



Review Article

Optimizing Vehicle-to-Grid System Sizing: A Review of Energy Management Algorithms

Abdullah Ali Yosof M Abodwair^{1,2*}, Muhammet T. Guneser³, Abdurazaq Elbaz^{4*}, Mohamed Khaleef⁵, Albahlol DAKhil⁶

¹Department of Electrical and Electronics Engineering, Faculty of Engineering and Natural Sciences, Karabuk University, Karabuk, 78050, Turkiye

²Department of Electrical Engineering, Faculty of Engineering, University of Zintan, Zintan, Libya
e-mail: 2138171025@karabuk.edu.tr, Abdullah.yosof@uoz.edu.ly

³Faculty of Electrical and Electronics, Istanbul Technical University, Istanbul, Turkiye
e-mail: guneserm@itu.edu.tr

⁴Department of Electrical and Electronics Engineering, University of Tripoli, Tripoli, Libya
e-mail: abdrazaklabz@gmail.com

⁵Department of Electrical and Electronics Engineering, Faculty of Engineering and Natural Sciences, Karabuk University, Karabuk, 78050, Turkiye
e-mail: mkhaleel@lsd.ly, lykhaleel@yahoo.co.uk

⁶The Higher Institute of Science and Technology Assaba, Libya
e-mail: bahloldakheel@gmail.com

ABSTRAT

Peak load management and grid stabilization have a strong potential in terms of Vehicle-to-Grid technology implementation in microgrids. Nevertheless, Vehicle-to-Grid systems are very sensitive to the size of the systems, as well as, powerful Energy Management Strategies. The paper is a critical review of optimization algorithms applied to sizing Vehicle-to-Grid systems in grid-connected microgrids. As opposed to general descriptions, this paper directly links optimization constraints, including, but not limited to battery degradation, and renewable intermittency, with system performance. Energy Management Strategies divide into Rule-Based and Optimization-Based strategies with trade-offs between their computational complexity, convergence rate, and solution quality. Moreover, the manuscript indicates the essential weaknesses of existing literature, namely, the absence of real-time hardware validation and the inability to scale up metaheuristic algorithms. Lastly, a decision framework is provided to help the researchers to choose the right algorithms depending on a certain microgrid setup and performance measures.

KEYWORDS

Electric Vehicles, Vehicle-to-Grid, Energy Management System, Optimization Algorithms, Microgrids, System Sizing

INTRODUCTION

The sustained high growth of electric vehicles (EVs) is fundamentally altering the energy landscapes in the world, bringing with it both challenging grid integration possibilities and substantial opportunities in operation[1] [2]. By conducting bi-directional energy exchange, smart charging and Vehicle-to-Grid (V2G) technologies can stabilize the power networks, as well as maximize the use of intermittent renewable energy sources (RES) [3], [4].

But as 390 million battery electric vehicles (BEVs) are predicted to be on the road by 2035, the threat of uncontrolled charging puts a strain on current infrastructure, especially during peak periods. V2G technology offers a possible tool to alleviate such instability and enhance the resilience of the systems [5] [6].

Although several review papers have independently investigated Vehicle-to-Grid (V2G) technologies, electric vehicle charging strategies, and microgrid energy management, little research has focused on the direct interaction between V2G system sizing and Energy Management System (EMS) algorithms in renewable-integrated microgrids. In [7], [8], [9], [10], [11], the majority of existing reviews focus on charging infrastructure, optimization techniques, or standalone EMS architectures without explicitly examining how EMS decisions affect optimal component sizing, battery degradation, operational flexibility, renewable energy utilization, and overall economic performance. Furthermore, previous review studies typically lack [12], [13], [14], [15], [16]: A comprehensive system-level comparison of rule-based, optimization-based, and learning-based EMS techniques; Quantitative comparison of sizing-oriented optimization algorithms under various grid conditions; A comparison of computing complexity, scalability, and implementation readiness; and a critical examination of practical deployment restrictions such as communication latency, battery aging, and EV user behavior uncertainty.

This paper provides a critical analysis of V2G applications and optimization algorithms in microgrids with a particular focus on energy management strategies that have not been explored in the current literature. While existing reviews have covered V2G concepts broadly, there is a lack of critical analysis focusing specifically on the intersection of system sizing and algorithm selection. Consequently, this paper addresses the following core research question: In order to answer the underlying research questions and give a coherent analysis, the rest of the paper is arranged in the following way: Section 2 outlines the methods adopted to conduct a systematic review of the literature. Section 3 discusses Microgrid Setups and Integration of Renewable Energy, which provides the architectural basis of the system. Section 4 is a detailed Classification of Energy Management and optimization Approaches, which assesses the trade-offs of each. In Section 5, the important Research Gaps and Future Directions are identified on which to base the future research, while Section 8 covers Critical Synthesis and Decision Framework. Section 9, addressing Research Gaps and Future Directions, and finally, in Section 10, is the Conclusion.

Methods

To ensure that the literature review approach is robust and reproducible, a systematic search strategy was created in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendations. The use of this standardized methodological framework improves transparency while reducing selection bias throughout the identification, screening, eligibility evaluation, and inclusion of relevant studies.

As a result, a thorough literature search was undertaken across four major scientific databases, namely IEEE Xplore, ScienceDirect, Scopus, and Web of Science, which included peer-reviewed journal articles and high-impact conference papers published since 2015. To investigate the association between V2G system size and energy management strategies, the following Boolean search query was used: ("Vehicle-to-Grid" OR "V2G") AND ("Optimization" OR "Sizing") AND ("Energy Management" OR "EMS") AND ("Microgrid").

This structured search Methods provided a solid and unbiased framework for critically analyzing existing V2G optimization and energy management approaches.

The study selection method was based on the following inclusion criteria: Peer-reviewed journal publications and top-notch conference proceedings; Studies on the quantitative evaluation of optimization or energy management algorithms, such as metaheuristic, rule-based, and hybrid techniques; research on V2G-enabled renewable microgrids and system sizing applications.

The analysis excluded studies that did not include technical analysis, duplicate records, non-English publications, or solely descriptive review papers.

Several review studies have already looked into various areas of electric car integration, energy management systems, and hybrid renewable microgrids. However, the majority of extant review papers focus on isolated viewpoints such as EV charging strategies, standalone EMS systems, and renewable energy scaling optimization.

For example, Zia et al. [17] examined microgrid energy management systems, with a focus on operational control structures, whereas Solanke et al. [18] concentrated on charging and discharging techniques for grid-connected electric vehicles. Similarly, Ouramdane et al. [19] examined optimal sizing and EMS approaches for V2G systems; however, their research did not provide a complete system-level comparison of optimization techniques in terms of scalability, computing complexity, and implementation readiness.

Unlike prior review studies, the current study incorporates V2G sizing optimization, EMS designs, metaheuristic and hybrid optimization methodologies, scalability considerations, and practical implementation restrictions into a single analytical framework. Furthermore, this study presents a comparative decision-making framework that connects algorithm selection to operational goals such as real-time control capacity, economic optimization, computational burden, and large-scale deployment feasibility. This integrated system-level perspective is the fundamental originality and scientific contribution of the current review.

MICROGRID SETUPS AND INTEGRATION OF RENEWABLE ENERGY

The electrical architectures of renewable energy are generally implemented in three main configurations: isolated, grid-connected and hybrid [20]. Although standalone applications target remote sites without utility infrastructure, grid-tied applications are designed to support load densities of urban areas that are higher in nature. Hybrid systems can fill this gap, combining the independence of individual models with reliability of the main grid to fit a variety of functional situations [21].

In addition to priorities of technical use, interconnection of different sources sustainability provides economic growth and technical skills in complex systems. In this direction, Electric Vehicles (EVs) are two-purpose assets that operate as both variable loads and mobile storage devices. V2G control strategy suggested can ease the intermittency of renewable sources of energy [22], [23]. Therefore, EVs integration has diverse advantages, such as grid stabilization and harmonic mitigation.

In terms of investment, the use of featured RES to charge cycles will enhance financial sustainability by lowering the power bills and tax amortization [24]. Complex hybrid microgrids are based on supervisory control in order to achieve component synchronization and stability of power. These algorithms can be broadly divided into three different classes, namely Learning-Based (LB), Optimization-Based (OB) and Rule-Based (RB) algorithms [25], [26], [27]. Controllable loads and distributed generators, which involve wind turbines, solar cells, and battery storage, are functionally coupled in a microgrid. It is characterized by the ability to work independently in the so-called islanded mode in case of utility outages, thus providing power to

essential loads. In addition to reduced peak demand, these systems can provide ancillary services such grid-connected voltage management that will increase productivity [28], [29].

Lastly, microgrids can be considered an essential component of decarbonization and resilience as a source of local energy security and flexible management, particularly in regions where energy independence is the main issue or in a location that frequently encounters outages [30], [31]. Figure 1 also indicates that micro-grids may be classified based on the way they are operated; on-grid (connected to the grid) and off-grid (separated with the grid). On-grid system generally performs better than the off-grid system on the aspect of reliability and cost effectiveness as the on-grid system has the ability to draw energy on the main electrical system which minimizes dependence on the local generation and enhances the stability of the system.

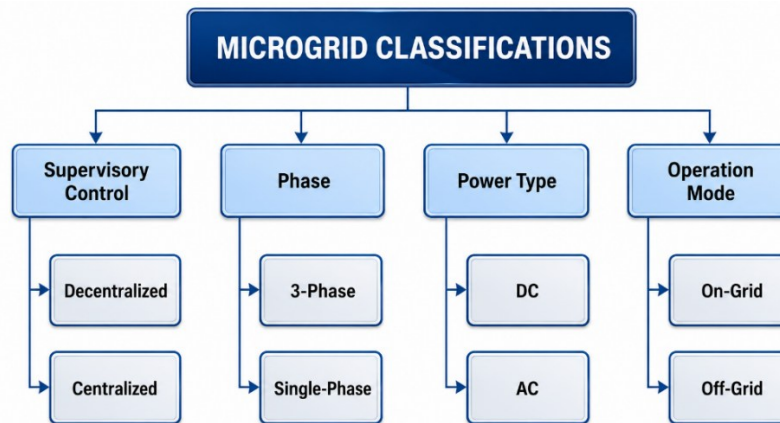


Figure 1. Microgrid classifications.

There are two types of supervisory control in EV charging: centralized and decentralized. Individual EVs independently choose their own charging schedules in decentralized charging, which provides energy management flexibility but lacks a globally ideal solution [32]. Centralized control, on the other hand, depends on master control and planned charging, which maximize charging coordination but have scalability issues as the number of EVs rises [33].

Along with other tactics like real-time and online control, hierarchical-based control has been established to overcome these constraints and improve the flexibility and efficiency of large-scale EV integration [34]. In micro-grids, which can function independently or in conjunction with the grid, the hierarchy controls communication and computing demands. In order to efficiently regulate and distribute electricity according to energy sources and grid requirements, micro-grids employ AC, DC, or hybrid busbar systems [23], [35], [36], [37], [38], [39].

Additionally Table 1 offers a comprehensive evaluation of the characteristics, functional benefits, and disadvantages of these different micro-grid bus bars, allowing selection based on specific operational requirements. Figure 2 also displays the electric circuit diagrams for the various bus bar categories.

Table 1. Overview of the latest advancements in microgrid busbar technologies [40], [41], [42], [43], [44], [45], [46].

Bus Type	Characteristics	Advantages	Limitations
AC Microgrid Bus	Suitable for AC renewable sources and conventional AC loads; widely used in industrial system.	Low initial cost and simple implementation	Higher maintenance requirements and conversion losses
DC Microgrid Bus	Designed for DC sources and low-power applications; reduces conversion stages	High efficiency, low installation cost, and simple operation	Vulnerable to inverter failures when supplying AC loads
Hybrid AC/DC Microgrid Bus	Integrates both AC and DC sources and loads within a unified architecture	High flexibility, reliability, and reduced power losses	Increased system complexity and maintenance requirements

The comparison indicates that AC, DC, and hybrid AC/DC microgrid buses offer distinct benefits depending on system requirements. AC buses provide simple and economic integration with conventional loads, whereas DC buses improve efficiency by reducing conversion stages in DC-based applications. Hybrid AC/DC buses offer the greatest flexibility, reliability, and compatibility with diverse sources and loads, although they introduce greater system complexity and maintenance demands. Therefore, the appropriate bus architecture should be selected according to load characteristics, energy-source types, efficiency objectives, and operational constraints.

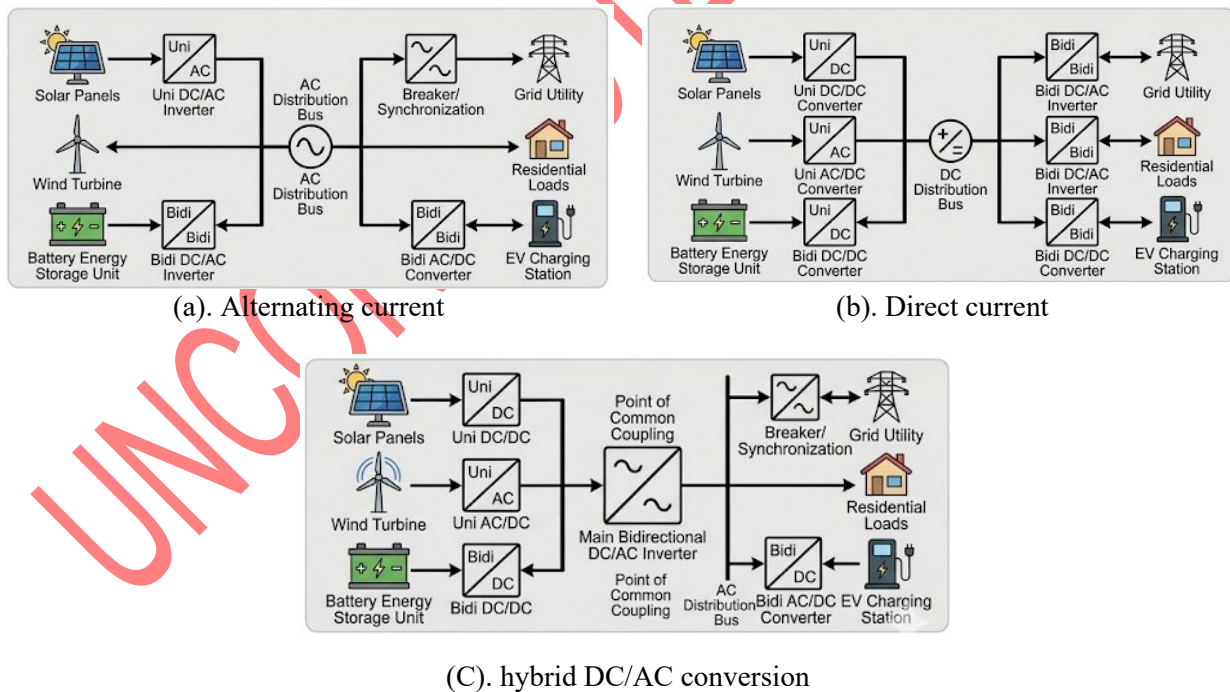


Figure 2. Three forms of buses: (a) alternating current, (b) direct current, and (c) hybrid DC/AC conversion.

CLASSIFICATION OF ENERGY MANAGEMENT AND OPTIMIZATION APPROACHES

During the decade from 2010 to 2019, the global adoption of electric vehicles (EVs) including passenger cars, buses, vans, and heavy-duty trucks accelerated rapidly, with approximately seven million new units entering service each year and a compound annual growth rate of nearly 30% [47]. More than twenty countries have now reached an EV market share above 1%, and nine of these nations have surpassed the threshold of 100,000 electric cars in active use [48], [49].

In this context, the Challenge of Load Growth, forecasts from the International Energy Agency's Global Electric Vehicle Outlook place the 2030 worldwide EV fleet at approximately 145 million units. In the circumstances of aggressive policies, electricity demand in connection with charging is expected to go beyond 550 TWh as early as 2030 - a sixfold increase compared to 2019 baselines. The regional effects are vastly different; as at the moment, EVs occupy about 4 percent of the total electricity consumption in Europe, the Australian Energy Market Operator (AEMO) predicts that by electrifying the 19 million vehicles of the country, the overall electricity consumption will harness nearly threefold [50], [51], [52], [52], [53], [54], [55].

