale electric vehicles into smart grid,” *Appl. Energy*, vol. 217, no. January, pp. 1–13, 2018, doi: 10.1016/j.apenergy.2018.02.084.
- [48] K. Zhou, L. Cheng, L. Wen, X. Lu, and T. Ding, “A coordinated charging scheduling method for electric vehicles considering different charging demands,” *Energy*, vol. 213, p. 118882, 2020, doi: 10.1016/j.energy.2020.118882.
- [49] L. Jian, Y. Zheng, and Z. Shao, “High efficient valley-filling strategy for centralized coordinated charging of large-scale electric vehicles,” *Appl. Energy*, vol. 186, pp. 46–55, 2017, doi: 10.1016/j.apenergy.2016.10.117.
- [50] L. Liu and K. Zhou, “Electric vehicle charging scheduling considering urgent demand under different charging modes,” *Energy*, vol. 249, p. 123714, 2022, doi: 10.1016/j.energy.2022.123714.
- [51] C. Crozier, T. Morstyn, and M. McCulloch, “Capturing diversity in electric vehicle charging behaviour for network capacity estimation,” *Transp. Res. Part D Transp. Environ.*, vol. 93, no. March, p. 102762, 2021, doi: 10.1016/j.trd.2021.102762.
- [52] G. F. Savari *et al.*, “Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: A review,” *Ain Shams Eng. J.*, vol. 14, no. 4, p. 101938, 2023, doi: 10.1016/j.asej.2022.101938.
- [53] S. Martinenas, K. Knezovic, and M. Marinelli, “Management of Power Quality Issues in Low Voltage Networks Using Electric Vehicles: Experimental Validation,” *IEEE Trans. Power Deliv.*, vol. 32, no. 2, pp. 971–979, 2017, doi: 10.1109/TPWRD.2016.2614582.
- [54] L. Gong, W. Cao, K. Liu, and J. Zhao, “Optimal charging strategy for electric vehicles in residential charging station under dynamic spike pricing policy,” *Sustain. Cities Soc.*, vol. 63, no. 2, p. 102474, 2020, doi: 10.1016/j.scs.2020.102474.
- [55] D. Y. Yamashita, I. Vechiu, and J. P. Gaubert, “A review of hierarchical control for building microgrids,” *Renew. Sustain. Energy Rev.*, vol. 118, no. October 2019, p. 109523, 2020, doi: 10.1016/j.rser.2019.109523.
- [56] M. S. Mahmoud, M. S. U. Rahman, and F. M. A. L. Sunni, “Review of microgrid architectures - A system of systems perspective,” *IET Renew. Power Gener.*, vol. 9, no. 8, pp. 1064–1078, 2015, doi: 10.1049/iet-rpg.2014.0171.
- [57] D. Wu, N. Radhakrishnan, and S. Huang, “A hierarchical charging control of plug-in electric vehicles with simple flexibility model,” *Appl. Energy*, vol. 253, no. July, 2019, doi: 10.1016/j.apenergy.2019.113490.
- [58] S. Sarabi, A. Davigny, V. Courtecuisse, Y. Riffonneau, and B. Robyns, “Potential of vehicle-to-grid ancillary services considering the uncertainties in plug-in electric vehicle availability and service/localization limitations in distribution grids,” *Appl. Energy*, vol. 171, pp. 523–540, 2016, doi: 10.1016/j.apenergy.2016.03.064.
- [59] Z. Xu, W. Su, Z. Hu, Y. Song, and H. Zhang, “A hierarchical framework for coordinated charging of plug-in electric vehicles in China,” *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 428–438, 2016, doi: 10.1109/TSG.2014.2387436.
- [60] X. Luo, S. Xia, K. W. Chan, and X. Lu, “A hierarchical scheme for utilizing plug-in electric vehicle power to hedge against wind-induced unit ramp cycling operations,” *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 55–69, 2018, doi: 10.1109/TPWRS.2017.2696540.
- [61] D. Yassuda Yamashita, I. Vechiu, and J. P. Gaubert, “Two-level hierarchical model predictive control with an optimised cost function for energy management in building microgrids,” *Appl. Energy*, vol. 285, no. November 2020, p. 116420, 2021, doi: 10.1016/j.apenergy.2020.116420.
- [62] M. Tavakoli, F. Shokridehaki, M. Marzband, R. Godina, and E. Pouresmaeil, “A two stage hierarchical control approach for the optimal energy management in commercial building microgrids based on local wind power and PEVs,” *Sustain. Cities Soc.*, vol. 41, no. January, pp. 332–340, 2018, doi: 10.1016/j.scs.2018.05.035.
- [63] Y. Wu, Z. Wang, Y. Huangfu, A. Ravey, D. Chrenko, and F. Gao, “Hierarchical Operation of Electric Vehicle Charging Station in Smart Grid Integration Applications — An Overview,” *Int. J. Electr. Power Energy Syst.*, vol. 139, no. February, 2022, doi: 10.1016/j.ijepes.2022.108005.
- [64] A. Abhishek, A. Ranjan, S. Devassy, B. Kumar Verma, S. K. Ram, and A. K. Dhakar, “Review of hierarchical control strategies for DC microgrid,” *IET Renew. Power Gener.*, vol. 14, no. 10, pp. 1631–
-

- 1640, 2020, doi: 10.1049/iet-rpg.2019.1136.
- [65] S. D. Tavakoli, J. Khajesalehi, M. Hamzeh, and K. Sheshyekani, “Decentralised voltage balancing in bipolar dc microgrids equipped with trans-z-source interlinking converter,” *IET Renew. Power Gener.*, vol. 10, no. 5, pp. 703–712, 2016, doi: 10.1049/iet-rpg.2015.0222.
- [66] F. Gao, R. Kang, J. Cao, and T. Yang, “Primary and secondary control in DC microgrids: a review,” *J. Mod. Power Syst. Clean Energy*, vol. 7, no. 2, pp. 227–242, 2019, doi: 10.1007/s40565-018-0466-5.
- [67] D. E. Olivares *et al.*, “Trends in microgrid control,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1905–1919, 2014, doi: 10.1109/TSG.2013.2295514.
- [68] S. Islam *et al.*, “Ideal current-based distributed control to compensate line impedance in DC microgrid,” *IET Power Electron.*, vol. 11, no. 7, pp. 1178–1186, 2018, doi: 10.1049/iet-pel.2017.0531.
- [69] C. N. Papadimitriou, E. I. Zountouridou, and N. D. Hatzargyriou, “Review of hierarchical control in DC microgrids,” *Electr. Power Syst. Res.*, vol. 122, pp. 159–167, 2015, doi: 10.1016/j.epr.2015.01.006.
- [70] A. C. Z. De Souza, M. Santos, M. Castilla, J. Miret, L. G. De Vicuña, and D. Marujo, “Voltage security in AC microgrids: A power flow-based approach considering droopcontrolled inverters,” *IET Renew. Power Gener.*, vol. 9, no. 8, pp. 954–960, 2015, doi: 10.1049/iet-rpg.2014.0406.
- [71] X. Wu, X. Wu, Y. Xu, and J. He, “A Hierarchical Control Framework for Islanded Multi-Microgrid Systems,” *IEEE Power Energy Soc. Gen. Meet.*, vol. 2018-Augus, pp. 1–5, 2018, doi: 10.1109/PESGM.2018.8586235.
- [72] Y. Guan, J. C. Vasquez, and J. M. Guerrero, “Hierarchical controlled grid-connected microgrid based on a novel autonomous current sharing controller,” *2015 IEEE Energy Convers. Congr. Expo. ECCE 2015*, pp. 2333–2340, 2015, doi: 10.1109/ECCE.2015.7309988.
- [73] M. H. Cintuglu, T. Youssef, and O. A. Mohammed, “Development and application of a real-time testbed for multiagent system interoperability: A case study on hierarchical microgrid control,” *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1759–1768, 2018, doi: 10.1109/TSG.2016.2599265.
- [74] P. R. C. Mendes, L. V. Isorna, C. Bordons, and J. E. Normey-Rico, “Energy management of an experimental microgrid coupled to a V2G system,” *J. Power Sources*, vol. 327, pp. 702–713, 2016, doi: 10.1016/j.jpowsour.2016.07.076.
- [75] M. Nassourou, V. Puig, J. Blesa, and C. Ocampo-Martinez, “Economic model predictive control for energy dispatch of a smart micro-grid system,” *2017 4th Int. Conf. Control. Decis. Inf. Technol. CoDIT 2017*, vol. 2017-Janua, pp. 944–949, 2017, doi: 10.1109/CoDIT.2017.8102719.
- [76] D. Wang, J. Qiu, L. Reedman, K. Meng, and L. L. Lai, “Two-stage energy management for networked microgrids with high renewable penetration,” *Appl. Energy*, vol. 226, no. March, pp. 39–48, 2018, doi: 10.1016/j.apenergy.2018.05.112.
- [77] F. J. Heredia, M. D. Cuadrado, and C. Corchero, “On optimal participation in the electricity markets of wind power plants with battery energy storage systems,” *Comput. Oper. Res.*, vol. 96, pp. 316–329, 2018, doi: 10.1016/j.cor.2018.03.004.
- [78] F. Bandejas, E. Pinheiro, M. Gomes, P. Coelho, and J. Fernandes, “Review of the cooperation and operation of microgrid clusters,” *Renew. Sustain. Energy Rev.*, vol. 133, no. March, p. 110311, 2020, doi: 10.1016/j.rser.2020.110311.
- [79] M. Mao, Y. Wang, L. Chang, and Y. Du, “Operation optimization for multi-microgrids based on centralized-Decentralized hybrid hierarchical energy management,” *2017 IEEE Energy Convers. Congr. Expo. ECCE 2017*, vol. 2017-Janua, no. 51577047, pp. 4813–4820, 2017, doi: 10.1109/ECCE.2017.8096818.
- [80] R. Chen, Y. Yang, and T. Jin, “A hierarchical coordinated control strategy based on multi-port energy router of urban rail transit,” *Prot. Control Mod. Power Syst.*, vol. 7, no. 1, 2022, doi: 10.1186/s41601-022-00237-y.
- [81] Q. Li, C. Peng, M. Wang, M. Chen, J. M. Guerrero, and D. Abbott, “Distributed secondary control and management of islanded microgrids via dynamic weights,” *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2196–2207, 2019, doi: 10.1109/TSG.2018.2791398.
- [82] T. Dragicevic, X. Lu, J. C. Vasquez, and J. M. Guerrero, “DC Microgrids - Part I: A Review of Control Strategies and Stabilization Techniques,” *IEEE Trans. Power Electron.*, vol. 31, no. 7, pp. 4876–4891, 2016, doi: 10.1109/TPEL.2015.2478859.
- [83] Zaheeruddin and M. Manas, “Renewable energy management through microgrid central controller design: An approach to integrate solar, wind and biomass with battery,” *Energy Reports*, vol. 1, pp. 156–163, 2015, doi: 10.1016/j.egy.2015.06.003.
- [84] S. Ishaq, I. Khan, S. Rahman, T. Hussain, A. Iqbal, and R. M. Elavarasan, “A review on recent developments in control and optimization of micro grids,” *Energy Reports*, vol. 8, pp. 4085–4103, 2022,

- doi: 10.1016/j.egy.2022.01.080.
- [85] P. Kou, D. Liang, and L. Gao, “Distributed EMPC of multiple microgrids for coordinated stochastic energy management,” *Appl. Energy*, vol. 185, pp. 939–952, 2017, doi: 10.1016/j.apenergy.2016.09.092.
- [86] N. I. Nimalsiri, C. P. Mediwaththe, E. L. Ratnam, M. Shaw, D. B. Smith, and S. K. Halgamuge, “A Survey of Algorithms for Distributed Charging Control of Electric Vehicles in Smart Grid,” *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 11, pp. 4497–4515, 2020, doi: 10.1109/TITS.2019.2943620.
- [87] C. Wang, Y. Liu, X. Li, L. Guo, L. Qiao, and H. Lu, “Energy management system for stand-alone diesel-wind-biomass microgrid with energy storage system,” *Energy*, vol. 97, pp. 90–104, 2016, doi: 10.1016/j.energy.2015.12.099.
- [88] V. Mohan, J. G. Singh, and W. Ongsakul, “An efficient two stage stochastic optimal energy and reserve management in a microgrid,” *Appl. Energy*, vol. 160, pp. 28–38, 2015, doi: 10.1016/j.apenergy.2015.09.039.
- [89] C. Chen, F. Wang, B. Zhou, K. W. Chan, Y. Cao, and Y. Tan, “An interval optimization based day-ahead scheduling scheme for renewable energy management in smart distribution systems,” *Energy Convers. Manag.*, vol. 106, pp. 584–596, 2015, doi: 10.1016/j.enconman.2015.10.014.
- [90] L. Wang, S. Sharkh, and A. Chipperfield, “Optimal decentralized coordination of electric vehicles and renewable generators in a distribution network using A* search,” *Int. J. Electr. Power Energy Syst.*, vol. 98, no. January, pp. 474–487, 2018, doi: 10.1016/j.ijepes.2017.11.036.
- [91] J. S. Tingting Wu, Gang Bao, Yuanyuan Chen, “A Review for Control Strategies in Microgrid,” in *37th Chinese Control Conference (CCC)*, 2018, pp. 30–35. doi: 10.23919/ChiCC.2018.8482549.