This massive growth requires the consideration of EVs as an active component of the grid, as opposed to a passive load. But at the same time, uncontrolled charging will disrupt distribution networks[56], [57]. Certain effects comprise violation of voltages, augmented real power loss, and thermal overloading of transformers and cables[58], [59]. Such operational risks still exist in V2G systems when there is no strict coordination of the bidirectional power transfers. To overcome these risks, the Energy Management Strategies (EMS) are the EMS solution which employs coordinated smart charging to control the power flow [60], [61]. The optimization of charge/discharge cycles not only postpones the upgrades of the infrastructure which are expensive to maintain, but also prolongs the life of the assets and the distribution losses are minimized as well by the EMS frameworks. At the same time, these measures provide the economic advantages to EV users by reducing the charging expenses by self-consumption maximization [62], [63].

In microgrid architecture, balancing between generation and demand and reducing battery degradation and generation costs is the primary EMS requirement. This will be possible by using a strong algorithmic selection that is complex owing to parameter sensitivity and scale variation [64], [65], [66]. In turn, metaheuristics that are based on nature concepts, in particular, the Grasshopper Optimization Algorithm (GOA), Ant Lion Optimizer (ALO) and Particle Swarm Optimization (PSO) are increasingly gaining popularity due to their ability to explore complex search domains and prevent early convergence. In general, EMS approaches can be categorized into three main groups: Rule-Based (RB), Optimization-Based (OB), and Learning-Based (LB) strategies. Table 2 illustrate widely used energy management strategies.

Table 2. Energy Management Strategy classification[64], [66], [67], [68], [69], [70], [71], [72]

Strategy Type	Classification	Advantages	Drawbacks
Rule-based	Rule-Based Deterministic Approach	<ul style="list-style-type: none">Simple implementation, low computational burden, fast decision-making, and reliable operation.	<ul style="list-style-type: none">Limited adaptability to changing operating conditions and predictive capabilities.

Strategy Type	Classification	Advantages	Drawbacks
	Approach Based on Fuzzy Rules	<ul style="list-style-type: none"> Handles uncertainty effectively and provides flexible decision-making. 	<ul style="list-style-type: none"> Requires expert knowledge for rule design and tuning.
Optimization-based	Real-Time Optimization	<ul style="list-style-type: none"> Suitable for complex optimization problems and dynamic operating conditions. 	<ul style="list-style-type: none"> High computational complexity and dependence on mathematical models
	Global Optimization	<ul style="list-style-type: none"> Provides near-optimal solutions and comprehensive system-level optimization 	<ul style="list-style-type: none"> Computationally intensive and may require significant storage and processing resources.
Learning-based	Reinforcement Learning	<ul style="list-style-type: none"> Adaptive and capable of learning from experiences. 	<ul style="list-style-type: none"> Can be time-consuming to train.
	Supervised and Unsupervised	<ul style="list-style-type: none"> Offers model-free control. 	<ul style="list-style-type: none"> Complexity in model selection and training.
	Neural Networks	<ul style="list-style-type: none"> Capable of handling large datasets and complex patterns. 	<ul style="list-style-type: none"> Difficult to interpret results and requires extensive data.

The classification highlights that energy management strategies involve a trade-off between simplicity, adaptability, computational demand, and interpretability. Rule-based methods are easy to implement but have limited flexibility, optimization-based approaches offer high-quality solutions at the cost of greater computational complexity, while learning-based methods provide adaptive and data-driven decision-making but require extensive training, careful model selection, and large datasets. Therefore, selecting an appropriate strategy should depend on system complexity, real-time requirements, available computational resources, and data availability.

Rule-based control

The Rule-Based algorithm, as presented in Table 3, is a control-based algorithm that depends on human knowledge and can be applied using many choices. This control method can greatly improve computation accuracy and reduce computation problems. One of the main benefits of metaheuristic algorithms are that they can obtain approximations to global optima in complex non-linear search spaces in which deterministic algorithms are frequently unsuccessful. The two types of Rule-Based algorithms are fuzzy-logic RB and deterministic RB, and they are both specified as conditions of the if-then statement [73], [74].

Additionally, Table 2, summarizes the different categories of Energy Management Strategy, while Figure 3, provides additional explanation. The micro grid system's power flow is managed by the deterministic RB. Similar to this, the fuzzy logic RB is also dependent on if-then statements and, because of its effective and beneficial results, is taken into consideration for EMS evaluation in the literature. It can be combined with other techniques at the same time[75], [76]. Although deterministic RB performs better, it can also regulate both the charging and discharging operations. However, while the fuzzy-logic approach may provide reliable outcomes

for a specific set of driving cycles, it is not guaranteed to function well when solving additional issues [77], [78].

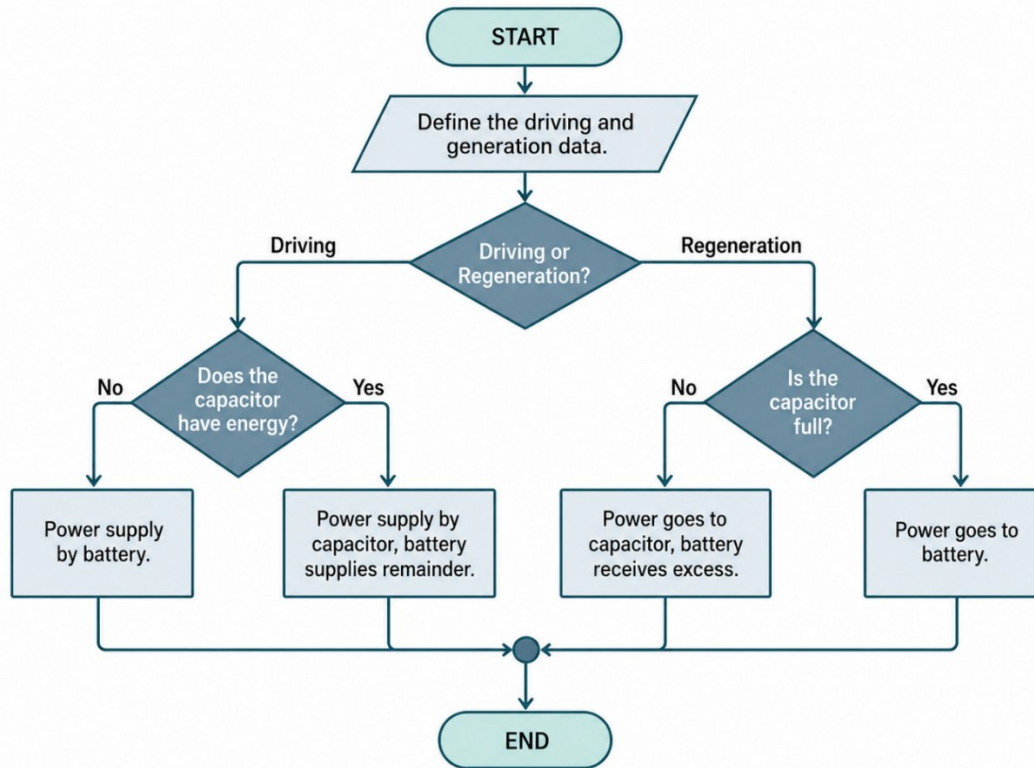


Figure 3. Sample of the rule-based algorithm[79], [80]

Several studies have used the Rule-Based algorithm in order to control the flow of power used to charge the appliances, BT, and EV. The distributed power in a microgrid managed by RB-EMS takes into account the PV/WT/BT in [81], [82]. The best power distribution to satisfy the design specifications for managing is provided by RB-EMS. Metaheuristic control methods can significantly enhance calculation accuracy, reduce computational challenges, and achieve high-quality optimization solutions for complex problems [83], [84].

Several researchers have applied rule-based supervisory control algorithms, also known as metaheuristic algorithms, which are well-suited for online applications [85], [86]. This approach is considered highly suitable for real-time decision-making because of its advantages, such as not requiring complex mathematical modelling, not depending on future data forecasts, and providing rapid solutions [87]. This flexibility enables the design of algorithms that can provide sound approximation in machine learning and other mathematical optimization applications [88]. The high-level control design has been taxonomically subdivided into two paradigms deterministic methods and fuzzy logic. In the fuzzy logic field, certain types of operations are, state-machine strategies, power-follower variants, and the binary thermostat-style regulation [89]. Moreover, the literature identifies three structural classes of fuzzy control, namely, fuzzy adaptive schemes, conventional controllers, and predictive strategies [90], [91], [92], [93]. The features of the operation and the defining features of these rule-based frameworks are summarized in Table 3.

Table 3. Rule-based algorithm classification RB strategies based on predetermined logical conditions (if-then statements) which formed by human experience and behaviour of historical systems.

Approaches	Algorithm Name	Main Feature	Advantages	Disadvantages	Ref.
Deterministic rule-based method	Thermostat (on/off) control strategy	Frequent switching may increase component wear and EMI issues	Simple structure, easy implementation, and robust operation	Potential contact wear due to frequent switching, electromagnetic interference (EMI) issues	[94]
	Modified power-following (baseline) approach	Limited consideration of fuel economy and emission policies	Improves energy utilization and emissions performance through SoC-based control	Does not account for policies on emission reduction and fuel economy	[95]
	Power follower (baseline) control strategy	May result in suboptimal drivetrain efficiency	Maintains battery SoC, improves energy efficiency, and reduces fuel consumption	Suboptimal drivetrain efficiency	[96]
	State machine-based strategy	Does not guarantee globally optimal fuel economy or emissions reduction	Supports multiple operating modes and flexible power management	Does not guarantee optimal fuel economy and emission levels	[97]
Fuzzy rule-based method	Fuzzy predictive strategy	Enhances fuel efficiency and reduces emissions through predictive decision-making	Requires GPS data and advanced prediction infrastructure	Complex implementation, requires advanced GPS and intelligent transportation system (ITS) integration	[98]
	Conventional fuzzy strategy & Fuzzy adaptive	Provides flexible energy allocation and adapts to varying driving conditions	Performance depends on rule design and operating scenarios	Performance is optimized for specific driving conditions, limiting flexibility	[99]

- **Benefits:** The main benefit of RB methods is they have very low computational overhead and hence can make decisions very fast in real time. Since they do not involve the use of complicated mathematical solvers, they are very strong in

providing real-time supervisory control (e.g., thermostat on/off policies or power-following baselines).

- **Limitations:** One of them is that they are very rigid. They are not able to dynamically adjust to unexpected situations. As a result, RB strategies are good when dispatching power in real time but they are essentially not optimal when initial sizing of components in a microgrid is needed, as it involves searching a multidimensional design space.

Optimization-based control

The algorithms, which are maximized by optimization, are the key to maximizing the efficiency of microgrid functioning in a wide variety of conditions. Although clear-cut conceptually and generalizable, these algorithms have often problems with nonlinear constraints that are found in complex systems [100], [101]. Optimization-based low-level control algorithms (LLCAs) low level control methodologies have been further subdivided into two broad areas, namely, Global (offline) and Real-Time (online) optimization as elaborated in Table 4.

Real-time strategies are used without any advance knowledge of driving cycles, but they use both Intelligent Transportation Systems (ITS) telemetry and GPS. Notable methods in this area such as Model Predictive Control (MPC), decoupling schemes, Pontryagin Minimum Principle (PMP) and Equivalent Consumption Minimization Strategy (ECMS) are more concerned with fuel minimization under dynamic conditions in a near-optimal way [102], [103], [104], [105], [106], [107], [108]. On the other hand, global optimization is an offline mode of operation subject to thorough anticipation of system behavior or driving tendencies [109], [110]. This category uses a large tool, whether deterministic (Dynamic Programming (DP)[111], Linear Programming (LP)[112]) or heuristic (Genetic Algorithms (GA)[55], Particle Swarm Optimization (PSO)[113], and Simulated Annealing (SA)[114]) in order to minimize the consumption of fuel. Other interesting applications are stochastic dynamic programming[115], adaptive fuzzy-rule systems[116], and varying control-theoretic models[117], [118].

In contrast to the RB approaches, the OB approaches are mathematically used to determine a particular objective (e.g., the Cost of Energy minimization or the Fraction of Renewable Energy maximization) with the system constraints. The most popular type of OB algorithms are metaheuristic algorithms, which have become the norm of dealing with non-linear, complex search spaces of V2G system sizing.

- **Performance:** Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are effective techniques that can be used to approximate the global optima when deterministic algorithms are not effective. Incidentally, research undertaking Multi-Objective PSO (MOPSO) has shown a maximum of 18% increment in renewable use and a 12-15% decrease in Cost of Energy (COE) than the ones that are baseline [119], [120], [121], [122].
- **Trade-offs:** The high computational complexity associated with mathematical accuracy of the techniques in the field of OB is a price to pay. Such algorithms as Model Predictive Control (MPC) provide almost global optimal solutions by predicting future states but require considerable processing power. The minimum principle (PMP) introduced by Pontryagin is a computationally complex method that is based on modeling approximations [67], [123], [124].

Table 4. Algorithm Classification Based on Optimization.

Approaches	Algorithm	principal characteristic	Advantages	Drawbacks	Ref.
Optimising in real time	An strategy to minimizing equivalent fuel use is known as ECMS.	Sensitive to driving cycles and may provide only locally optimal solutions.	Cost function interpretation. Online utilization	Main factor driving cycle sensitivity Locally Optimal Complexity of the system	[120], [125]
	Decoupling control	Increased control-system complexity.	controlling the state of charge (SoC) of the battery to guarantee ideal energy distribution.	The system's complexity	[126], [127]
	Robust control approach	Requires sophisticated mathematical modeling.	Improves fuel economy and power-split management under uncertainties.	Used complicated mathematical formulas	[119], [128]
	Model predictive control (MPC)	Depends on accurate prediction of future driving conditions.	Reduced complexity of computing Capacity to predict Solution near global optimality.	Require in-depth understanding of driving trends	[129], [130]
	Pontryagin's minimum principle (PMP)	High computational complexity and dependence on model accuracy	Focuses on optimizing the overall trajectory of the system to achieve the most efficient performance	It involves high computational complexity, demanding substantial processing power, and relies on modeling approximations, which may introduce inaccuracies in real-world applications.	[131], [132]
Global optimization	SDP, or stochastic dynamic programming	Applied to optimize fuel consumption in hybrid electric vehicles, helping to minimize energy usage	To determine the optimal operating strategy for driving cycles, ensuring a robust implementation	It is not designed to provide a real-time solution. Instead, it focuses on developing an optimal strategy based on pre-defined conditions and scenarios.	[133], [134]
	Applying control theory	Requires complex mathematical calculations	Capable of achieving globally optimal energy management solutions.	Using a complex calculation system	[135]

	Fuzzy rule-based adaptive	Requires extensive driving and operational information	Enhances adaptability and improves fuel economy under varying driving conditions.	Taking into account the driving information (roadway type, energy flow, and drive train),	[136]
	AI, or artificial intelligence	High implementation cost and computational requirements	Fast convergence toward optimal solutions and improved sizing decisions.	It can be costly, as it relies on specialized machines	[137]
	Optimal control	Requires advanced mathematical formulations.	Forecasting future system behaviors and optimizing control actions.	Applying Calculus of Variations and Derivatives	[138]
	Simulated Annealing (SA)	Computationally intensive for large-scale applications.	It solves power estimation problems efficiently, bypassing the need for complex equations.		[139]

A Strategy for Learning-Based Energy Management

The Learned-Based Energy Management Strategy is a control-oriented algorithm for machine learning applications, utilizing data mining techniques to provide real-time insights for enhanced system efficiency. It is divided into four primary categories: neural networks, supervised and unsupervised learning paradigms, and reinforcement learning frameworks[140], [141], [142]. In this perspective, a key difference between the Reactive-Based (RB) and Optimal-Based (OB) approaches is that the RB method does not use historical data for decision-making.

Micro grid Sizing Optimization Algorithms

The strategy for determining the optimum option from a variety of applicable solutions for a particular issue is known as optimization. The task of sizing and controlling power flow is particularly regarding renewable energy systems (RESs), because of the complexity of the desired function and the many features of system components. Stochastic and deterministic micro grid sizing optimization algorithms can be applied to overcome the constraints imposed by design variables[143], [144], [145]. In addition, compared to the deterministic approach, stochastic algorithms are much more probable to succeed. It is divided into two categories: heuristic and metaheuristic, which are subcategories of artificial intelligence (AI) algorithms [146], [147].