- [92] T. Bian, Y. Jiang, and Z. P. Jiang, “Decentralized Adaptive Optimal Control of Large-Scale Systems with Application to Power Systems,” *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2439–2447, 2015, doi: 10.1109/TIE.2014.2345343.
- [93] M. Mohiti, H. Monsef, and H. Lesani, “A decentralized robust model for coordinated operation of smart distribution network and electric vehicle aggregators,” *Int. J. Electr. Power Energy Syst.*, vol. 104, no. July 2018, pp. 853–867, 2019, doi: 10.1016/j.ijepes.2018.07.054.
- [94] M. Shamshirband, J. Salehi, and F. S. Gazijahani, “Decentralized trading of plug-in electric vehicle aggregation agents for optimal energy management of smart renewable penetrated microgrids with the aim of CO₂ emission reduction,” *J. Clean. Prod.*, vol. 200, pp. 622–640, 2018, doi: 10.1016/j.jclepro.2018.07.315.
- [95] A. T. Lemeski, R. Ebrahimi, and A. Zakariazadeh, “Optimal decentralized coordinated operation of electric vehicle aggregators enabling vehicle to grid option using distributed algorithm,” *J. Energy Storage*, vol. 54, no. June, p. 105213, 2022, doi: 10.1016/j.est.2022.105213.
- [96] H. Yu, S. Niu, Z. Shao, and L. Jian, “A scalable and reconfigurable hybrid AC/DC microgrid clustering architecture with decentralized control for coordinated operation,” *Int. J. Electr. Power Energy Syst.*, vol. 135, no. August 2021, p. 107476, 2022, doi: 10.1016/j.ijepes.2021.107476.
- [97] S. Zou, Z. Ma, and N. Yang, “Decentralised hierarchical coordination of electric vehicles in multi-microgrid systems,” *IET Gener. Transm. Distrib.*, vol. 13, no. 13, pp. 2899–2906, 2019, doi: 10.1049/iet-gtd.2018.6767.
- [98] L. Yang and Z. Hu, “Coordination of generators and energy storage to smooth power fluctuations for multi-area microgrid clusters: A robust decentralized approach,” *IEEE Access*, vol. 9, pp. 12506–12520, 2021, doi: 10.1109/ACCESS.2021.3052043.
- [99] Y. Ma, M. Zhang, H. Yang, X. Wang, J. Xu, and X. Hu, “Decentralized and coordinated scheduling model of interconnected multi-microgrid based on virtual energy storage,” *Int. J. Electr. Power Energy Syst.*, vol. 148, no. April 2022, p. 108990, 2023, doi: 10.1016/j.ijepes.2023.108990.
- [100] L. Fiorini and M. Aiello, “Energy management for user’s thermal and power needs: A survey,” *Energy Reports*, vol. 5, pp. 1048–1076, 2019, doi: 10.1016/j.egy.2019.08.003.
- [101] E. J. Davison, A. G. Aghdam, and D. E. Miller, *Decentralized control of large-scale systems*. 2019. doi: 10.1007/978-1-4419-6014-6.
- [102] A. Ahmed, M. F. Nadeem, A. T. Kiani, and I. Khan, “An Overview on Optimal Planning of Distributed Generation in Distribution System and Key Issues,” *2021 IEEE Texas Power Energy Conf. TPEC 2021*, 2021, doi: 10.1109/TPEC51183.2021.9384976.
- [103] A. Ahmed, M. F. Nadeem, I. A. Sajjad, R. Bo, and I. A. Khan, “Optimal Allocation of Wind DG with Time Varying Voltage Dependent Loads Using Bio-Inspired: Salp Swarm Algorithm,” *2020 3rd Int. Conf. Comput. Math. Eng. Technol. Idea to Innov. Build. Knowl. Econ. iCoMET 2020*, pp. 1–7, 2020, doi: 10.1109/iCoMET48670.2020.9074118.
- [104] H. H. Eldeeb, S. Faddel, and O. A. Mohammed, “Multi-Objective Optimization Technique for the

-
- Operation of Grid tied PV Powered EV Charging Station,” *Electr. Power Syst. Res.*, vol. 164, no. July, pp. 201–211, 2018, doi: 10.1016/j.epsr.2018.08.004.
- [105] J. Fu, S. Song, Z. Fu, and J. Ma, “Hierarchical Model Predictive Control for Parallel Hybrid Electrical Vehicles,” *Asian J. Control*, vol. 20, no. 6, pp. 2331–2342, 2018, doi: 10.1002/asjc.1759.
- [106] T. U. Solanke, V. K. Ramachandaramurthy, J. Y. Yong, J. Pasupuleti, P. Kasinathan, and A. Rajagopalan, “A review of strategic charging–discharging control of grid-connected electric vehicles,” *J. Energy Storage*, vol. 28, no. November 2019, p. 101193, 2020, doi: 10.1016/j.est.2020.101193.
- [107] Z. Ji, X. Huang, C. Xu, and H. Sun, “Accelerated model predictive control for electric vehicle integrated microgrid energy management: A hybrid robust and stochastic approach,” *Energies*, vol. 9, no. 11, 2016, doi: 10.3390/en9110973.
- [108] W. Huang, C. Gao, R. Li, R. Bhakar, N. Tai, and M. Yu, “A Model Predictive Control-Based Voltage Optimization Method for Highway Transportation Power Supply Networks with Soft Open Points,” *IEEE Trans. Ind. Appl.*, vol. PP, pp. 1–10, 2023, doi: 10.1109/TIA.2023.3296574.
- [109] M. B. Abdelghany, A. Al-Durra, and F. Gao, “A Coordinated Optimal Operation of a Grid-Connected Wind-Solar Microgrid Incorporating Hybrid Energy Storage Management Systems,” *IEEE Trans. Sustain. Energy*, no. July, 2023, doi: 10.1109/TSTE.2023.3263540.
- [110] A. Santhi Mary Antony *et al.*, “Dynamic and Model Predictive Controllers for Frequency Regulation of an Isolated Micro–Grid with Electrical Vehicles and the ESS Integration,” *Electr. Power Components Syst.*, vol. 0, no. 0, pp. 1–19, 2023, doi: 10.1080/15325008.2023.2226141.
- [111] L. I. Minchala-Avila, L. E. Garza-Castañón, A. Vargas-Martínez, and Y. Zhang, “A review of optimal control techniques applied to the energy management and control of microgrids,” *Procedia Comput. Sci.*, vol. 52, no. 1, pp. 780–787, 2015, doi: 10.1016/j.procs.2015.05.133.
- [112] Á. O. Topa Gavilema, J. D. Álvarez, J. L. Torres Moreno, and M. P. García, “Towards optimal management in microgrids: An overview,” *Energies*, vol. 14, no. 16, 2021, doi: 10.3390/en14165202.
- [113] A. S. Azad, M. S. Md, J. Watada, P. Vasant, and J. A. G. Vintaned, “Optimization of the hydropower energy generation using Meta-Heuristic approaches: A review,” *Energy Reports*, vol. 6, pp. 2230–2248, 2020, doi: 10.1016/j.egy.2020.08.009.
- [114] A. Dini, S. Pirouzi, M. Norouzi, and M. Lehtonen, “Hybrid stochastic/robust scheduling of the grid-connected microgrid based on the linear coordinated power management strategy,” *Sustain. Energy, Grids Networks*, vol. 24, p. 100400, 2020, doi: 10.1016/j.segan.2020.100400.
- [115] S. T. P. Srinivas and K. S. Swarup, “Optimal relay coordination for microgrids using hybrid modified particle swarm optimization - Interval linear programming approach,” *2017 North Am. Power Symp. NAPS 2017*, 2017, doi: 10.1109/NAPS.2017.8107254.
- [116] S. Yao, P. Wang, and T. Zhao, “Transportable Energy Storage for More Resilient Distribution Systems with Multiple Microgrids,” *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3331–3341, 2019, doi: 10.1109/TSG.2018.2824820.
- [117] E. Rodriguez-Diaz, E. J. Palacios-Garcia, A. Anvari-Moghaddam, J. C. Vasquez, and J. M. Guerrero, “Real-time Energy Management System for a hybrid AC/DC residential microgrid,” *2017 IEEE 2nd Int. Conf. Direct Curr. Microgrids, ICDCM 2017*, pp. 256–261, 2017, doi: 10.1109/ICDCM.2017.8001053.
- [118] O. Ouramdane, E. Elbouchikhi, Y. Amirat, and E. S. Gooya, “Optimal sizing and energy management of microgrids with Vehicle-to-Grid technology: A critical review and future trends,” *Energies*, vol. 14, no. 14, 2021, doi: 10.3390/en14144166.
- [119] V. Vita, G. Fotis, C. Pavlatos, and V. Mladenov, “A New Restoration Strategy in Microgrids after a Blackout with Priority in Critical Loads,” *Sustain.*, vol. 15, no. 3, pp. 1–21, 2023, doi: 10.3390/su15031974.
- [120] A. C. Luna, N. L. Diaz, M. Graells, J. C. Vasquez, and J. M. Guerrero, “Mixed-integer-linear-programming-based energy management system for hybrid PV-wind-battery microgrids: Modeling, design, and experimental verification,” *IEEE Trans. Power Electron.*, vol. 32, no. 4, pp. 2769–2783, 2017, doi: 10.1109/TPEL.2016.2581021.
- [121] J. M. Raya-Armenta, N. Bazmohammadi, J. G. Avina-Cervantes, D. Sáez, J. C. Vasquez, and J. M. Guerrero, “Energy management system optimization in islanded microgrids: An overview and future trends,” *Renew. Sustain. Energy Rev.*, vol. 149, no. June, p. 111327, 2021, doi: 10.1016/j.rser.2021.111327.
- [122] S. M. R. H. Shawon, X. Liang, and M. Janbakhsh, “Optimal Placement of Distributed Generation Units for Microgrid Planning in Distribution Networks,” *IEEE Trans. Ind. Appl.*, vol. 59, no. 3, pp. 2785–2795, 2023, doi: 10.1109/TIA.2023.3236363.
- [123] A. Kumar *et al.*, “Impact of demand side management approaches for the enhancement of voltage
-

- stability loadability and customer satisfaction index,” *Appl. Energy*, vol. 339, no. March, p. 120949, 2023, doi: 10.1016/j.apenergy.2023.120949.
- [124] Y. Li *et al.*, “Two-stage real-time optimal electricity dispatch strategy for urban residential quarter with electric vehicles’ charging load,” *Energy*, vol. 268, no. August 2022, p. 126702, 2023, doi: 10.1016/j.energy.2023.126702.
- [125] M. M. Hosseini, L. Rodriguez-Garcia, and M. Parvania, “Hierarchical Combination of Deep Reinforcement Learning and Quadratic Programming for Distribution System Restoration,” *IEEE Trans. Sustain. Energy*, vol. 14, no. 2, pp. 1088–1098, 2023, doi: 10.1109/TSTE.2023.3245090.
- [126] H. Bahlawan, M. Morini, M. Pinelli, P. R. Spina, and M. Venturini, “Optimization of energy and economic scheduling of a hybrid energy plant by using a dynamic programming approach,” *Appl. Therm. Eng.*, vol. 187, no. January, p. 116577, 2021, doi: 10.1016/j.applthermaleng.2021.116577.
- [127] X. Hu, Z. Zhan, D. Ma, T. Wang, and H. Liu, “Adaptive Dynamic Programming-Based Method for Signal Evaluation of Energy Transportation System,” *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–8, 2023, doi: 10.1109/TIM.2023.3264024.
- [128] J. Li, S. Chen, C. Jiang, F. Liu, and W. Xiao, “Adaptive Dynamic Programming Approach for Micro-grid Optimal Energy Transmission Scheduling,” *Chinese Control Conf. CCC*, vol. 2020-July, pp. 6190–6195, 2020, doi: 10.23919/CCC50068.2020.9189579.
- [129] J. Islam, P. M. Vasant, B. M. Negash, M. B. Laruccia, M. Myint, and J. Watada, “A holistic review on artificial intelligence techniques for well placement optimization problem,” *Adv. Eng. Softw.*, vol. 141, no. December 2019, p. 102767, 2020, doi: 10.1016/j.advengsoft.2019.102767.
- [130] A. Hamann, G. Hug, and S. Rosinski, “Real-Time Optimization of the Mid-Columbia Hydropower System,” *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 157–165, 2017, doi: 10.1109/TPWRS.2016.2550490.
- [131] M. Nazari-Heris, B. Mohammadi-Ivatloo, and G. B. Gharehpetian, “Short-term scheduling of hydro-based power plants considering application of heuristic algorithms: A comprehensive review,” *Renew. Sustain. Energy Rev.*, vol. 74, no. February, pp. 116–129, 2017, doi: 10.1016/j.rser.2017.02.043.
- [132] T. Yang, X. Gao, S. L. Sellars, and S. Sorooshian, “Improving the multi-objective evolutionary optimization algorithm for hydropower reservoir operations in the California Oroville-Thermalito complex,” *Environ. Model. Softw.*, vol. 69, pp. 262–279, 2015, doi: 10.1016/j.envsoft.2014.11.016.