Another way to describe the heuristic is as a method for striking a balance between exploitation and exploration, or between global and local search (also known as diversification and intensification). As a result, metaheuristic algorithms can efficiently improve calculation accuracy while decreasing computational complexity. Additionally, solve difficult optimization problems and get better-quality outcomes[148], [149]. Furthermore, because the two stochastic algorithms presented are interchangeable and there is no universally accepted definition for them

in the literature [150], [151]. Both traditional nature-inspired metaheuristic techniques or software tools can be implemented to optimize the size of hybrid system components. The three categories of nature-inspired algorithms, trajectory, evolutionary, and swarm are utilized to identify the best method for solving optimization problems.

The software tools that have been published in the literature, like HOMER, In the field of modeling and control systems, tools like RETScreen, iHOGA, MATLAB/Simulink, and TRNSys have been widely utilized. These software tools are commonly employed in the power systems sector due to their well-established accuracy [120], [152], [153], [154], [155], [156], [157], [158]. However, they also encounter challenges such as black-box coding, the need for extended computational time, and difficulties in minimizing specific functions. Metaheuristic algorithms optimize the amount of components in hybrid systems by using software tools, which helps solve restrictions. Most of the key metaheuristic methods are the Cuckoo Search Algorithm (CSA), Antlion Optimization (ALO), and Particle Swarm Optimization (PSO). Although these algorithms are effective, one of the main challenges is the intricate computational equations needed to find an acceptable result. They are also helpful in the resolution of Vehicle-to-Grid (V2G) problems, including lowering production costs and power losses. Figure 4 demonstrates classifications of micro grid sizing algorithms.

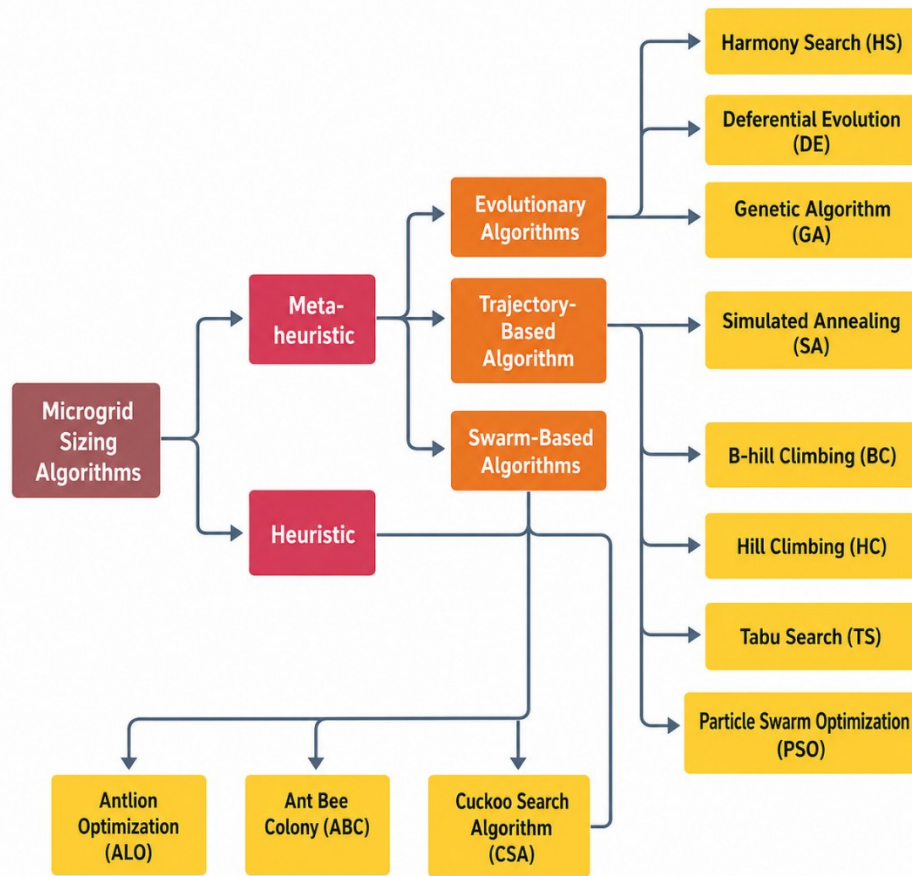


Figure 4. Classifications of micro grid sizing algorithms [159], [160].

VEHICLE-TO-GRID SYSTEM ARCHITECTURES AND CONSTRAINTS

Vehicle-to-Grid (V2G) systems enable bidirectional energy exchange between electric vehicles and the grid, supporting peak shaving, frequency regulation, renewable energy integration, and demand response. Their operation is constrained by battery degradation, user mobility, infrastructure, communication, and uncertainty. Mathematical programming, metaheuristic algorithms, and hybrid approaches are widely used to optimize V2G scheduling, while comparative analysis assesses their accuracy, speed, robustness, and scalability.

Contributions of Vehicle-To-Grid to Energy Systems

Vehicle-to-grid (V2G) generation permits electric automobiles to function as bidirectional power units, allowing their batteries to each draw electricity from and supply strength returned to the electric network [161], [162]. For this functionality to be finished, numerous critical elements have to be in region, including a reliable physical connection to the grid and powerful manage framework that manages the interaction among the automobile and the V2G operator , [160], [160], [162]. When these conditions are met, electric-powered automobiles can function as decentralized and flexible electricity assets, contributing to power machine assist. In this function, they assist enhance the resilience, stability, and operational performance of the grid with the aid of presenting services inclusive of lively and reactive energy regulation, load-leveling, mitigation of current harmonics, and numerous ancillary services associated with voltage and frequency manage.

Mathematical Programming

Early V2G sizing research is overtaken by linear, mixed integer and stochastic programming methods. These techniques are globally optimality guaranteed with scalability and computational limitations in large-scale systems.

Metaheuristic Algorithms

Particle Swarm Optimization, Differential Evolution, Genetic Algorithms, and other related methods are gaining popularity since they are flexible and can address nonlinear multi objective problems. Reported findings indicate a reduction of costs of 5-25 per cent relative to the baseline strategies although with increased computational costs [160].

Hybrid Approaches

Hybrid EMSs balance between robustness and optimality between rule-based logic and optimization or learning parts. Although promising, its implementation is at the low technology readiness levels in most cases.

Comparative Performance Analysis

Table 5 demonstrates that metaheuristic and optimization techniques are widely applied to V2G sizing and energy-management problems involving hybrid renewable-energy systems. Methods such as MOPSO, PSO, GOA, MOSaDE, ALO, and hybrid control frameworks effectively address multiple objectives, including cost reduction, renewable-energy utilization, emissions mitigation, power-loss minimization, and optimal component sizing. The reported results indicate improvements such as lower cost, reduced CAPEX and NPC, increased renewable-energy fractions, and decreased greenhouse-gas emissions. However, most studies rely primarily on simulation-based validation, indicating the need for further experimental and

real-time implementation to verify robustness under practical operating conditions [161], [162], [163].

Table 5. Quantitative Review of Metaheuristic and Optimization Algorithms in V2G Sizing.

Ref.	System Configuration	Grid Mode	EMS / Optimization Approach	Key Objectives	Quantitative Outcomes (Reported)	Validation Level
[164]	PV-WT-FC-BT-EV	On-grid	MOPSO + MPC	Minimize COE, maximize RES utilization	RES utilization ↑ ~18%; COE ↓ ~12%	Simulation
[165]	PV-WT-BT-EV	On-grid	MOPSO+ MCS	Minimize LPSP and COE under EV uncertainty	COE ↓ 9–15% vs baseline	Simulation
[166]	PV-WT-BT-EV	On-grid	MOPSO	Maximize REF, minimize COE and GHG	REF ↑ 20%; GHG ↓ 17%	Simulation
[167]	Multi-carrier MG + EV	On-grid	PSO + MCS	Optimal sizing and coordinated EMS	NPC ↓ ~10%	Simulation
[168]	PV-WT-BT-EV	Off-grid	GOA (vs PSO, CS)	Minimize CAPEX, improve efficiency	CAPEX ↓ 14–19.3%	Simulation
[169]	PV-WT-BT-EV	On-grid	PSO	Minimize energy cost, smooth power	Cost ↓ ~11%	Simulation
[170]	PV-WT-DG-BT-EV	Off-grid	MOSaDE	Minimize COE and LPSP	COE ↓ ~13%	Simulation
[170]	PV-WT-BT-	Off-	ALO, PSO,	Minimize COE,	COE ↓ 8–	Simulation

	EV	grid	HS, FA	losses, NPC	16%	
[171]	PV-WT-BT-EV	On-grid	HOMER	Cost-optimal sizing	COE ↓ ~10%	Simulation
[172]	PV-BT-EV	On-grid	FIS-based EMS	Cost reduction, peak shaving	Peak load ↓ ~15%	Simulation

The level of validation shows whether the results were generated through simulation based only, experimental, or field validation. The majority of the studies reviewed are at the simulation level, which presents one of the research gaps.

Key trends indicate that:

- Rule-based EMSs are appropriate for small residential systems and less uncertainty.
- Mathematical programming is best in well-defined, small, medium-sized systems.
- Metaheuristic and hybrid methods can more effectively be used in the implementation of V2G systems that are large scale, multi objective, and demand additional machinery. systems that are large scale, multi objective, and require more machinery can have a better implementation with metaheuristic and hybrid methods.

PRACTICAL IMPLEMENTATION AND SCALABILITY CONSIDERATIONS

Although the simulation showed promising outcomes, the real-world implementation is associated with difficulties that concern the computational complexity, communications latency, modelling battery degradation, and uncertainty about the user behavior. Few of them are experimentally validated, which means that there is a major gap in research. Vehicle-to-grid (V2G) systems enable electric vehicle (EV) batteries to operate as flexible, distributed energy resources by permitting electricity to flow in both directions between the vehicle and the power grid [173], [174].

This bidirectional interaction allows EVs to contribute to several grid-support functions, including load leveling, frequency stabilization, and voltage regulation, thereby strengthening overall grid resilience. The V2G technology removes peak load stress, manages load distribution profiles and increases the system-wide efficiency through effective management of power exchange dynamics. Moreover, EVs enhance grid reliability through the ancillary service, namely reactive power injection. The synergy between Renewable Energy Sources (RES) and Electric Vehicle Charging Facilities (EVCF), which enables the operation of both the Grid-to-Vehicle (G2V) and V2G operational modes, is confirmed by recent scholarship [175], [176]. Figure 5 illustrates the G2V and V2G bidirectional power flow diagrams.

V2G is also unique in the broader Vehicle-to-Everything (V2X) ecosystem as it could have high-impact environmental and economic utility, including zero tailpipe emissions and potentially generate income through tariff arbitrage. However, there exist significant obstacles to mass implementation. These problems are complex, including both economic impediments such as high capital expenditure (CAPEX) and operational expenses as well as technical factors such

as battery degradation anxiety and the pressing need to have uniform communication protocols. A typical battery-electric car comprises of quite a number of crucial components such as an energy storage system, charging interface, DC/DC conversion unit, traction drive system, power electronic controller, onboard charger, and so forth, which together makes it possible to engage it in G2V interactions and V2G interactions [176], [177], [178].

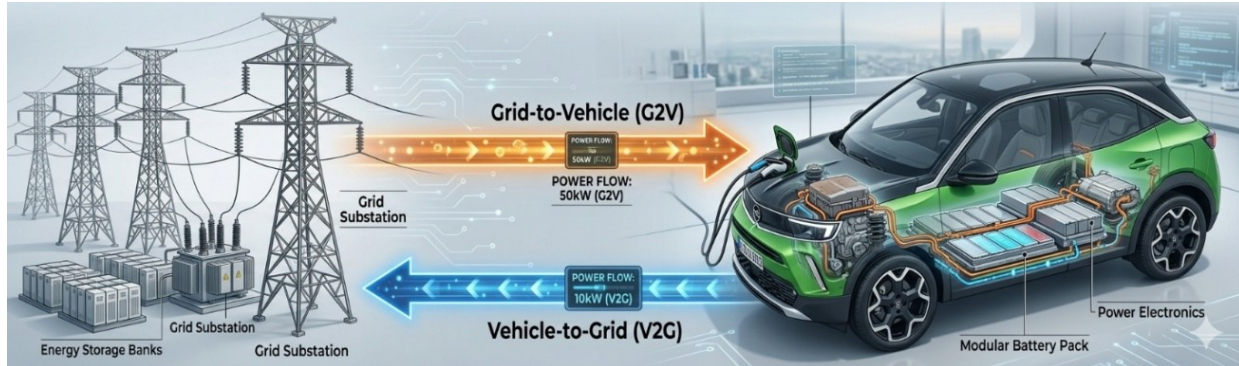


Figure 5. The G2V and V2G bidirectional power flow diagrams[120], [179].

The types include, but are not limited to the US, China, India, Indonesia, Nigeria, Turkey, Ethiopia, Japan, Kenya, Algeria, Germany, and Spain. Besides these countries, EV charging technology is also used for Brazil, Denmark, the Netherlands, Morocco, Malaysia, and the United Kingdom. While the above-mentioned countries exploit on EVs, Germany, UK, China, and USA much bigger pieces of the pie of EVs market [[180], [181], [182], [183], [184]. An electric motor's (EM) primary benefit is its ability to transform electrical energy from batteries into mechanical energy, which is then utilized to move vehicles forward[185].

Compared to ICEVs, it is more desirable to favor EVs, most importantly: EVs are silent and eco-friendly[186], [187]. In addition, since RESs have boundaries in integrating a large number of RESs to generate electricity due to climatology, when assessed as a generation source, EVs are more reliable and more stable than RESs[188], [189]. But it stresses the grid significantly when used as a load. Manufacturers around the world offer vehicles with different engines to provide green electricity or zero-emission mobility[190], [191], [192], [193].

The frequently used EVs for discharging and charging are electric vehicles including battery electric, hybrid, and plug-in hybrid types vehicles (PHEV, HEV, and BEV)[194], [195]. The PHEV, in contrast to HEVs, is capable of integration with grid and larger storage systems and is less reliant on oil. It is suitable for highway and city driving, It operates in dual modes of operation: charge-depleting and sustaining[196], [197]. As illustrated in Figure 6, residential and non-residential (commercial) stations are the two different kinds of charging stations.

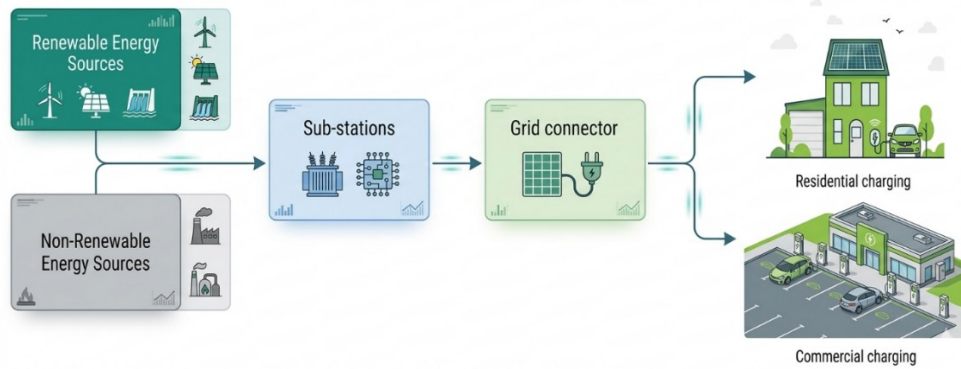


Figure 6. Residential and non-residential (commercial) stations[198].

Electric vehicle (EV) Three basic power levels are used for charging: Level 1 (AC), Level 2 (AC), and Level 3 (DC). Level 1 charging, which operates on single-phase power, is typically for on-board charging, charging takes a long time, and uses the SAE J1772 connector standard. In the U.S. The price range for Level 1 charging installation is \$500 to \$880, and it's typically installed at homes or offices, requiring cables for use. Level 2 charging can operate on either three-phase or single-phase power, offers a shorter charging time compared to Level 1, and is more commonly preferred for private or public charging. It costs approximately \$150 to install and uses either the SAE J1772 or IEC 61851-1 connector standards. Level 3 charging makes use of an off-board DC architecture, mostly used in commerce[199], [200], [201].