- [133] M. Saadatpour, A. Afshar, and S. S. Solis, “Surrogate-Based Multiperiod, Multiobjective Reservoir Operation Optimization for Quality and Quantity Management,” *J. Water Resour. Plan. Manag.*, vol. 146, no. 8, pp. 1–12, 2020, doi: 10.1061/(asce)wr.1943-5452.0001252.
- [134] Y. C. Tsao and V. Van Thanh, “Toward sustainable microgrids with blockchain technology-based peer-to-peer energy trading mechanism: A fuzzy meta-heuristic approach,” *Renew. Sustain. Energy Rev.*, vol. 136, no. August 2020, p. 110452, 2021, doi: 10.1016/j.rser.2020.110452.
- [135] D. Fioriti, G. Lutzemberger, D. Poli, P. Duenas-Martinez, and A. Micangeli, “Heuristic approaches to size microgrids: A methodology to compile multiple design options,” *Proc. - 2020 IEEE Int. Conf. Environ. Electr. Eng. 2020 IEEE Ind. Commer. Power Syst. Eur. IEEEIC / I CPS Eur. 2020*, 2020, doi: 10.1109/IEEEIC/ICPSEurope49358.2020.9160842.
- [136] T. Dokeroglu, E. Sevinc, T. Kucukyilmaz, and A. Cosar, “A survey on new generation metaheuristic algorithms,” *Comput. Ind. Eng.*, vol. 137, no. May, p. 106040, 2019, doi: 10.1016/j.cie.2019.106040.
- [137] V. Lai, Y. F. Huang, C. H. Koo, A. N. Ahmed, and A. El-Shafie, “A Review of Reservoir Operation Optimisations: from Traditional Models to Metaheuristic Algorithms,” *Arch. Comput. Methods Eng.*, vol. 29, no. 5, pp. 3435–3457, 2022, doi: 10.1007/s11831-021-09701-8.
- [138] M. De and K. K. Mandal, “Energy management strategy and renewable energy integration within multi-microgrid framework utilizing multi-objective modified personal best particle swarm optimization,” *Sustain. Energy Technol. Assessments*, vol. 53, no. PA, p. 102410, 2022, doi: 10.1016/j.seta.2022.102410.
- [139] M. Abdolrasol, R. Mohamed, M. Hannan, A. Al-Shetwi, M. Mansor, and F. Blaabjerg, “Artificial Neural Network Based Particle Swarm Optimization for Microgrid Optimal Energy Scheduling,” *IEEE Trans. Power Electron.*, vol. 36, no. 11, pp. 12151–12157, 2021, doi: 10.1109/TPEL.2021.3074964.
- [140] W. Jefimowski, A. Szeląg, M. Steczek, and A. Nikitenko, “Vanadium redox flow battery parameters optimization in a transportation microgrid: A case study,” *Energy*, vol. 195, 2020, doi: 10.1016/j.energy.2020.116943.
- [141] M. Nemati, M. Braun, and S. Tenbohlen, “Optimization of unit commitment and economic dispatch in microgrids based on genetic algorithm and mixed integer linear programming,” *Appl. Energy*, vol. 210, pp. 944–963, 2018, doi: 10.1016/j.apenergy.2017.07.007.

-
- [142] M. A. Zamee, D. Han, and D. Won, "Integrated grid forming-grid following inverter fractional order controller based on Monte Carlo Artificial Bee Colony Optimization," *Energy Reports*, vol. 9, pp. 57–72, 2023, doi: 10.1016/j.egy.2022.11.149.
- [143] H. U. R. Habib, U. Subramaniam, A. Waqar, B. S. Farhan, K. M. Kotb, and S. Wang, "Energy cost optimization of hybrid renewables based V2G microgrid considering multi objective function by using artificial bee colony optimization," *IEEE Access*, vol. 8, pp. 62076–62093, 2020, doi: 10.1109/ACCESS.2020.2984537.
- [144] V. Suresh, P. Janik, M. Jasinski, J. M. Guerrero, and Z. Leonowicz, "Microgrid energy management using metaheuristic optimization algorithms," *Appl. Soft Comput.*, vol. 134, p. 109981, 2023, doi: 10.1016/j.asoc.2022.109981.
- [145] M. Z. Kreishan and A. F. Zobaa, "Scenario-Based Uncertainty Modeling for Power Management in Islanded Microgrid Using the Mixed-Integer Distributed Ant Colony Optimization," *Energies*, vol. 16, no. 10, 2023, doi: 10.3390/en16104257.
- [146] Q. Li, Z. Cui, Y. Cai, and Y. Su, "Multi-objective operation of solar-based microgrids incorporating artificial neural network and grey wolf optimizer in digital twin," *Sol. Energy*, vol. 262, no. May, p. 111873, 2023, doi: 10.1016/j.solener.2023.111873.
- [147] H. S. Ramadan, A. M. Helmi, and F. K. Abo-Elyousr, "Optimal resilient facade thermal photovoltaic clustering allocation for microgrid enhanced voltage profile," *Int. J. Electr. Power Energy Syst.*, vol. 148, no. December 2022, p. 108940, 2023, doi: 10.1016/j.ijepes.2022.108940.
- [148] G. K. Suman, J. M. Guerrero, and O. P. Roy, "Optimisation of solar/wind/bio-generator/diesel/battery based microgrids for rural areas: A PSO-GWO approach," *Sustain. Cities Soc.*, vol. 67, no. January, p. 102723, 2021, doi: 10.1016/j.scs.2021.102723.
- [149] A. M. Jasim, B. H. Jasim, F. C. Baiceanu, and B. C. Neagu, "Optimized Sizing of Energy Management System for Off-Grid Hybrid Solar/Wind/Battery/Biogasifier/Diesel Microgrid System," *Mathematics*, vol. 11, no. 5, 2023, doi: 10.3390/math11051248.
- [150] Y. Zheng, J. Shao, and L. Jian, "The peak load shaving assessment of developing a user-oriented vehicle-to-grid scheme with multiple operation modes: The case study of Shenzhen, China," *Sustain. Cities Soc.*, vol. 67, no. January, p. 102744, 2021, doi: 10.1016/j.scs.2021.102744.
- [151] H. Najafzad, H. Davari-Ardakani, and R. Nemati-Lafmejani, "Multi-skill project scheduling problem under time-of-use electricity tariffs and shift differential payments," *Energy*, vol. 168, pp. 619–636, 2019, doi: 10.1016/j.energy.2018.11.070.
- [152] M. Zhang, J. Yan, Y. Zhang, and S. Yan, "Optimization for energy-efficient flexible flow shop scheduling under time of use electricity tariffs," *Procedia CIRP*, vol. 80, no. March, pp. 251–256, 2019, doi: 10.1016/j.procir.2019.01.062.