Notable ones are the CHAdeMO protocol that was developed by the Japanese. Such systems incur installation capital expenditure (CAPEX) that has a wide range of 3,000 to one hundred and sixty thousand dollars[202], [203]. Finally, the choice of power ratings, connector typologies, and circuit structures is determined by the particulars of the work of the Electric Vehicle Charging Station (EVCS) [204]. These technical specifications are outlined in Table 6, which maps the infrastructure requirements to places of deployment.

Table 6. Structures of charging Electric Vehicles[205], [206], [207].

Category	Classification	Features
Power Flow Direction	Unidirectional	<ul style="list-style-type: none"> - Used for charging (G2V mode). - Incorporates a diode rectifier and DC-DC converter. - Simplified design with fewer components.
	Bidirectional	<ul style="list-style-type: none"> - Enables both charging (G2V) and discharging (V2G). - supports further services including frequency regulation and peak load shaving. - Useful for grid stabilization.
Power Types	AC	<ul style="list-style-type: none"> - Alternating current with intermittent frequency. - Common for slower charging.
	DC	<ul style="list-style-type: none"> - DC current with continuous flow. - Suitable for faster charging. - Allows charging without utility supplier approval.
Charging Circuit	On-board	<ul style="list-style-type: none"> - Integrated within the vehicle itself. - Recharges whenever electricity is available.

Category	Classification	Features
Communication		- Less costly compared to off-board systems.
	Off-board	- Located outside the vehicle (e.g., at charging stations). - Installation is more expensive.
	Wireless	- Uses electromagnetic waves for charging. - Offers convenience and eliminates physical connectors.
Contact Types	Contactless	- depends on wireless power transfer (WPT) or inductive power transfer (IPT). - Ideal for long-distance charging.
	Conductive	- Both quick (DC fast charging or Level 3) and slow (Level 1 and 2) charging are supported. - Best suited for short distances.

The classification demonstrates that electric-vehicle charging technologies vary considerably in power-flow direction, supply type, circuit location, and connection method. Unidirectional charging offers simpler and more economical implementation, whereas bidirectional charging enables vehicle-to-grid services, peak shaving, and grid support. DC and off-board systems are generally better suited to fast charging, while AC and on-board configurations remain practical for routine charging. Wireless charging improves convenience and accessibility, whereas conductive charging provides higher efficiency and is currently more suitable for widespread short-distance applications.

System Components

The nature of three main subsystems of V2G-integrated microgrid, namely renewable generation, interaction architecture, and energy storage, limits the optimal sizing of a microgrid system. This is to avoid the stochasticity of single-source generation this hybrid is selected to even out the curve of power supply; the solar optimal hours are often balanced with the wind pattern. The variable weather of the sun and the wind speed however introduces the variables of uncertainty which sizing algorithms must consider in order to ensure that a corresponding load reliability is attained [208], [209], [210], [211], [212], [213].

- **Vehicle-to-Everything (V2X) Architecture:** The technical relationship between the EV and the grid preconditions the potential constraints of power flow. The Vehicle-to-Everything (V2X) system must have bidirectional power converters and high-power communication interfaces (e.g., ISO 15118) to manage the flow of energy. The total power rating of these bidirectional chargers is limited by the hard limit of the volume of ancillary service that the fleet can provide to the grid in system sizing.
- **Energy Storage and Degradation:** A major variable decision variable insofar as energy storage is concerned is battery chemistry. Today Lithium-ion (Li-ion) technology is already established as the new standard of modern EVs as it has a higher energy density, efficiency and falling cost curve than older ones. Nevertheless, battery degradation is the primary restriction of usage. Aging and capacity deterioration effect have significant effects on long term economic sustainability of V2G projects. It is then concluded that the powerful Energy Management Strategies (EMS) must explicitly position the battery health models to the objective function, and the profit of arbitrage in the short run should compensate the nonlinear quality of the cost of decreasing the battery living.

CONSEQUENCES EV INTEGRATION FOR ELECTRICAL NETWORKS

Vehicle-to-Grid (V2G) technology exerts both positive and negative influences on the power system. Positively, it supports grid stability through improved voltage and frequency regulation, enhances overall power quality, and enables more effective energy and demand-side

Type of Impacts	Remarks	Effects
-----------------	---------	---------

management. On the other hand, unselective EV infiltration is also a significant problem to grid integrity. High-density adoption, as it is observed in [212], [213], [214], may create instability in voltage profiles and contribute to the worsening of peak congestion, which will eventually lower the quality of power. Figure 7 classifies these operational liabilities of V2G integration.

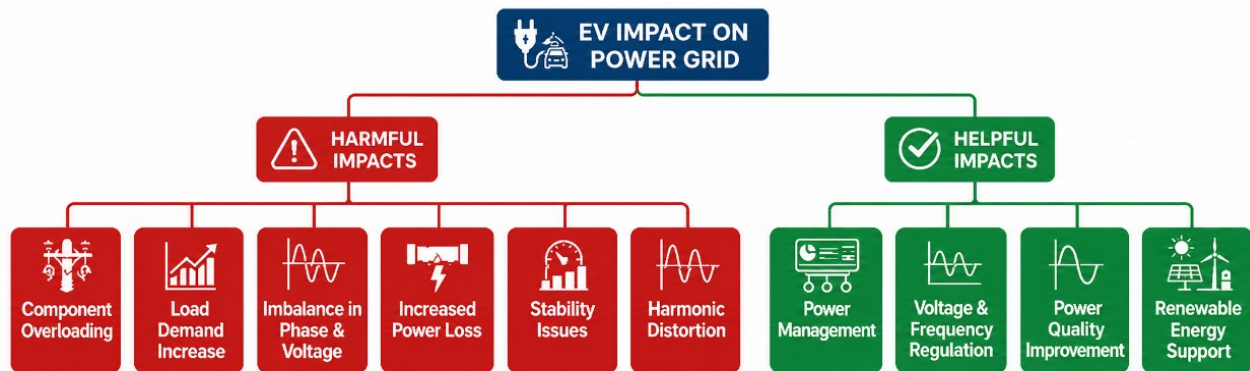


Figure 7. Effects of implementing vehicle-to-grid technology[6], [82].

Complex power control specifications are necessary to counter these instabilities. Table 7 and Table 8 compare the resulting systemic risks with the operational dividends.

Table 7. Synopsis of ancillary services and grid-stabilizing mechanisms conferred by EV

Power Quality Improvement	It helps mitigate problems associated with poor power quality, including voltage imbalances, harmonic distortions, and excessive real power consumption.	Affects the system's lifespan.
Voltage and Frequency Stability Management	It addresses the consequences of voltage surges and frequency fluctuations resulting from grid imbalances.	Impacts system quality and lifespan.
Power Management	In practice, an effective Energy Management System (EMS) will organize the dynamics of power flows to reduce operational costs (OPEX) and optimize the service life of individual components at the same time, to strengthen the overall system stability.	Can lead to system degradation.
Renewable Energy Support	Integrating renewable energy increases grid flexibility, it offers an environmentally sustainable solution while decreasing reliance on conventional energy sources.	Comes with uncertainties related to renewable energy sources.

integration[142], [215], [216].

Electric-vehicle integration can significantly enhance grid performance by improving power quality, supporting voltage and frequency regulation, and enabling more effective power management. Through coordinated charging, discharging, and energy management systems, EVs can reduce peak demand, optimize power flows, lower operating costs, and contribute to greater system stability and equipment longevity. Moreover, EVs can also facilitate higher penetration of renewable energy by absorbing surplus generation and supplying stored energy when renewable output is limited. However, these benefits depend on effective control strategies, reliable communication infrastructure, accurate forecasting, and proper management of charging uncertainty to prevent system degradation and adverse impacts on grid operation. Table 8 also illustrates that the grid impacts and power quality disturbances associated with uncontrolled EV loading.

Table 8. Catalogue of adverse grid impacts, and power quality disturbances associated with uncontrolled EV loading[217], [218], [219].

Type of Impacts	Remarks	Effects
Harmonic	Voltage waveform distortion, resonance risk, electromagnetic interference (EMI), and degraded power quality.	Results in poor power quality and EMI issues.
Stability	Voltage fluctuations, reduced system stability, and longer recovery times following disturbances	Causes an unstable power system and prolonged recovery time to reach a steady state after disturbances.

Rising Power Losses in the Grid	Increased real power losses and reduced overall network efficiency.	Consequently, it results in increased power losses in the electrical distribution network..
Phase and Voltage Imbalance	Voltage unbalance, neutral current increase, voltage deviations, and deterioration of power quality.	The operation of EV chargers may result in voltage drops and deviations at their grid interconnection points, potentially affecting local power quality.
Load Demand Increase	EV grid integration adds substantial load, causing challenges for utilities during peak load periods.	Results in uncertainties for utilities during peak hours.
Component Overloading	Overloading is caused by high vehicle demand and the strain on other electric components.	This additional load can negatively affect the operational lifespan of the system..

In this direction, uncontrolled electric-vehicle charging can impose substantial technical stress on distribution networks by increasing harmonic distortion, voltage fluctuations, phase imbalance, neutral currents, and real power losses. The simultaneous connection of numerous nonlinear EV chargers may degrade waveform quality, create electromagnetic interference, reduce system stability, and prolong post-disturbance recovery. These effects are particularly severe in weak grids and low-voltage feeders with limited hosting capacity.

Moreover, rapid growth in EV charging demand can intensify peak loading and overload transformers, cables, and other network components, thereby accelerating equipment ageing and reducing operational lifespan. Effective charging coordination, phase balancing, harmonic filtering, demand-response programs, and intelligent energy management are therefore essential to mitigate these adverse impacts while maintaining reliable, efficient, and high-quality grid operation.

Interfacing Renewable Systems with Modern Grids

This review of the literature summarizes the architectural paradigms, objective functions, as well as deployment scenarios currently used in the literature. Although a structural consistency can be deduced by looking at the nature-inspired optimization heuristics in detail, as in Table 9, which specifically lists them, core microgrid components are universally flexible in both islanded and grid connected topologies. Nevertheless, EV integration strategies are an exception with a significant number of cases needing different configuration logic depending on the grid connection status. Validation Methodologically, numerical simulation is the most common method of attaining validation.

Computational engines like MATLAB are the major tools used in solving these complicated mathematical equations and validating the system performance indices.

Table 9. Integration of RESs without EVs: The State-of-the-Art.

Ref	System Configuration					Approach	Objectives	Scenario
	BT	WT	FC	PV	DG			

[220]	✓	✓	x	✓	x	Economic CSA-PSO- GA MCS	<ul style="list-style-type: none"> To address the optimization constraints, this paper applies the Crow Search Algorithm (CSA), and its application is compared with much used metaheuristics: The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In addition to this, Monte Carlo Simulation (MCS) is called to find the best set-up of Photovoltaic (PV), Wind Turbine (WT), and Battery (BT) subsystems. The corresponding stochastic model is a measure of both the important reliability measures, namely the Loss of Load Expectancy (LOLE) and Expected Energy Not Supplied (EENS). 	Residential Off-grid
[221]	✓	x	x	✓	✓	Mathematical model PSO	<ul style="list-style-type: none"> The main focus of this research is based on the Algerian operating environment, and it aims at minimizing the lifecycle costs of the system, the Loss of Load Probability (LOLP) and the carbon dioxide emission. The suggested Hybrid Microgrid System (HMGS) structure is built around Photovoltaic (PV) arrays and battery storage with support of Diesel Generators (DG). A solver, Particle Swarm Optimization (PSO), is used to calculate the preferred size of these parts. Benchmarking of the algorithmic output against HOMER software simulations is then done to ensure the output is rigorously benchmarked. 	Residential Off-grid
[222]	✓	✓	x	✓	x	• MOPSO	<ul style="list-style-type: none"> This study aims at maximizing the Renewable Energy Fraction (REF) with the primary goal of maximizing the energy costs and Loss of Power Supply Probability (LPSP) minimized, but subject to stochastic meteorological constraints. The system is based on predictive mathematical modeling as the logic of its output. Thereafter, Multi-Objective Particle Swarm Optimization (MOPSO) algorithm is used to outline the solution space. The accruing data have been stratified in a performance triad of Cost of Energy (COE) reduction, REF augmentation and Greenhouse Gas (GHG) mitigation. 	Residential On-grid
[223]	✓	✓	✓	x	x	<ul style="list-style-type: none"> MCS PSO 	<ul style="list-style-type: none"> The suggested Energy Management System (EMS) manages a heterogeneous topology of the microgrid. The Micro-turbines (MT), Fuel Cells (FC), Wind Turbines (WT) and Waste-to-Energy (WtE) units are called Generation assets that were integrated with boilers and anaerobic reactor-reformers. As far as the balance of plant in terms of Batteries (BT) and power conditioning interfaces (rectifiers/inverters) dimensioning is concerned it is done through Monte Carlo Simulation (MCS). The Particle Swarm Optimization (PSO) metaheuristic is then used to prove this sizing logic. 	Residential On-grid

[224]	✓	✓	x	✓	✓	<ul style="list-style-type: none"> • MATLAB is used to simulate the RB-EMS for performance assessment. • GOA 	<ul style="list-style-type: none"> • The objective is to find out the best arrangement and size of the elements of the micro grid system with the aim of attaining maximized efficiency and stable operation. In order to resolve the issue of optimization in terms of power, the Grasshopper Optimization Algorithm (GOA) is used, and the results are compared with those of the Particle Swarm Optimization (PSO) and the Crow Search (CS) algorithms. • The proposed system achieves reductions in capital cost, with decreases of 14% and 19.3% observed under different operating scenarios. 	Residential Off-grid
[225]	✓	✓	x	✓	x	<ul style="list-style-type: none"> • PSO coupled with a filter algorithm 	<ul style="list-style-type: none"> • The objective is to reduce energy costs while smoothing variations in the power supply. Particle Swarm Optimization (PSO) is applied to identify the optimal sizing of the system's components. 	Residential On-grid

In addition, a compilation of the research conducted on integrating EVs with PV and WT systems has been given in Table 10, which has highlighted the technical and operational aspects between PV and WT systems under load conditions in residential and business settings. Overall, the evaluated studies deal with EV integration in micro grid configurations, both standalone and grid-connected. Micro grids can be used in a variety of contexts, such as commercial, industrial, military, and residential ones[226]. Several studies have investigated charging loads at shopping malls, universities, military installations, and commercial venues in connection to various EV charging places. Residential charging, which accounts for about 32% of all energy use worldwide, is the subject of some studies.

The charging time, power levels, and related expenses (charging rates) are the main distinctions between residential and commercial charging. Because residential charging is more cost-effective than commercial charging due to a variety of optimization and management strategies, it is frequently chosen. Further lowering overall charging costs are home charging's increased flexibility, reduced feed-in tariffs, and cost savings due to the absence of service fees[227], [228], [229]. To address sizing optimization issues in hybrid systems, two primary techniques are frequently employed: Single-Objective (SO) and Multi-Objective (MO) optimization. Due to its advantages, such providing the best answer for a particular problem, SO is used more often in the literature. Nonetheless, MO optimization is more complicated and time-consuming, though, it addresses numerous mathematical equations and is intended to be applied in those situations when more than one objective function must be considered. MO method of decision making balances a number of goals. Furthermore, sizing optimization problems are usually addressed by the help of heuristic and metaheuristic algorithm[230], [231], [232].

Table 10. The most advanced off-grid and on-grid micro grid systems with electric vehicles in the literature.