- [153] A. Amin *et al.*, "A review of optimal charging strategy for electric vehicles under dynamic pricing schemes in the distribution charging network," *Sustain.*, vol. 12, no. 23, pp. 1–28, 2020, doi: 10.3390/su122310160.
- [154] M. P. Abdullah, N. S. M. Nazar, M. Y. Hassan, and F. Hussin, "Optimizing time of use (ToU) electricity pricing in regulated market," *J. Teknol.*, vol. 78, no. 5–7, pp. 49–54, 2016, doi: 10.11113/jt.v78.8712.
- [155] S. S. Jodeiri-Seyedian, A. Fakour, M. Jalali, K. Zare, B. Mohammadi-Ivatloo, and S. Tohidi, "Grid-aware pricing scheme in future distribution systems based on real-time power tracing and bi-level optimization," *Sustain. Energy, Grids Networks*, vol. 32, p. 100934, 2022, doi: 10.1016/j.segan.2022.100934.
- [156] Y. C. Tsao and V. T. Linh, "A new three-part tariff pricing scheme for the electricity microgrid considering consumer regret," *Energy*, vol. 254, p. 124387, 2022, doi: 10.1016/j.energy.2022.124387.
- [157] B. Dey, S. Raj, S. Mahapatra, and F. P. G. Márquez, "Optimal scheduling of distributed energy resources in microgrid systems based on electricity market pricing strategies by a novel hybrid optimization technique," *Int. J. Electr. Power Energy Syst.*, vol. 134, 2022, doi: 10.1016/j.ijepes.2021.107419.
- [158] X. Pan, R. Khezri, A. Mahmoudi, and S. M. Muyeen, "Optimal planning of solar PV and battery storage with energy management systems for Time-of-Use and flat electricity tariffs," *IET Renew. Power Gener.*, vol. 16, no. 6, pp. 1206–1219, 2022, doi: 10.1049/rpg2.12433.
- [159] J. An, T. Hong, and M. Lee, "Determining the optimal trading price of electricity for energy consumers and prosumers," *Renew. Sustain. Energy Rev.*, vol. 154, no. September 2021, p. 111851, 2022, doi: 10.1016/j.rser.2021.111851.
- [160] H. Sahebi, M. Khodoomi, M. Seif, M. S. Pishvae, and T. Hanne, "The benefits of peer-to-peer renewable energy trading and battery storage backup for local grid," *J. Energy Storage*, vol. 63, no. September 2022, p. 106970, 2023, doi: 10.1016/j.est.2023.106970.
-

-
- [161] V. M. Taghvaei, C. Mavuka, and J. K. Shirazi, "Economic growth and energy consumption in Iran: an ARDL approach including renewable and non-renewable energies," *Environ. Dev. Sustain.*, vol. 19, no. 6, pp. 2405–2420, 2017, doi: 10.1007/s10668-016-9862-z.
- [162] F. Belaïd, "Implications of poorly designed climate policy on energy poverty: Global reflections on the current surge in energy prices," *Energy Res. Soc. Sci.*, vol. 92, no. February, p. 102790, 2022, doi: 10.1016/j.erss.2022.102790.
- [163] K. Wang, Y. X. Wang, K. Li, and Y. M. Wei, "Energy poverty in China: An index based comprehensive evaluation," *Renew. Sustain. Energy Rev.*, vol. 47, pp. 308–323, 2015, doi: 10.1016/j.rser.2015.03.041.
- [164] P. Mulder, F. Dalla Longa, and K. Straver, "Energy poverty in the Netherlands at the national and local level: A multi-dimensional spatial analysis," *Energy Res. Soc. Sci.*, vol. 96, no. September 2022, p. 102892, 2023, doi: 10.1016/j.erss.2022.102892.
- [165] M. A. Brown, A. Soni, M. V Lapsa, K. Southworth, and M. Cox, "High energy burden and low-income energy affordability: conclusions from a literature review," *Prog. Energy*, vol. 2, no. 4, p. 042003, 2020, doi: 10.1088/2516-1083/abb954.
- [166] M. A. Azni, R. Md Khalid, U. A. Hasran, and S. K. Kamarudin, "Review of the Effects of Fossil Fuels and the Need for a Hydrogen Fuel Cell Policy in Malaysia," *Sustain.*, vol. 15, no. 5, 2023, doi: 10.3390/su15054033.
- [167] N. Abas, A. Kalair, and N. Khan, "Review of fossil fuels and future energy technologies," *Futures*, vol. 69, pp. 31–49, 2015, doi: 10.1016/j.futures.2015.03.003.
- [168] J. Curtin, C. McInerney, B. Ó Gallachóir, C. Hickey, P. Deane, and P. Deeney, "Quantifying stranding risk for fossil fuel assets and implications for renewable energy investment: A review of the literature," *Renew. Sustain. Energy Rev.*, vol. 116, no. January, p. 109402, 2019, doi: 10.1016/j.rser.2019.109402.
- [169] S. R. Sharvini, Z. Z. Noor, C. S. Chong, L. C. Stringer, and R. O. Yusuf, "Energy consumption trends and their linkages with renewable energy policies in East and Southeast Asian countries: Challenges and opportunities," *Sustain. Environ. Res.*, vol. 28, no. 6, pp. 257–266, 2018, doi: 10.1016/j.serj.2018.08.006.
- [170] A. I. Osman *et al.*, "Cost, environmental impact, and resilience of renewable energy under a changing climate: a review," *Environ. Chem. Lett.*, vol. 21, no. 2, pp. 741–764, 2023, doi: 10.1007/s10311-022-01532-8.
- [171] N. Maamoun, R. Kennedy, X. Jin, and J. Urpelainen, "Identifying coal-fired power plants for early retirement," *Renew. Sustain. Energy Rev.*, vol. 126, no. April, p. 109833, 2020, doi: 10.1016/j.rser.2020.109833.
- [172] Y. Yang, P. E. Campana, and J. Yan, "Potential of unsubsidized distributed solar PV to replace coal-fired power plants, and profits classification in Chinese cities," *Renew. Sustain. Energy Rev.*, vol. 131, no. June, p. 109967, 2020, doi: 10.1016/j.rser.2020.109967.
- [173] S. Fawzy, A. I. Osman, J. Doran, and D. W. Rooney, "Strategies for mitigation of climate change: a review," *Environ. Chem. Lett.*, vol. 18, no. 6, pp. 2069–2094, 2020, doi: 10.1007/s10311-020-01059-w.
- [174] M. Farghali, A. I. Osman, K. Umetsu, and D. W. Rooney, *Integration of biogas systems into a carbon zero and hydrogen economy: a review*, vol. 20, no. 5. Springer International Publishing, 2022. doi: 10.1007/s10311-022-01468-z.
- [175] Q. Kang, J. Wang, M. Zhou, and A. C. Ammari, "Centralized Charging Strategy and Scheduling Algorithm for Electric Vehicles under a Battery Swapping Scenario," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 3, pp. 659–669, 2016, doi: 10.1109/TITS.2015.2487323.
- [176] M. Akil, E. Dokur, and R. Bayindir, "Energy Management for EV Charging Based on Solar Energy in an Industrial Microgrid," *9th Int. Conf. Renew. Energy Res. Appl. ICRERA 2020*, pp. 489–493, 2020, doi: 10.1109/ICRERA49962.2020.9242663.
- [177] R. Singh, S. M. Amrr, and M. S. Jamil Asghar, "Supervisory control strategy for the effective solar energy utilization in a residential microgrid system using a cost-effective controller," *Int. J. Electr. Power Energy Syst.*, vol. 132, no. August 2020, p. 107170, 2021, doi: 10.1016/j.ijepes.2021.107170.
- [178] S. M. Tercan, A. Demirci, E. Gokalp, and U. Cali, "Maximizing self-consumption rates and power quality towards two-stage evaluation for solar energy and shared energy storage empowered microgrids," *J. Energy Storage*, vol. 51, no. February, p. 104561, 2022, doi: 10.1016/j.est.2022.104561.
- [179] G. Yuan and F. Xie, "Digital Twin-Based economic assessment of solar energy in smart microgrids using reinforcement learning technique," *Sol. Energy*, vol. 250, no. September 2022, pp. 398–408, 2023, doi: 10.1016/j.solener.2022.12.031.
- [180] A. Daniel Icaza, David Borge-Diez, Santiago Pulla Galindo and C. Flores-Vázquez, "Modeling and Simulation of a Hybrid System of Solar Panels and Wind Turbines for the Supply of the," *Sol. Energy*, vol. 24, no. 1, pp. 1–24, 2020, [Online]. Available:
-

- <https://doi.org/10.1016/j.energy.2019.03.131><https://doi.org/10.1016/j.egypro.2019.01.211>
- [181] H. Bani-Hani, Z. Alabdullah, S. Ghafoory, and N. Al-Dhamer, "Experimental Study on Wind-Solar Renewable Energy Hybrid System," *Ind. Pollut. Control*, vol. 34, no. 2, pp. 2211–2219, 2018, [Online]. Available: www.icontrolpollution.com
- [182] B. Singh Niranjana and A. Pandey, "Mathematical Modelling of a Hybrid Solar-Wind Power Generator," *Int. Res. J. Eng. Technol.*, vol. 188, pp. 188–193, 2018, [Online]. Available: www.irjet.net
- [183] Y. Sawle, S. C. Gupta, and A. K. Bohre, "PV-wind hybrid system: A review with case study," *Cogent Eng.*, vol. 3, no. 1, 2016, doi: 10.1080/23311916.2016.1189305.
- [184] P. Roy, J. He, T. Zhao, and Y. V. Singh, "Recent Advances of Wind-Solar Hybrid Renewable Energy Systems for Power Generation: A Review," *IEEE Open J. Ind. Electron. Soc.*, vol. 3, no. February, pp. 81–104, 2022, doi: 10.1109/OJIES.2022.3144093.
- [185] X. H. Nguyen and M. P. Nguyen, "Mathematical modeling of photovoltaic cell/module/arrays with tags in Matlab/Simulink," *Environ. Syst. Res.*, vol. 4, no. 1, 2015, doi: 10.1186/s40068-015-0047-9.
- [186] B. M. Kiran Kumar, M. S. Indira, and S. Nagaraja Rao, "Mathematical Modeling and Evaluation of Performance Characteristics of a Hybrid Solar PV and Wind Energy System," *J. Appl. Sci. Eng.*, vol. 25, no. 4, pp. 685–697, 2022, doi: 10.6180/jase.202208_25(4).0014.
- [187] G. Janevska, "Mathematical Modeling of Hybrid Renewable Energy System," 2017, [Online]. Available: <https://www.researchgate.net/publication/322245010>
- [188] N. K. Singh and M. R. Bachawad, "A Review on Mathematical Modeling of Solar, Wind and Hydro Pumped Energy Storage System," *Int. J. Adv. Res. Electr.*, vol. 4, no. 12, pp. 9506–9512, 2015, doi: 10.15662/IJAREEIE.2015.0412016.
- [189] B. Bhandari, S. R. Poudel, K. T. Lee, and S. H. Ahn, "Mathematical modeling of hybrid renewable energy system: A review on small hydro-solar-wind power generation," *Int. J. Precis. Eng. Manuf. - Green Technol.*, vol. 1, no. 2, pp. 157–173, 2014, doi: 10.1007/s40684-014-0021-4.
- [190] J. Qi, W. Zhao, and X. Bian, "Comparative Study of SVC and STATCOM Reactive Power Compensation for Prosumer Microgrids with DFIG-Based Wind Farm Integration," *IEEE Access*, vol. 8, pp. 209878–209885, 2020, doi: 10.1109/ACCESS.2020.3033058.
- [191] H. Tan, Z. Ren, W. Yan, Q. Wang, and M. Mohamed, "A Wind Power Accommodation Capability Assessment Method for Multi-Energy Microgrids," *IEEE Trans. Sustain. Energy*, vol. 12, no. 4, pp. 2482–2492, 2021, doi: 10.1109/TSTE.2021.3103910.
- [192] G. Msigwa, J. O. Ighalo, and P. S. Yap, "Considerations on environmental, economic, and energy impacts of wind energy generation: Projections towards sustainability initiatives," *Sci. Total Environ.*, vol. 849, no. March, p. 157755, 2022, doi: 10.1016/j.scitotenv.2022.157755.
- [193] J. Knauf, "Can't buy me acceptance? Financial benefits for wind energy projects in Germany," *Energy Policy*, vol. 165, no. March, p. 112924, 2022, doi: 10.1016/j.enpol.2022.112924.
- [194] J. le Maitre, G. Ryan, B. Power, and E. O'Connor, "Empowering onshore wind energy: A national choice experiment on financial benefits and citizen participation," *Energy Policy*, vol. 173, no. November 2022, p. 113362, 2023, doi: 10.1016/j.enpol.2022.113362.
- [195] A. Acakpovi, P. Adjei, N. Nwulu, and N. Y. Asabere, "Optimal Hybrid Renewable Energy System: A Comparative Study of Wind/Hydrogen/Fuel-Cell and Wind/Battery Storage," *J. Electr. Comput. Eng.*, vol. 2020, 2020, doi: 10.1155/2020/1756503.
- [196] S. Baurzhan, G. P. Jenkins, and G. O. Olasehinde-Williams, "The economic performance of hydropower dams supported by the world bank group, 1975–2015," *Energies*, vol. 14, no. 9, 2021, doi: 10.3390/en14092673.