Ref	System Architecture					Approach	Objectives	Scenario
	BT	WT	FC	PV	DG			
[233], [234]	✓	✓	✓	✓	x	<ul style="list-style-type: none"> •MOPSO •MPC •Matlab/Simulink 	<ul style="list-style-type: none"> • To describe the V2G system as a hybrid system that integrates EVs into the grid and is grid-connected with RESs. 	Residential On-grid

							<ul style="list-style-type: none"> • To solve the energy management optimization and calculate and allocate the power for every time step using MOPSO • To increase the utilization of RESs by using MPC to plan PEV charging energy 	
[235], [236]	✓	✓	x	✓	✓	• MOSaDE	<ul style="list-style-type: none"> • The MOSaDE algorithm is applied to optimize system performance by ensuring load satisfaction with low COE, minimal LPSP, and a maximized REF. • To achieve the best possible economic structure. • To employ EMS power techniques. 	Residential Off-grid
[237], [238]	✓	✓	x	✓	x	<ul style="list-style-type: none"> • ALO, PSO • HS, FA, and DE 	<ul style="list-style-type: none"> • In order to minimize COE, losses, and NPC in Iran, an off-grid system can be optimized by using ALO to determine the ideal value to satisfy load demand. 	Residential Off-grid
[239]	✓	x	x	✓	x	• Matlab/Simulink	<ul style="list-style-type: none"> • To control the flow of energy for a grid-connected system that uses a DC bus to satisfy demand and is integrated with RESs and batteries (PV-BT). 	Residential On-grid
[240]	✓	✓	x	✓	x	• HOMER	<ul style="list-style-type: none"> • Utilizing RESs to charge EVs in order to save money and generate investment; sizing system components (PV-WT-BT) using HOMER for EV charging in Izmir, Turkey as a case study. 	Residential On-grid
[241]	✓	✓	x	✓	x	<ul style="list-style-type: none"> • MOPSO • MCS 	<ul style="list-style-type: none"> • To model and quantify the variability in the number of arriving and departing EVs. • To examine the LPSP and COE • Multi-Objective Particle Swarm Optimization (MOPSO) is employed to determine the optimal sizing of the system components 	Residential On-grid
[242]	✓	✓	x	✓	x	• HGS	<ul style="list-style-type: none"> • Utilizing the Hunger Games Search Algorithm (HGS), a system comprising PV-WT-BT-EV will be analyzed and optimized. 	Residential On-grid
[243]	✓	✓	x	✓	x	<ul style="list-style-type: none"> • ABC • PSO 	<ul style="list-style-type: none"> • The study involves developing a mathematical model for a PV-WT-BT system integrated with EVs to analyze performance and interactions. • To minimize power exchange between EVs and the grid, thereby reducing system losses and achieving the lowest possible electricity costs in India. 	Residential On-grid
[244]	✓	x	x	✓	✓	• HOMER pro	<ul style="list-style-type: none"> • Creating sustainable electrification in Gaza by integrating biogas and solar 	Residential On-grid

							with the main grid. • The residential area's simulation outcome was 2.30\$ NPC and \$0.438/kWh COE.	
[245]	✓	x	x	✓	x	• FIS	• EMS for micro grids with EVs that use batteries and fuzzy inference systems (FIS)	Residential On-grid
[246]	x	✓	x	✓	x	• MPPT controller	• Using MPPT to power large-scale EV charging stations with innovative grid-connected wind and solar generation. • V2G technology implementation via a DC bus	Residential On-grid
[247]	✓	✓	✓	✓	✓	• MOPSO • NGA-II • MCS	• This research executes a multi-scenario optimization of a complex heptagonal hybrid architecture integrating Photovoltaic (PV), Wind (WT), Battery (BT), Fuel Cell (FC), Electrolyzer (EL), Hydrogen Tank (HT), and Diesel (DG) assets. By using the Multi-Objective Particle Swarm Optimization (MOPSO) solver, the performance of the system is strictly compared to the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The essence is to find a combination that will reduce three competing variables, which are; Loss of Power Supply Probability (LPSP), Life Cycle Cost (LCC), and CO2 emissions. The Taguchi method and Monte Carlo Simulation (MCS) is used to describe the stochasticity of the RES generation and load demand to account systemic volatility, and dynamically incorporates the active use of dynamic Electric Vehicle (EV) behavioral profiles.	Residential On-grid
[248]	✓	✓	x	✓	x	• HOMER	• It focuses on five different geoclimatic regions in China in the study to examine the techno-economic viability of integrating Battery Energy Storage Systems (BESS) with hybridRES (PV and WT). The main goal is to maximize the EV charging system, which is a successful compromise between fiscal suitability and decarbonization. • Sensitivity Analysis: This is a vigorous sensitivity framework which questions the stability of the system. In particular, it determines the elasticity of economic and reliability indices in relation to parametric changes in the base load demand, EV fleet dynamics, and battery storage kinetics.	Commercial On-grid

V2G integration validates domestic charging investments by delivering critical utility dividends, specifically, outage mitigation and generation capacity deferral. By transforming EVs into bidirectional grid assets, this architecture yields a dual economic advantage: monetizing discharge cycles for grid support while directly compressing household electricity expenditures.

CRITICAL SYNTHESIS AND DECISION FRAMEWORK

The literature reveals a distinct trade-off between solution accuracy and computational speed. Table 11 depicts the selection of algorithm framework selection.

- Rule-Based (RB) and Optimization-Based (OB):** Rule-Based (RB): RB (deterministic) algorithms are highly used in real-time due to low penalization (execution time of less than one second). They on the other hand rely on pre-programmed levels that do not mirror dynamically pricing markets and result in sub-optimal returns to the economy. Instead, the global search space can be optimally brought to 10-15 percent cost savings using metaheuristic methods (e.g., PSO, GA), which place very high processing hardware requirements and thus are not as well adapted to low-cost embedded controllers.

Table 11. Algorithm Selection Framework[120], [248], [249], [250].

Scenario	Priority Goal	Recommended Approach	Justification
Real-time / Embedded	System Stability & Speed	Rule-Based / Fuzzy Logic	Low latency required; exact optimality is secondary to stability.
Day-ahead Planning	Economic Profit (Arbitrage)	Metaheuristic (PSO/GA)	Computation time is not critical; finding global optimum maximizes profit.
Complex Microgrid	Multi-objective (Cost + Life)	Hybrid (e.g., GA-PSO)	Overcomes premature convergence of single algorithms.

The algorithm-selection framework demonstrates that no single optimization method is universally suitable for all energy-management scenarios. Real-time and embedded applications require rapid and stable decision-making; therefore, rule-based and fuzzy-logic approaches are preferred because of their low computational burden and short response time. Although these methods may not always provide globally optimal solutions, their reliability and speed make them appropriate for safety-critical and time-sensitive control tasks. For day-ahead planning, metaheuristic algorithms such as particle swarm optimization and genetic algorithms are more suitable because sufficient computation time is available to search for economically optimal schedules. In complex microgrids involving competing objectives, such as operating cost, battery lifetime, reliability, and emissions, hybrid algorithms can provide a better balance between exploration, convergence speed, and solution quality. Consequently, algorithm selection should be based on the application timescale, computational resources, system complexity, and required optimization objectives.

RESEARCH GAPS AND FUTURE DIRECTIONS

The literature has decided on Rule-Based Energy Management System (RB-EMS) as the most significant supervisory system in response to the shortcomings of the planning that exists in hybrid grid-connected systems. The system of microgrid control is widespread, RB-EMS offers a clear and heuristically oriented organization of the control on the dynamics of power flows [9, 153]. Natural uncompromisingness is present in the architecture, though, in using non-adaptable, expert-authored logic will tend to preclude the possibility that performance can be optimal globally, and will tie performance to the subjective competence of the designer. In order to improve the performance of RB-EMS, scholars have proposed its addition to other sophisticated algorithms such as Improved Ant Lion Optimizer (IALO).

This nature-based algorithm is capable of maximizing power and size aspects of the micro grid, which offers an adaptive and automated process that minimizes the use of human control and can potentially overcome some RB-EMS constraints. Combining RB-EMS and IALO may thus enhance the control and efficiency of the hybrid grid-connected micro grids that are integrated to EVs. Nonetheless, combining different energy sources and the unpredictability of the number of vehicles contribute to overloading, V2G integration problem.

In this way, the difficulty mentioned above can be researched further. The issue mentioned above could be addressed by scheduling the charging process either at night or daytime. The Stochastic Monte Carlo Method (SMCM) is often used as a stochastic method to determine the effect on the electrical load when a variable and uncertain number of electric vehicles (EVs) have been introduced into grid-connected systems.

The analyzed studies show that no single EMS or optimization technique can meet all of the technological, economic, and computational criteria of V2G-enabled microgrids. Instead, the viability of any strategy is heavily dependent on the operational scale, uncertainty level, computational resources, and control objectives.

Rule-based EMS techniques are still popular for real-time applications due to their simplicity, resilience, and minimal computing overhead. However, their reliance on established expert rules restricts their adaptability to dynamic power pricing, stochastic renewable generation, and unpredictable EV charging behavior. As a result, whereas RB techniques perform well in operational dispatching, they are often insufficient for global sizing optimization problems with multidimensional search spaces.

Optimization-based and metaheuristic techniques, such as PSO, GA, and MOPSO, offer greater global search capacity and economic performance. Several evaluated studies found COE savings ranging from 10% to 20% compared to traditional baseline procedures. Nonetheless, these technologies add significant computational complexity and frequently need high-performance computing resources, making them unsuitable for embedded or low-cost real-time applications.

Hybrid EMS frameworks that combine rule-based logic with optimization or learning algorithms appear to strike the best balance between operational reliability and global optimality. However, the bulk of documented implementations are limited to simulation environments, with only a few studies offering experimental validation, hardware-in-the-loop testing, or real-world pilot deployment.

Another significant problem found in the literature is the limited incorporation of battery deterioration models and EV user-behavior uncertainty into optimization objectives. Most present research focus on short-term economic improvements while underestimating long-term battery aging costs and stochastic charging patterns. This identifies a significant research gap for potential large-scale V2G adoption. Therefore, future research should focus on: scalable hybrid EMS architectures; real-time adaptive optimization; battery-aware objective functions;

uncertainty-aware stochastic optimization; and experimentally verified V2G deployment frameworks.

CONCLUSION

The paper presented a critical review of the sizing of the Vehicle-to-Grid (V2G) system and energy management algorithm in modern microgrids. The comparative study of the Rule-Based (RB) control techniques and the metaheuristic optimization techniques disclosed the strengths, and the weaknesses, of the two techniques. As it was revealed, Rule-Based approaches are highly suitable within the framework of real-time operational control as they are easy, need minimal calculations, as well as they can easily be implemented. These characteristics make them useful in systems that have high demands in terms of decision making and stability of the systems is paramount. Metaheuristic optimization algorithms on the other hand were demonstrated to do better in system sizing, economic dispatch and multi-objective optimization problems of complexity.

This enables them to explore a far broader solution space, which has higher chances of finding the optimal fit to the nonlinear constraints and uncertainty that are commonly found in the microgrid setups. However, they are too expensive to implement them directly in real-time controlled systems. Based on these findings, the next research should be guided by hybrid energy management control methods in which the accuracy and global search capability of metaheuristic optimization methods can be integrated with the efficiency and speed of Rule-Based control in managing the next generation control. These compounds would significantly improve the effectiveness of functionality and economic viability in the V2G enabled microgrids. Secondly, the study also emphasizes the importance of simulation based outgrowing research. As much as a simulation is an excellent method of obtaining useful information, the validity in the real world must be verified through experimental methods of validation with laboratory prototypes and hardware-in-the-loop tests and pilot implementations. Advancement of experiment implementation will essentially contribute to demonstrations of technical performance and viability of V2G integration on the smart grid of the future.

REFERENCES

- [1] C. Zhang, H. Kitamura, and M. Goto, "Behavioral insights into vehicle-to-grid (V2G) adoption: Beyond economic perspectives," *Renew. Sustain. Energy Rev.*, vol. 228, p. 116603, 2026.
- [2] M. A. Razzaque, S. K. Khadem, S. Patra, G. Okwata, and Md. Noor-A-Rahim, "Cybersecurity in vehicle-to-grid (V2G) systems: A systematic review," *Appl. Energy*, vol. 398, p. 126364, Nov. 2025, doi: 10.1016/j.apenergy.2025.126364.
- [3] O. Štogl, M. Miltner, C. Zanocco, M. Traverso, and O. Starý, "Electric vehicles as facilitators of grid stability and flexibility: A multidisciplinary overview," *WIREs Energy Environ.*, vol. 13, no. 5, p. e536, Sep. 2024, doi: 10.1002/wene.536.
- [4] M. Khaleel et al., "Battery technologies In electrical power Systems: Pioneering secure energy transitions," *J. Power Sources*, vol. 653, p. 237709, Oct. 2025, doi: 10.1016/j.jpowsour.2025.237709.
- [5] N. Daina, A. Sivakumar, and J. W. Polak, "Electric vehicle charging choices: Modelling and implications for smart charging services," *Transp. Res. Part C Emerg. Technol.*, vol. 81, pp. 36–56, Aug. 2017, doi: 10.1016/j.trc.2017.05.006.
- [6] C. Soderman, S. Y. Kim, J. Yip, and M. Shirgaokar, "Electric vehicles as grid resources: Barriers to vehicle-to-grid (V2G) in the United States," *Util. Policy*, vol. 101, p. 102175, Aug. 2026, doi: 10.1016/j.jup.2026.102175.

- [7] Q. Yang *et al.*, “An improved vehicle to the grid method with battery longevity management in a microgrid application,” *Energy*, vol. 198, p. 117374, May 2020, doi: 10.1016/j.energy.2020.117374.
- [8] Y. Achour, A. E. Mokriini, and A. Berrada, “Integration of gravity energy storage and deep learning for optimal vehicle-to-grid (V2G) systems in residential microgrids,” *Energy Storage Sav.*, p. S2772683526000294, Feb. 2026, doi: 10.1016/j.enss.2025.08.003.
- [9] A. Abodwair, M. T. Guneser, and M. Khaleel, “The Role of Energy Storage Technology in EVs: Classification, Evaluation, Optimization, Current Trends and Future Perspective”.
- [10] X. Yang, P. Su, and Y. Dong, “Reliability Assessment and Optimization of Multi-State Aggregated Grid Systems Based on V2G Technology,” *ICCK Trans. Syst. Saf. Reliab.*, vol. 2, no. 2, pp. 123–139, May 2026, doi: 10.62762/TSSR.2026.977328.
- [11] S. Mollik *et al.*, “Vehicle-to-grid energy technologies: A patent landscape analysis and technology updates,” *Energy Strategy Rev.*, vol. 66, p. 102316, Jul. 2026, doi: 10.1016/j.esr.2026.102316.
- [12] A. Alsharif, C. W. Tan, R. Ayop, A. Ali Ahmed, M. Mohamed Khaleel, and A. K. Abobaker, “Power Management and Sizing Optimization for Hybrid Grid-Dependent System Considering Photovoltaic Wind Battery Electric Vehicle,” in *2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*, Sabratha, Libya: IEEE, May 2022, pp. 645–649. doi: 10.1109/MI-STA54861.2022.9837749.
- [13] A. A. Ahmed *et al.*, “Integrating Renewable Energy Sources with Electric Vehicle Infrastructure for Enhanced Renewability,” in *Proceedings of the EAI 3rd International Conference on Intelligent Systems and Machine Learning, ICISML 2024, January 5-6, 2024, Pune, India*, Pune, India: EAI, 2024. doi: 10.4108/eai.5-1-2024.2342575.
- [14] A. Alsharif *et al.*, “Impact of Electric Vehicle on Residential Power Distribution Considering Energy Management Strategy and Stochastic Monte Carlo Algorithm,” *Energies*, vol. 16, no. 3, p. 1358, Jan. 2023, doi: 10.3390/en16031358.
- [15] A. Abodwair, M. Guneser, M. Khaleel, Y. Nassar, H. El-Khozondar, and A. Elbaz, “Feasibility Assessment of Hybrid Renewable Energy Based EV Charging Station in Libya,” *Sol. Energy Sustain. Dev. J.*, vol. 13, no. 2, pp. 311–349, Nov. 2024, doi: 10.51646/jsesd.v13i2.292.
- [16] A. A. Ahmed, A. Alsharif, T. Triwiyanto, M. Khaleel, C. W. Tan, and R. Ayop, “Using of Neural Network-Based Controller to Obtain the Effect of Hub Motors Weight on Electric Vehicle Ride Comfort,” in *2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*, Sabratha, Libya: IEEE, May 2022, pp. 189–192. doi: 10.1109/MI-STA54861.2022.9837608.
- [17] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, “Microgrids energy management systems: A critical review on methods, solutions, and prospects,” *Appl. Energy*, vol. 222, pp. 1033–1055, Jul. 2018, doi: 10.1016/j.apenergy.2018.04.103.
- [18] M. Boulakhbar *et al.*, “Towards a large-scale integration of renewable energies in Morocco,” *J. Energy Storage*, vol. 32, p. 101806, Dec. 2020, doi: 10.1016/j.est.2020.101806.
- [19] 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, p. 101193, Apr. 2020, doi: 10.1016/j.est.2020.101193.
- [20] O. Ouramdane, E. Elbouchikhi, Y. Amirat, and E. Sedgh Gooya, “Optimal Sizing and Energy Management of Microgrids with Vehicle-to-Grid Technology: A Critical Review and Future Trends,” *Energies*, vol. 14, no. 14, p. 4166, Jul. 2021, doi: 10.3390/en14144166.
- [21] S. Guliyeva, “Design and optimization of grid-connected hybrid renewable energy systems with EV integration for supermarkets,” *Energy Rep.*, vol. 15, p. 109098, Jun. 2026, doi: 10.1016/j.egy.2026.109098.
- [22] Md. M. H. Tuhin, Md. E. Azam, Md. F. Ali, Sk. A. Shezan, M. A. Razzak, and I. Kamwa, “Techno-economic and reliability analysis of a grid connected hybrid microgrid with hydrogen storage for sustainable rural electrification,” *Discov. Sustain.*, vol. 7, no. 1, p. 564, Mar. 2026, doi: 10.1007/s43621-026-02919-1.
- [23] M. Khaleel *et al.*, “Evolution of Emissions: The Role of Clean Energy in Sustainable Development,” *Chall. Sustain.*, vol. 12, no. 2, pp. 122–135, Jul. 2024, doi: 10.56578/cis120203.

- [24] R. Sedaghati and M. R. Shakarami, "A novel control strategy and power management of hybrid PV/FC/SC/battery renewable power system-based grid-connected microgrid," *Sustain. Cities Soc.*, vol. 44, pp. 830–843, Jan. 2019, doi: 10.1016/j.scs.2018.11.014.
- [25] S. T. Saranya and P. Bhowmik, "A comprehensive review of microgrid architectures, power management and resilient operation," *Energy Rep.*, vol. 15, p. 109021, Jun. 2026, doi: 10.1016/j.egyr.2025.109021.
- [26] S. V. Veni, J. Jayachandran, S. Malathi, R. A. Prakash, J. Jayavignesh, and N. Prabakaran, "Dynamic power management based on Model Predictive Control and PSO for hybrid microgrid," *Sci. Rep.*, vol. 15, no. 1, p. 39225, Nov. 2025, doi: 10.1038/s41598-025-23204-7.
- [27] H. G. Murtza Qamar, X. Guo, E. Seif Ghith, M. Tlija, and A. Siddique, "Assessment of energy management and power quality improvement of hydrogen based microgrid system through novel PSO-MWWO technique," *Sci. Rep.*, vol. 15, no. 1, p. 863, Jan. 2025, doi: 10.1038/s41598-024-78153-4.
- [28] M. N. Suneetha and C. L. Narayana, "Hybrid optimized evolutionary control strategy for microgrid power system," *Electr. Eng.*, vol. 107, no. 2, pp. 1745–1762, Feb. 2025, doi: 10.1007/s00202-024-02591-6.
- [29] M. Khaleel, Z. Yusupov, A. Hesri, P. Odil, R. Jahongir, and I. Imbayah, "AI Applications for Power Quality Challenges in Distribution Systems: Technical Barriers and Emerging Trends," in *2026 IEEE 5th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*, Sebha, Libya: IEEE, Apr. 2026, pp. 846–851. doi: 10.1109/MI-STA68962.2026.11511188.
- [30] K. E. Ojo, A. K. Saha, and V. M. Srivastava, "Review of Advances in Renewable Energy-Based Microgrid Systems: Control Strategies, Emerging Trends, and Future Possibilities," *Energies*, vol. 18, no. 14, p. 3704, Jul. 2025, doi: 10.3390/en18143704.
- [31] M. Khaleel et al., "Effect of Fuel Cells on Voltage Sag Mitigation in Power Grids Using Advanced Equilibrium Optimizer and Particle Swarm Optimization," *Jordan J. Electr. Eng.*, vol. 9, no. 2, p. 175, 2023, doi: 10.5455/jjee.204-1669996684.
- [32] A. Zabihi and M. Parhamfar, "Decentralized energy solutions: The impact of smart grid-enabled EV charging stations," *Heliyon*, vol. 11, no. 13, p. e41815, Aug. 2025, doi: 10.1016/j.heliyon.2025.e41815.
- [33] T. D. De Lima, C. Reiz, J. Soares, F. Lezama, J. F. Franco, and Z. Vale, "Distributed Energy Resources and EV Charging Stations Expansion Planning for Grid-Connected Microgrids," in *Energy Informatics*, vol. 14468, B. N. Jørgensen, L. C. P. Da Silva, and Z. Ma, Eds., in *Lecture Notes in Computer Science*, vol. 14468, Cham: Springer Nature Switzerland, 2024, pp. 33–48. doi: 10.1007/978-3-031-48652-4_3.
- [34] D. Qiu, Y. Wang, W. Hua, and G. Strbac, "Reinforcement learning for electric vehicle applications in power systems: A critical review," *Renew. Sustain. Energy Rev.*, vol. 173, p. 113052, Mar. 2023, doi: 10.1016/j.rser.2022.113052.
- [35] M. M. Khaleel, M. R. Adzman, and S. M. Zali, "An Integrated of Hydrogen Fuel Cell to Distribution Network System: Challenging and Opportunity for D-STATCOM," *Energies*, vol. 14, no. 21, p. 7073, Oct. 2021, doi: 10.3390/en14217073.
- [36] S. Behera and N. B. Dev Choudhury, "Adaptive optimal energy management in multi-distributed energy resources by using improved slime mould algorithm with considering demand side management," *E-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 3, p. 100108, Mar. 2023, doi: 10.1016/j.prime.2023.100108.
- [37] G. Ahmad, A. Hassan, A. Islam, M. Shafiullah, M. A. Abido, and M. Al-Dhaifallah, "Distributed Control Strategies for Microgrids: A Critical Review of Technologies and Challenges," *IEEE Access*, vol. 13, pp. 60702–60719, 2025, doi: 10.1109/ACCESS.2025.3552940.
- [38] N. Ramalingam, G. Ramya, M. Suganya, and K. R. N. Kalis, "Enhancement of DC voltage regulations in micro grid by using super capacitor and series compensator," *J. Electr. Syst. Inf. Technol.*, vol. 13, no. 1, p. 50, May 2026, doi: 10.1186/s43067-026-00349-7.

- [39] M. Khaleel and Z. Yusupov, "Advancing sustainable energy transitions: Insights on finance, policy, infrastructure, and demand-side integration," *Unconv. Resour.*, vol. 9, p. 100274, Jan. 2026, doi: 10.1016/j.uncres.2025.100274.
- [40] 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, p. 5202, Aug. 2021, doi: 10.3390/en14165202.
- [41] M. Elmadawy et al., "Comprehensive Study of DC Microgrids Protection: Challenges, Cutting-Edge Techniques, Machine-Learning-Driven Solutions," *IET Renew. Power Gener.*, vol. 20, no. 1, p. e70258, Jan. 2026, doi: 10.1049/rpg2.70258.
- [42] N. Khosravi, D. Çelik, H. Bevrani, and S. Echalih, "Microgrid stability: A comprehensive review of challenges, trends, and emerging solutions," *Int. J. Electr. Power Energy Syst.*, vol. 170, p. 110829, Sep. 2025, doi: 10.1016/j.ijepes.2025.110829.
- [43] K. Ebenezer Ojo, A. K. Saha, and V. M. Srivastava, "A Critical Review of Advanced Protection Devices in AC Microgrid," *IEEE Access*, vol. 13, pp. 203931–203971, 2025, doi: 10.1109/ACCESS.2025.3638604.
- [44] A. W. Adegboyega, S. Sepasi, H. O. R. Howlader, B. Griswold, M. Matsuura, and L. R. Roose, "DC Microgrid Deployments and Challenges: A Comprehensive Review of Academic and Corporate Implementations," *Energies*, vol. 18, no. 5, p. 1064, Feb. 2025, doi: 10.3390/en18051064.
- [45] A. A. Kebede, T. Kalogiannis, J. Van Mierlo, and M. Berecibar, "A comprehensive review of stationary energy storage devices for large scale renewable energy sources grid integration," *Renew. Sustain. Energy Rev.*, vol. 159, p. 112213, May 2022, doi: 10.1016/j.rser.2022.112213.
- [46] A. F. Güven, M. H. Hassan, and S. Kamel, "Optimization of a hybrid microgrid for a small hotel using renewable energy and EV charging with a quadratic interpolation beluga whale algorithm," *Neural Comput. Appl.*, vol. 37, no. 5, pp. 3973–4008, Feb. 2025, doi: 10.1007/s00521-024-10865-0.
- [47] Y. E. García Vera, R. Dufo-López, and J. L. Bernal-Agustín, "Energy Management in Microgrids with Renewable Energy Sources: A Literature Review," *Appl. Sci.*, vol. 9, no. 18, p. 3854, Sep. 2019, doi: 10.3390/app9183854.
- [48] M. İnci, M. Büyük, M. H. Demir, and G. İlbey, "A review and research on fuel cell electric vehicles: Topologies, power electronic converters, energy management methods, technical challenges, marketing and future aspects," *Renew. Sustain. Energy Rev.*, vol. 137, p. 110648, Mar. 2021, doi: 10.1016/j.rser.2020.110648.
- [49] J. Bauer, P. Letmathe, and R. Woeste, "Total cost of ownership for battery electric vehicles: The role of energy prices," *Appl. Energy*, vol. 389, p. 125764, Jul. 2025, doi: 10.1016/j.apenergy.2025.125764.
- [50] M. W. Byun, O. H. Kwon, and W. Do, "Bayesian Estimation of Electric Vehicle Conversion Rates by Average Daily Vehicle Kilometers Traveled in South Korea," *Appl. Sci.*, vol. 16, no. 10, p. 4837, May 2026, doi: 10.3390/app16104837.
- [51] O. J. Oluwalana and K. Grzesik, "Solar-Powered Electric Vehicles: Comprehensive Review of Technology Advancements, Challenges, and Future Prospects," *Energies*, vol. 18, no. 14, p. 3650, Jul. 2025, doi: 10.3390/en18143650.
- [52] F. Castellacci and A. Santoalha, "Does digitalisation affect the adoption of electric vehicles? New regional-level evidence from Google Trends data," *Reg. Stud.*, vol. 59, no. 1, p. 2358829, Dec. 2025, doi: 10.1080/00343404.2024.2358829.
- [53] M. Khaleel, Y. Nassar, H. El-Khozondar, M. Elmnif, Z. Rajab, and E. Yaghoubi, "Electric Vehicles in China, Europe, and the United States: Current Trend and Market Comparison".
- [54] A. Alsharif et al., "Applications of Solar Energy Technologies in North Africa: Current Practices and Future Prospects".
- [55] G. Zhou, Z. Zhu, and S. Luo, "Location optimization of electric vehicle charging stations: Based on cost model and genetic algorithm," *Energy*, vol. 247, p. 123437, May 2022, doi: 10.1016/j.energy.2022.123437.

- [56] M. Masud Rana *et al.*, “Comprehensive Review on the Charging Technologies of Electric Vehicles (EV) and Their Impact on Power Grid,” *IEEE Access*, vol. 13, pp. 35124–35156, 2025, doi: 10.1109/ACCESS.2025.3538663.
- [57] S. Wang, Y. Luo, P. Yu, and R. Yu, “Integrated Coordinated Control of Source–Grid–Load–Storage in Active Distribution Network with Electric Vehicle Integration,” *Processes*, vol. 13, no. 5, p. 1285, Apr. 2025, doi: 10.3390/pr13051285.
- [58] S. Meraj, S. Mekhilef, M. Binti Mubin, H. Ramiah, M. Seyedmahmoudian, and A. Stojcevski, “Bidirectional Wireless Charging System for Electric Vehicles: A Review of Power Converters and Control Techniques in V2G Application,” *IEEE Access*, vol. 13, pp. 75246–75264, 2025, doi: 10.1109/ACCESS.2025.3561396.
- [59] S. Meraj, S. Mekhilef, M. Binti Mubin, H. Ramiah, M. Seyedmahmoudian, and A. Stojcevski, “Bidirectional Wireless Charging System for Electric Vehicles: A Review of Power Converters and Control Techniques in V2G Application,” *IEEE Access*, vol. 13, pp. 75246–75264, 2025, doi: 10.1109/ACCESS.2025.3561396.
- [60] A. K. Abbas, R. Ayop, C. W. Tan, Y. Al Mashhadany, and A. S. Takialddin, “Advanced energy-management and sizing techniques for renewable microgrids with electric-vehicle integration: A review,” *Results Eng.*, vol. 27, p. 106252, Sep. 2025, doi: 10.1016/j.rineng.2025.106252.
- [61] Y. Farajpour, A. Lotfy, H. Chaoui, and S. Kelouwani, “Cutting-Edge EMS Technologies for EVs and HEVs: Recent Developments and Future Directions,” *IEEE Access*, vol. 13, pp. 130256–130303, 2025, doi: 10.1109/ACCESS.2025.3582527.
- [62] H. Wang *et al.*, “Optimization of energy management strategies for multi-mode hybrid electric vehicles driven by travelling road condition data,” *Sci. Rep.*, vol. 15, no. 1, p. 12684, Apr. 2025, doi: 10.1038/s41598-025-97521-2.
- [63] X. Liu, G. Shi, C. Yang, E. Xu, and Y. Meng, “Co-Optimization of Speed Planning and Energy Management for Plug-In Hybrid Electric Trucks Passing Through Traffic Light Intersections,” *Energies*, vol. 17, no. 23, p. 6022, Nov. 2024, doi: 10.3390/en17236022.
- [64] F. Wang, Y. Hong, and X. Zhao, “Research and Comparative Analysis of Energy Management Strategies for Hybrid Electric Vehicles: A Review,” *Energies*, vol. 18, no. 11, p. 2873, May 2025, doi: 10.3390/en18112873.
- [65] Z. Teimoori and A. Yassine, “A Review on Intelligent Energy Management Systems for Future Electric Vehicle Transportation,” *Sustainability*, vol. 14, no. 21, p. 14100, Oct. 2022, doi: 10.3390/su142114100.
- [66] A. Kermansaravi, S. S. Refaat, M. Trabelsi, and H. Vahedi, “AI-based energy management strategies for electric vehicles: Challenges and future directions,” *Energy Rep.*, vol. 13, pp. 5535–5550, Jun. 2025, doi: 10.1016/j.egy.2025.04.053.
- [67] N. Sulaiman, M. A. Hannan, A. Mohamed, E. H. Majlan, and W. R. Wan Daud, “A review on energy management system for fuel cell hybrid electric vehicle: Issues and challenges,” *Renew. Sustain. Energy Rev.*, vol. 52, pp. 802–814, Dec. 2015, doi: 10.1016/j.rser.2015.07.132.
- [68] B. Huang, W. Yu, M. Ma, X. Wei, and G. Wang, “Artificial-Intelligence-Based Energy Management Strategies for Hybrid Electric Vehicles: A Comprehensive Review,” *Energies*, vol. 18, no. 14, p. 3600, Jul. 2025, doi: 10.3390/en18143600.
- [69] A. Khalatbarisoltani, H. Zhou, X. Tang, M. Kandidayeni, L. Boulon, and X. Hu, “Energy Management Strategies for Fuel Cell Vehicles: A Comprehensive Review of the Latest Progress in Modeling, Strategies, and Future Prospects,” *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 1, pp. 14–32, Jan. 2024, doi: 10.1109/TITS.2023.3309052.
- [70] Md. S. Munsif and H. Chaoui, “Energy Management Systems for Electric Vehicles: A Comprehensive Review of Technologies and Trends,” *IEEE Access*, vol. 12, pp. 60385–60403, 2024, doi: 10.1109/ACCESS.2024.3371483.
- [71] N. Kumaresan and A. Rammohan, “A comprehensive review on energy management strategies of hybrid energy storage systems for electric vehicles,” *J. Braz. Soc. Mech. Sci. Eng.*, vol. 46, no. 3, p. 146, Mar. 2024, doi: 10.1007/s40430-024-04736-x.