- [197] M. Sibtain, X. Li, H. Bashir, and M. I. Azam, "Hydropower exploitation for Pakistan's sustainable development: A SWOT analysis considering current situation, challenges, and prospects," *Energy Strateg. Rev.*, vol. 38, p. 100728, 2021, doi: 10.1016/j.esr.2021.100728.
- [198] V. Adomavičius, G. Šimkonienė, and B. Azzopardi, "Advantages of the microgrids based on a small-scale hydropower plants," pp. 64–69, 2023, doi: 10.1049/icp.2022.3304.
- [199] H. Shukla and M. Raju, "Load Frequency Control of Microgrid including Small Hydro Power Plant and Distributed Generation with EV Penetration," *2021 IEEE 2nd Int. Conf. Electr. Power Energy Syst. ICEPES 2021*, pp. 1–5, 2021, doi: 10.1109/ICEPES52894.2021.9699744.
- [200] B. A. Bhatti, S. Hanif, J. Alam, B. Mitra, R. Kini, and D. Wu, "Using energy storage systems to extend the life of hydropower plants," *Appl. Energy*, vol. 337, no. June 2022, 2023, doi: 10.1016/j.apenergy.2023.120894.
- [201] A. Rahman, O. Farrok, and M. M. Haque, "Environmental impact of renewable energy source based electrical power plants: Solar, wind, hydroelectric, biomass, geothermal, tidal, ocean, and osmotic,"

-
- Renew. Sustain. Energy Rev.*, vol. 161, no. March, p. 112279, 2022, doi: 10.1016/j.rser.2022.112279.
- [202] M. A. Hannan *et al.*, “Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues,” *J. Energy Storage*, vol. 42, no. May, p. 103023, 2021, doi: 10.1016/j.est.2021.103023.
- [203] T. F. Yi *et al.*, “A review of niobium oxides based nanocomposites for lithium-ion batteries, sodium-ion batteries and supercapacitors,” *Nano Energy*, vol. 85, no. March, p. 105955, 2021, doi: 10.1016/j.nanoen.2021.105955.
- [204] X. Luo, J. Wang, M. Dooner, and J. Clarke, “Overview of current development in electrical energy storage technologies and the application potential in power system operation,” *Appl. Energy*, vol. 137, pp. 511–536, 2015, doi: 10.1016/j.apenergy.2014.09.081.
- [205] M. R. M. Cruz, D. Z. Fitiwi, S. F. Santos, and J. P. S. Catalão, “A comprehensive survey of flexibility options for supporting the low-carbon energy future,” *Renew. Sustain. Energy Rev.*, vol. 97, no. September 2017, pp. 338–353, 2018, doi: 10.1016/j.rser.2018.08.028.
- [206] J. Chen, J. Li, Y. Zhang, G. Bao, X. Ge, and P. Li, “A hierarchical optimal operation strategy of hybrid energy storage system in distribution networks with high photovoltaic penetration,” *Energies*, vol. 11, no. 2, 2018, doi: 10.3390/en11020389.
- [207] K. Lourenssen, J. Williams, F. Ahmadpour, R. Clemmer, and S. Tasnim, “Vanadium redox flow batteries: A comprehensive review,” *J. Energy Storage*, vol. 25, no. April, 2019, doi: 10.1016/j.est.2019.100844.
- [208] J. A. Wang, X. Y. Wen, and B. Y. Hou, “Advanced stability criteria for static neural networks with interval time-varying delays via the improved Jensen inequality,” *Neurocomputing*, vol. 377, pp. 49–56, 2020, doi: 10.1016/j.neucom.2019.10.034.
- [209] N. N. S. Torres, H. F. Scherer, O. H. Ando Junior, and J. J. G. Ledesma, “Application of Neural Networks in a Sodium-Nickel Chloride Battery Management System,” *J. Control. Autom. Electr. Syst.*, vol. 33, no. 4, pp. 1188–1197, 2022, doi: 10.1007/s40313-021-00847-1.
- [210] P. Edalati *et al.*, “High-entropy alloys as anode materials of nickel - metal hydride batteries,” *Scr. Mater.*, vol. 209, p. 114387, 2022, doi: 10.1016/j.scriptamat.2021.114387.
- [211] E. Blumbergs, V. Serga, E. Platacis, M. Maiorov, and A. Shishkin, “Cadmium recovery from spent ni-cd batteries: A brief review,” *Metals (Basel)*, vol. 11, no. 11, pp. 1–14, 2021, doi: 10.3390/met11111714.
- [212] Y. Popat, D. Trudgeon, C. Zhang, F. C. Walsh, P. Connor, and X. Li, “Carbon Materials as Positive Electrodes in Bromine-Based Flow Batteries,” *Chempluschem*, vol. 87, no. 1, 2022, doi: 10.1002/cplu.202100441.
- [213] Z. Xu, Q. Fan, Y. Li, J. Wang, and P. D. Lund, “Review of zinc dendrite formation in zinc bromine redox flow battery,” *Renew. Sustain. Energy Rev.*, vol. 127, no. 2, p. 109838, 2020, doi: 10.1016/j.rser.2020.109838.
- [214] E. Zarate-Perez, E. Rosales-Asensio, A. González-Martínez, M. de Simón-Martín, and A. Colmenar-Santos, “Battery energy storage performance in microgrids: A scientific mapping perspective,” *Energy Reports*, vol. 8, no. May, pp. 259–268, 2022, doi: 10.1016/j.egy.2022.06.116.
- [215] E. Rahmani, S. Mohammadi, M. Zadehbagheri, and M. Kiani, “Probabilistic reliability management of energy storage systems in connected/islanding microgrids with renewable energy,” *Electr. Power Syst. Res.*, vol. 214, no. PA, p. 108891, 2023, doi: 10.1016/j.epsr.2022.108891.
- [216] X. Liu, X. C. Liu, C. Xie, and X. Ma, “Impacts of photovoltaic and energy storage system adoption on public transport: A simulation-based optimization approach,” *Renew. Sustain. Energy Rev.*, vol. 181, no. June 2022, 2023, doi: 10.1016/j.rser.2023.113319.
- [217] L. G. González, D. Cordero-Moreno, and J. L. Espinoza, “Public transportation with electric traction: Experiences and challenges in an Andean city,” *Renew. Sustain. Energy Rev.*, vol. 141, no. August 2020, 2021, doi: 10.1016/j.rser.2021.110768.
- [218] J. Engel, T. Schmitt, T. Rodemann, and J. Adamy, “Hierarchical Economic Model Predictive Control Approach for a Building Energy Management System with Scenario-Driven EV Charging,” *IEEE Trans. Smart Grid*, vol. 13, no. 4, pp. 3082–3093, 2022, doi: 10.1109/TSG.2022.3160390.
-