- [72] Y. Wang, Z. Sun, and Z. Chen, "Development of energy management system based on a rule-based power distribution strategy for hybrid power sources," *Energy*, vol. 175, pp. 1055–1066, May 2019, doi: 10.1016/j.energy.2019.03.155.
- [73] C. K. Wai, T. Sadeq, and L. C. Hau, "Advanced Adaptive Rule-Based Energy Management for Hybrid Energy Storage Systems (HESSs) to Enhance the Driving Range of Electric Vehicles," *Vehicles*, vol. 7, no. 1, p. 6, Jan. 2025, doi: 10.3390/vehicles7010006.
- [74] S. F. Tie and C. W. Tan, "A review of energy sources and energy management system in electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 20, pp. 82–102, Apr. 2013, doi: 10.1016/j.rser.2012.11.077.
- [75] N. Andrenacci and M. P. Valentini, "A Literature Review on the Charging Behaviour of Private Electric Vehicles," *Appl. Sci.*, vol. 13, no. 23, p. 12877, Nov. 2023, doi: 10.3390/app132312877.
- [76] D. Bhattacharjee, S. Mandol, and T. Ghosh, "Meta-model-based optimization of rule-based energy management in second-hand plug-in hybrid electric vehicles," *Data Sci. Manag.*, vol. 8, no. 3, pp. 388–402, Sep. 2025, doi: 10.1016/j.dsm.2024.12.003.
- [77] S. Alshahr, A. Alshahir, H. Alnuman, M. D. Alanazi, A. Yousef, and G. Abbas, "Dynamic renewable energy integration for EV charging via model-based reinforcement learning," *Ain Shams Eng. J.*, vol. 17, no. 3, p. 104040, Mar. 2026, doi: 10.1016/j.asej.2026.104040.
- [78] S. Zou et al., "Rule-Based Control Strategy for a Novel Dual-Motor PHEV Improved by Dynamic Programming," *Electronics*, vol. 14, no. 7, p. 1450, Apr. 2025, doi: 10.3390/electronics14071450.
- [79] E. L. Karfopoulos and N. D. Hatziaargyriou, "Distributed Coordination of Electric Vehicles Providing V2G Services," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 329–338, Jan. 2016, doi: 10.1109/TPWRS.2015.2395723.
- [80] J. Huang, C. Mao, B. Liu, D. Wang, R. Gao, and B. Gu, "An Improved Rule-Based Energy Management System: Effective Solution to Achieve Collaborative Control of Batteries in Multi-Prosumers Community Microgrid," *IEEE Access*, vol. 13, pp. 135634–135651, 2025, doi: 10.1109/ACCESS.2025.3588035.
- [81] M. R. Elkadeem, K. M. Kotb, A. S. Alzahrani, and M. A. Abido, "Smart and Resilient Microgrid for EV Mobility and Commercial Applications with Demand Response," *Transp. Res. Procedia*, vol. 84, pp. 362–369, 2025, doi: 10.1016/j.trpro.2025.03.084.
- [82] J. L. D. Paixão, A. D. R. Abaide, G. H. Danielsson, J. P. Sausen, L. N. F. Da Silva, and N. K. Neto, "Optimized Strategy for Energy Management in an EV Fast Charging Microgrid Considering Storage Degradation," *Energies*, vol. 18, no. 5, p. 1060, Feb. 2025, doi: 10.3390/en18051060.
- [83] W. Hu, Q. Shang, X. Bian, and R. Zhu, "Energy management strategy of hybrid energy storage system based on fuzzy control for ships," *Int. J. Low-Carbon Technol.*, vol. 17, pp. 169–175, Feb. 2022, doi: 10.1093/ijlct/ctab094.
- [84] A. Hussain and H.-M. Kim, "A Rule-Based Modular Energy Management System for AC/DC Hybrid Microgrids," *Sustainability*, vol. 17, no. 3, p. 867, Jan. 2025, doi: 10.3390/su17030867.
- [85] S. Sen and M. Kumar, "Distributed-MPC Type Optimal EMS for Renewables and EVs Based Grid-Connected Building Integrated Microgrid," *IEEE Trans. Ind. Appl.*, vol. 60, no. 2, pp. 2390–2408, Mar. 2024, doi: 10.1109/TIA.2023.3332055.
- [86] A. M. Jasim, B. H. Jasim, B.-C. Neagu, and S. Attila, "Electric Vehicle Battery-Connected Parallel Distribution Generators for Intelligent Demand Management in Smart Microgrids," *Energies*, vol. 16, no. 6, p. 2570, Mar. 2023, doi: 10.3390/en16062570.
- [87] Faculty of Electrical Engineering Technology, University Malaysia Perlis, 02600, Arau, Malaysia, M. M. Khaleel, M. R. Adzman, S. M. Zali, M. M. Graisa, and A. A. Ahmed, "A Review of Fuel Cell to Distribution Network Interface Using D-FACTS: Technical Challenges and Interconnection Trends," *Int. J. Electr. Electron. Eng. Telecommun.*, pp. 319–332, 2021, doi: 10.18178/ijeetc.10.5.319-332.
- [88] H. Huang et al., "SREM: Smart renewable energy management scheme with distributed learning and EV network," *Eng. Rep.*, vol. 6, no. 5, p. e12763, May 2024, doi: 10.1002/eng2.12763.
- [89] M. Khaleel et al., "An Optimization Approaches and Control Strategies of Hydrogen Fuel Cell Systems in EDG-Integration Based on DVR Technology," *J. Eur. Systèmes Autom.*, vol. 57, no. 2, pp. 551–565, Apr. 2024, doi: 10.18280/jesa.570224.

- [90] R. Pitakaso *et al.*, “Fuzzy Logic-Enhanced Sustainable and Resilient EV Public Transit Systems for Rural Tourism,” *IEEE Open J. Intell. Transp. Syst.*, vol. 6, pp. 407–432, 2025, doi: 10.1109/OJITS.2025.3554204.
- [91] A. Triviño, A. López, A. J. Yuste, and J. C. Cuevas, “Decentralized EV charging and discharging scheduling algorithm based on Type-II fuzzy-logic controllers,” *J. Energy Storage*, vol. 93, p. 112054, Jul. 2024, doi: 10.1016/j.est.2024.112054.
- [92] J. C. Vinitha, G. Ramadas, and P. U. Rani, “PSO Based Fuzzy Logic Controller for Load Frequency Control in EV Charging Station,” *J. Electr. Eng. Technol.*, vol. 19, no. 1, pp. 193–208, Jan. 2024, doi: 10.1007/s42835-023-01568-y.
- [93] P. J. Raj, V. V. Prabhu, V. Krishnakumar, and M. C. J. Anand, “Solar Powered Charging of Fuzzy Logic Controller (FLC) Strategy with Battery Management System (BMS) Method Used for Electric Vehicle (EV),” *Int. J. Fuzzy Syst.*, vol. 25, no. 7, pp. 2876–2888, Oct. 2023, doi: 10.1007/s40815-023-01537-7.
- [94] H. Mohan *et al.*, “Fuzzy logic-based reactive power control for power factor enhancement in EV drives,” *Sci. Rep.*, vol. 16, no. 1, p. 4043, Jan. 2026, doi: 10.1038/s41598-025-34125-w.
- [95] S. Priya, R. Radha, P. Anandha Prakash, and R. Nandhini, “Optimizing the Selection of Intermediate Charging Stations in EV Routing Through Neuro-Fuzzy Logic,” *IEEE Access*, vol. 12, pp. 140021–140038, 2024, doi: 10.1109/ACCESS.2024.3468471.
- [96] C. Liu, Y. Chen, R. Xu, H. Ruan, C. Wang, and X. Li, “Co-optimization of energy management and eco-driving considering fuel cell degradation via improved hierarchical model predictive control,” *Green Energy Intell. Transp.*, vol. 3, no. 6, p. 100176, Dec. 2024, doi: 10.1016/j.geits.2024.100176.
- [97] D. Zhu, E. Pritchard, S. R. Dadam, V. Kumar, and Y. Xu, “Optimization of rule-based energy management strategies for hybrid vehicles using dynamic programming,” *Combust. Engines*, vol. 184, no. 1, pp. 3–10, Mar. 2021, doi: 10.19206/CE-131967.
- [98] A. Latif, S. M. S. Hussain, A. Al-Durra, and A. Iqbal, “Hierarchical Fuzzy Framework for EV Supported Islanded Microgrid Frequency Stabilization,” *IEEE Open J. Ind. Electron. Soc.*, vol. 5, pp. 704–721, 2024, doi: 10.1109/OJIES.2024.3421669.
- [99] G. H. Danielsson, L. N. F. Da Silva, J. L. Da Paixão, A. D. R. Abaide, and N. K. Neto, “Rules-Based Energy Management System for an EV Charging Station Nanogrid: A Stochastic Analysis,” *Energies*, vol. 18, no. 1, p. 26, Dec. 2024, doi: 10.3390/en18010026.
- [100] P. Chaudhuri, R. Manikandan, and R. Sakthivel, “Particle Swarm Optimization based Linear Quadratic Gaussian Semi Active Control Algorithm for Space Framed Structure using Magneto-Rheological Damper,” *J. Vib. Eng. Technol.*, vol. 13, no. 5, p. 262, Jun. 2025, doi: 10.1007/s42417-025-01813-w.
- [101] J. Wu, L. Dai, S. Dou, and Y. Xia, “Accelerated Successive Convex Approximation for Nonlinear Optimization-Based Control,” *IEEE Trans. Autom. Control*, vol. 70, no. 9, pp. 6237–6244, Sep. 2025, doi: 10.1109/TAC.2025.3555375.
- [102] V. N. Rajput and K. S. Pandya, “A Novel Approach for Optimum Coordination of Directional Overcurrent Relays Including Far-End Faults in Interconnected Power Systems,” *Int. J. Eng. Technol.*, vol. 8, no. 6, pp. 2481–2493, Dec. 2016, doi: 10.21817/ijet/2016/v8i6/160806411.
- [103] T. Pradeesshma, R. Raju, V. S. K. Venkatachalapathy, and P. Raja, “An effective of bio-inspired multiverse optimization based controller placement in software defined networks environment,” *Int. J. Inf. Technol.*, vol. 17, no. 4, pp. 2035–2048, May 2025, doi: 10.1007/s41870-025-02434-y.
- [104] M. A. Ebrahim, A. S. Ragab, B. A. Aziz, and H. A. AbdelHadi, “Electric Eel foraging optimization based control design of islanded microgrid,” *Sci. Rep.*, vol. 15, no. 1, p. 8144, Mar. 2025, doi: 10.1038/s41598-025-91006-y.
- [105] İ. Avcı and M. Koca, “Intelligent Transportation System Technologies, Challenges and Security,” *Appl. Sci.*, vol. 14, no. 11, p. 4646, May 2024, doi: 10.3390/app14114646.
- [106] D. El Hafiane, A. El Magri, A. Mansouri, and R. Lajouad, “Cost-based energy management of low-voltage hybrid microgrids with vehicle-to-grid (V2G) integration with real-time monitoring,” *Energy*, vol. 13, p. 100900, Oct. 2026, doi: 10.1016/j.nxener.2026.100900.

- [107] M. Sicilia, D. Cervone, P. Polverino, and C. Pianese, "Adaptive Equivalent Consumption Minimization Strategies for Plug-In Hybrid Electric Vehicles: A Review," *Energies*, vol. 18, no. 20, p. 5475, Oct. 2025, doi: 10.3390/en18205475.
- [108] J. Yin, J. He, Y. Zhang, Z. Chen, and X. He, "Energy Storage Control and Capacity Optimization for Regenerative Braking Power Fluctuation Mitigation Under Port Renewable Energy Integration," *IET Renew. Power Gener.*, vol. 19, no. 1, p. e70173, Jan. 2025, doi: 10.1049/rpg2.70173.
- [109] L. Leng, Y. Liu, J. Cheng, Z. Cheng, L. Shi, and K. Deng, "A review of model-based offline and online optimization control systems for combustion engines," *Int. J. Engine Res.*, vol. 27, no. 9, pp. 1496–1515, Sep. 2026, doi: 10.1177/14680874261416376.
- [110] M. Kim et al., "Offline Model-Based Optimization: Comprehensive Review," Jan. 06, 2026, *arXiv*: arXiv:2503.17286. doi: 10.48550/arXiv.2503.17286.
- [111] H. Lee, H. Kim, H. Kim, and H. Kim, "Optimal Vehicle-to-Grid Charge Scheduling for Electric Vehicles Based on Dynamic Programming," *Energies*, vol. 18, no. 5, p. 1109, Feb. 2025, doi: 10.3390/en18051109.
- [112] C. Gómez-Quiles, P. Paramo-Balsa, J. Riquelme-Santos, and A. Gómez-Expósito, "Minimum-time MILP-based EV charging scheduling for prosumers," *Int. J. Electr. Power Energy Syst.*, vol. 172, p. 111293, Nov. 2025, doi: 10.1016/j.ijepes.2025.111293.
- [113] F. Masood, Z. F. Siddiqui, A. R. Faridi, A. W. Siddiqui, and A. H. Shamsan, "Human-centric EV charging optimization using stress-aware particle swarm optimization," *Discov. Comput.*, vol. 29, no. 1, p. 164, Mar. 2026, doi: 10.1007/s10791-026-10053-9.
- [114] W. T. Bosch, H. Hoogeveen, M. V. K. Niekerk, and P. D. Bruin, "Scheduling electric vehicles by simulated annealing with recombination through ILP," *Public Transp.*, vol. 18, no. 1, pp. 211–228, Mar. 2026, doi: 10.1007/s12469-026-00424-2.
- [115] H. Lotfi, "Stochastic bi-level modelling and optimization of dynamic distribution networks with DG and EV integration," *Energy Inform.*, vol. 8, no. 1, p. 98, Jul. 2025, doi: 10.1186/s42162-025-00557-x.
- [116] M. J. Khan, R. M. Singh, R. K. Kaushal, H. Malik, A. Afthanorhan, and V. K. Jadoun, "Optimized fuzzy-MPPT approach for superior solar power management in EV battery charging systems," *Energy Rep.*, vol. 15, p. 109034, Jun. 2026, doi: 10.1016/j.egyr.2026.109034.
- [117] M. Schwenzer, M. Ay, T. Bergs, and D. Abel, "Review on model predictive control: an engineering perspective," *Int. J. Adv. Manuf. Technol.*, vol. 117, no. 5–6, pp. 1327–1349, Nov. 2021, doi: 10.1007/s00170-021-07682-3.
- [118] M. Faizal, S. Y. Feng, M. F. Zureel, B. E. Sinidol, D. Wong, and G. K. Jian, "A REVIEW ON CHALLENGES AND OPPORTUNITIES OF ELECTRIC VEHICLES (EVS)," *J. Mech. Eng. Res. Dev.*, vol. 42, no. 4, pp. 130–137, Jun. 2019, doi: 10.26480/jmerd.04.2019.130.137.
- [119] S. Kewat, B. Singh, and I. Hussain, "Power management in PV-battery-hydro based standalone microgrid," *IET Renew. Power Gener.*, vol. 12, no. 4, pp. 391–398, Mar. 2018, doi: 10.1049/iet-rpg.2017.0566.
- [120] C. K. Wai, T. Sadeq, and L. C. Hau, "Advanced Adaptive Rule-Based Energy Management for Hybrid Energy Storage Systems (HESSs) to Enhance the Driving Range of Electric Vehicles," *Vehicles*, vol. 7, no. 1, p. 6, Jan. 2025, doi: 10.3390/vehicles7010006.
- [121] D. Sadeghi, A. Hesami Naghshbandy, and S. Bahramara, "Optimal sizing of hybrid renewable energy systems in presence of electric vehicles using multi-objective particle swarm optimization," *Energy*, vol. 209, p. 118471, Oct. 2020, doi: 10.1016/j.energy.2020.118471.
- [122] Y. F. Nassar et al., "Sensitivity of global solar irradiance to transposition models: Assessing risks associated with model discrepancies," *E-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 11, p. 100887, Mar. 2025, doi: 10.1016/j.prime.2024.100887.
- [123] T. Khatib and D. H. Muhsen, "Optimal Sizing of Standalone Photovoltaic System Using Improved Performance Model and Optimization Algorithm," *Sustainability*, vol. 12, no. 6, p. 2233, Mar. 2020, doi: 10.3390/su12062233.

- [124] M. Jha, F. Blaabjerg, M. A. Khan, V. S. Bharath Kurukuru, and A. Haque, "Intelligent Control of Converter for Electric Vehicles Charging Station," *Energies*, vol. 12, no. 12, p. 2334, Jun. 2019, doi: 10.3390/en12122334.
- [125] A. R. Singh et al., "A scalable cloud-integrated AI platform for real-time optimization of EV charging and resilient microgrid energy management," *Sci. Rep.*, vol. 15, no. 1, p. 37692, Oct. 2025, doi: 10.1038/s41598-025-21531-3.
- [126] Shreasth, C. A. Ooi, N. Khan, M. K. B. M. Desa, M. K. Ishak, and K. Ammar, "A novel active lithium-ion cell balancing method based on charging and discharging state of power in electric vehicles," *Sci. Rep.*, vol. 15, no. 1, p. 15764, May 2025, doi: 10.1038/s41598-025-96581-8.
- [127] M. Albakri and A. Darwish, "A Review of Modelling, State of Charge Estimation and Management Methods of EV Lithium-Ion Batteries," *Batteries*, vol. 12, no. 3, p. 92, Mar. 2026, doi: 10.3390/batteries12030092.
- [128] S. Poorani, P. Kathirvel, T. M. Murugan, and P. J. Shermila, "A Novel Differential Flatness Control Approach of an Electric Vehicle Using Energy Management Methodology," *Iran. J. Sci. Technol. Trans. Electr. Eng.*, vol. 49, no. 4, pp. 1977–1991, Dec. 2025, doi: 10.1007/s40998-025-00819-0.
- [129] A. Jain and M. Karimi-Ghartemani, "Mitigating Adverse Impacts of Increased Electric Vehicle Charging on Distribution Transformers," *Energies*, vol. 15, no. 23, p. 9023, Nov. 2022, doi: 10.3390/en15239023.
- [130] Y. Li, B. Dong, X. Wang, and Y. Qiu, "A novel differentiable predictive control (DPC) approach for safe and optimal EV charging and discharging scheduling," *Appl. Energy*, vol. 402, p. 127032, Jan. 2026, doi: 10.1016/j.apenergy.2025.127032.
- [131] D. Shi, K. Liu, Y. Wang, R. Liu, S. Li, and Y. Sun, "Adaptive energy control strategy of PHEV based on the Pontryagin's minimum principle algorithm," *Adv. Mech. Eng.*, vol. 13, no. 8, p. 16878140211035598, Aug. 2021, doi: 10.1177/16878140211035598.
- [132] L. Montalto, N. Murgovski, and J. Fredriksson, "Electrical Vehicles Charging: An Optimal Control Approach via Pontryagin's Maximum Principle," in *2025 IEEE 28th International Conference on Intelligent Transportation Systems (ITSC)*, Gold Coast, Australia: IEEE, Nov. 2025, pp. 3198–3203. doi: 10.1109/ITSC60802.2025.11423091.
- [133] M. Akil, E. Dokur, and R. Bayindir, "Analysis of Electric Vehicle Charging Demand Forecasting Model based on Monte Carlo Simulation and EMD-BO-LSTM," in *2022 10th International Conference on Smart Grid (icSmartGrid)*, Istanbul, Turkey: IEEE, Jun. 2022, pp. 356–362. doi: 10.1109/icSmartGrid55722.2022.9848555.
- [134] V. Dhanawat, V. Shinde, R. Alami, A. Akhunzada, Z. B. Faheem, and A. Biswas, "Electric Vehicles Charging Station Load Forecasting Integration With Renewable Energy Using Novel Deep EfficientBiLSTMNet," *IEEE Open J. Veh. Technol.*, vol. 6, pp. 2642–2661, 2025, doi: 10.1109/OJVT.2025.3608287.
- [135] T. Alharbi, A. Abdalrahman, M. H. Mostafa, and L. Alkhalifa, "Joint Optimization of EV Charging and Renewable Distributed Energy With Storage Systems Under Uncertainty," *IEEE Access*, vol. 13, pp. 76838–76856, 2025, doi: 10.1109/ACCESS.2025.3562531.
- [136] W. Diao, W. He, K. Liang, and X. Tan, "Adaptive impulsive consensus of nonlinear multi-agent systems via a distributed self-triggered strategy," *Int. J. Syst. Sci.*, vol. 55, no. 11, pp. 2224–2238, Aug. 2024, doi: 10.1080/00207721.2024.2346760.
- [137] A. Prajapati, P. Paraye, B. K. Ahirwar, and C. F. Tam, "Artificial intelligence integration in solar-powered EV charging systems: challenges, opportunities, and future perspectives," *J. Therm. Anal. Calorim.*, vol. 150, no. 16, pp. 12103–12134, Aug. 2025, doi: 10.1007/s10973-025-14558-1.
- [138] B. Heydaryan, M. A. Khatib, and N. Bajcinca, "Optimal control strategy for bidirectional EV charging hubs contributing to energy market," *J. Energy Storage*, vol. 119, p. 116282, May 2025, doi: 10.1016/j.est.2025.116282.
- [139] C.-H. Ou, C.-C. Cheng, C.-Y. Chen, K. Bhumkittipich, and S. Romphochai, "Solving optimal electric vehicle charging station placement problem using digital quantum annealing," *J. Commun. Netw.*, vol. 27, no. 4, pp. 252–263, Aug. 2025, doi: 10.23919/JCN.2025.000048.

- [140] H. Song *et al.*, “Smart optimization in battery energy storage systems: An overview,” *Energy AI*, vol. 17, p. 100378, Sep. 2024, doi: 10.1016/j.egyai.2024.100378.
- [141] W. Khan *et al.*, “Deep reinforcement learning-based energy management for design and control of off-grid renewable microgrids with dual-battery storage,” *Energy Explor. Exploit.*, vol. 44, no. 2, pp. 821–869, Mar. 2026, doi: 10.1177/01445987251387368.
- [142] A. U. Rehman, J. Lu, B. Du, F. Bai, M. J. Sanjari, and M. A. Hossain, “Vehicle-to-grid technology for load balancing and energy management: A comprehensive review of technical, economic and environmental perspectives,” *Appl. Energy*, vol. 402, p. 126974, Jan. 2026, doi: 10.1016/j.apenergy.2025.126974.
- [143] M. Khaleel, Z. Yusupov, and S. Rekik, “Exploring trends and predictions in renewable energy generation,” *Energy 360*, vol. 4, p. 100030, Dec. 2025, doi: 10.1016/j.energ.2025.100030.
- [144] I. Amoussou *et al.*, “Optimal Modeling and Feasibility Analysis of Grid-Interfaced Solar PV/Wind/Pumped Hydro Energy Storage Based Hybrid System,” *Sustainability*, vol. 15, no. 2, p. 1222, Jan. 2023, doi: 10.3390/su15021222.
- [145] F. Agha Kassab, B. Celik, F. Locment, M. Sechilariu, S. Liaquat, and T. M. Hansen, “Microgrid sizing with EV flexibility: Cascaded MILP and embedded APSO-MILP approaches,” *Appl. Energy*, vol. 396, p. 126273, Oct. 2025, doi: 10.1016/j.apenergy.2025.126273.
- [146] A. F. M. Correia, P. Moura, and A. T. De Almeida, “Technical and Economic Assessment of Battery Storage and Vehicle-to-Grid Systems in Building Microgrids,” *Energies*, vol. 15, no. 23, p. 8905, Nov. 2022, doi: 10.3390/en15238905.
- [147] N. K. K., J. N. S., and V. K. Jadoun, “Optimization of distribution network operating parameters in grid tied microgrid with electric vehicle charging station placement and sizing in the presence of uncertainties,” *Int. J. Green Energy*, vol. 22, no. 8, pp. 1552–1569, Jun. 2025, doi: 10.1080/15435075.2023.2281334.
- [148] Z. Wang, P. J. Raj, B. R. Babu, and G. B. Ramaiah, “Innovative EV Charging Optimization: Fuzzy DSS Algorithm Unveils Benefits,” *Int. J. Fuzzy Syst.*, vol. 27, no. 6, pp. 1924–1934, Sep. 2025, doi: 10.1007/s40815-024-01881-2.
- [149] Y. Yin, X. Liu, F. Chu, and D. Wang, “An exact algorithm for the home health care routing and scheduling with electric vehicles and synergistic-transport mode,” *Ann. Oper. Res.*, vol. 359, no. 2, pp. 1661–1696, Apr. 2026, doi: 10.1007/s10479-023-05313-6.
- [150] L. Chen, Y. Zhu, and K. Y. Lee, “Two-step Genetic Algorithm for Dynamic Route Optimization of Electric Vehicles Based on Demand Analysis,” *Arab. J. Sci. Eng.*, vol. 50, no. 19, pp. 15973–15989, Oct. 2025, doi: 10.1007/s13369-025-10076-2.
- [151] S. L. Pappu and V. Janamala, “Enhanced Hunter–Prey optimization for dynamic DSTATCOM-based reactive power management in EV–PV–ESS integrated distribution networks,” *Unconv. Resour.*, vol. 15, p. 100438, Jan. 2027, doi: 10.1016/j.uncres.2026.100438.
- [152] H. A. Kazem, M. T. Chaichan, A. H. A. Al-Waeli, and A. Gholami, “A systematic review of solar photovoltaic energy systems design modelling, algorithms, and software,” *Energy Sources Part Recovery Util. Environ. Eff.*, vol. 44, no. 3, pp. 6709–6736, Sep. 2022, doi: 10.1080/15567036.2022.2100517.
- [153] S. Ahmad *et al.*, “A Review of Hybrid Renewable and Sustainable Power Supply System: Unit Sizing, Optimization, Control, and Management,” *Energies*, vol. 17, no. 23, p. 6027, Nov. 2024, doi: 10.3390/en17236027.
- [154] M. Bareev-Rudy, S. Schedler, and T. Clees, “Sizing optimization of hybrid hydrogen energy storage systems: A metamodel-based approach,” *Int. J. Hydrog. Energy*, vol. 179, p. 149134, Oct. 2025, doi: 10.1016/j.ijhydene.2025.04.299.
- [155] A. Al Makky, H. Kanjo, M. M. Farag, A.-K. Hamid, M. Hussein, and T. Salameh, “Techno-Economic Feasibility of Green Hydrogen Production Using Hybrid Solar-Wind Energy Systems in Oman,” 2025, *SSRN*. doi: 10.2139/ssrn.5167457.
- [156] Y. F. Nassar *et al.*, “Assessing the Viability of Solar and Wind Energy Technologies in Semi-Arid and Arid Regions: A Case Study of Libya’s Climatic Conditions,” *Appl. Sol. Energy*, vol. 60, no. 1, pp. 149–170, Feb. 2024, doi: 10.3103/S0003701X24600218.

- [157] M. Khaleel, Z. Yusupov, Y. Nassar, H. J. El-khozondar, A. Ahmed, and A. Alsharif, "Technical challenges and optimization of superconducting magnetic energy storage in electrical power systems," *E-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 5, p. 100223, Sep. 2023, doi: 10.1016/j.prime.2023.100223.
- [158] M. Khaleel et al., "Harnessing nuclear power for sustainable electricity generation and achieving zero emissions," *Energy Explor. Exploit.*, vol. 43, no. 3, pp. 1126–1148, May 2025, doi: 10.1177/01445987251314504.
- [159] K. Nand, Z. Zhang, and J. Hu, "A Comprehensive Survey on the Usage of Machine Learning to Detect False Data Injection Attacks in Smart Grids," *IEEE Open J. Comput. Soc.*, vol. 6, pp. 1121–1132, 2025, doi: 10.1109/OJCS.2025.3585248.
- [160] A. Varone, G. Porruvecchio, and A. Romanino, "Smart charge management of Electric Vehicle fleets from Renewable Energy through innovative deferring strategies," *Energy Convers. Manag.*, vol. 350, p. 120957, Feb. 2026, doi: 10.1016/j.enconman.2025.120957.
- [161] S. Martin, W. A. Paxton, and R. Rajagopal, "Residential vehicle-to-grid profits under dynamic pricing: The role of real-world charging behavior," *Adv. Appl. Energy*, vol. 21, p. 100259, Mar. 2026, doi: 10.1016/j.adapen.2025.100259.
- [162] C. Zhong, Q. Ma, M. Ren, and L. Xiong, "An optimization framework for battery health management in vehicle-to-grid systems integrating transformer-based degradation prediction and grid service requirements," *Sci. Rep.*, vol. 16, no. 1, p. 12258, Mar. 2026, doi: 10.1038/s41598-026-38862-4.
- [163] O. Aldosari, Z. M. Ali, S. H. E. Abdel Aleem, and M. H. Mostafa, "Optimizing microgrid performance: Strategic integration of electric vehicle charging with renewable energy and storage systems for total operation cost and emissions minimization," *PLOS ONE*, vol. 19, no. 10, p. e0307810, Oct. 2024, doi: 10.1371/journal.pone.0307810.
- [164] C. Yarramsetty, T. Moger, D. Jena, and V. Srinivasa Rao, "A Novel Transformer-Based Approach for Reliability Evaluation of Composite Systems With Renewables and Plug-in Hybrid Electric Vehicles," *IEEE Access*, vol. 13, pp. 74032–74046, 2025, doi: 10.1109/ACCESS.2025.3564407.
- [165] N. Mohamed, F. Aymen, A. Altamimi, Z. A. Khan, and S. Lassaad, "Power Management and Control of a Hybrid Electric Vehicle Based on Photovoltaic, Fuel Cells, and Battery Energy Sources," *Sustainability*, vol. 14, no. 5, p. 2551, Feb. 2022, doi: 10.3390/su14052551.
- [166] 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, Jan. 2018, doi: 10.1080/23080477.2017.1419054.
- [167] A. Ahmed et al., "Strategic Renewable Energy Source Integration for Charging Stations in Plugin Hybrid Electric Vehicle Networks," in *Proceedings of the EAI 3rd International Conference on Intelligent Systems and Machine Learning, ICISML 2024, January 5-6, 2024, Pune, India*, Pune, India: EAI, 2024, doi: 10.4108/eai.5-1-2024.2342576.
- [168] G. Srihari, R. S. R. Krishnam Naidu, P. Falkowski-Gilski, P. Bidare Divakarachari, and R. Kiran Varma Penmatsa, "Integration of electric vehicle into smart grid: a meta heuristic algorithm for energy management between V2G and G2V," *Front. Energy Res.*, vol. 12, p. 1357863, Apr. 2024, doi: 10.3389/fenrg.2024.1357863.
- [169] N. Gurav, P. H. M. S. Adhokshaja, P. Anoor, and S. K. Bilgundi, "Mitigation of electric vehicles impact on grid current harmonics using DERs," *Aust. J. Electr. Electron. Eng.*, vol. 21, no. 3, pp. 228–242, Jul. 2024, doi: 10.1080/1448837X.2024.2312490.
- [170] M. A. M. Ramli, H. R. E. H. Boucekara, and A. S. Alghamdi, "Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm," *Renew. Energy*, vol. 121, pp. 400–411, Jun. 2018, doi: 10.1016/j.renene.2018.01.058.
- [171] O. Ekren, C. Hakan Canbaz, and Ç. B. Güvel, "Sizing of a solar-wind hybrid electric vehicle charging station by using HOMER software," *J. Clean. Prod.*, vol. 279, p. 123615, Jan. 2021, doi: 10.1016/j.jclepro.2020.123615.

- [172] M. Jafari, Z. Malekjamshidi, J. Zhu, and M.-H. Khooban, "A Novel Predictive Fuzzy Logic-Based Energy Management System for Grid-Connected and Off-Grid Operation of Residential Smart Microgrids," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 8, no. 2, pp. 1391–1404, Jun. 2020, doi: 10.1109/JESTPE.2018.2882509.
- [173] Md. R. H. Mojumder, F. Ahmed Antara, Md. Hasanuzzaman, B. Alamri, and M. Alsharif, "Electric Vehicle-to-Grid (V2G) Technologies: Impact on the Power Grid and Battery," *Sustainability*, vol. 14, no. 21, p. 13856, Oct. 2022, doi: 10.3390/su142113856.
- [174] Y. Qin, Y. Rao, Z. Xu, J. Du, and M. Ouyang, "Title: Toward flexibility of user side in China: virtual power plant (VPP) and vehicle-to-grid (V2G) interaction".
- [175] L. Strezoski and I. Stefani, "Enabling mass integration of electric vehicles through distributed energy resource management systems," *Int. J. Electr. Power Energy Syst.*, vol. 157, p. 109798, Jun. 2024, doi: 10.1016/j.ijepes.2024.109798.
- [176] S. Micari and G. Napoli, "Electric Vehicles for a Flexible Energy System: Challenges and Opportunities," *Energies*, vol. 17, no. 22, p. 5614, Nov. 2024, doi: 10.3390/en17225614.
- [177] M. Hasan, S. Mohan, T. Shimizu, and H. Lu, "Securing Vehicle-to-Everything (V2X) Communication Platforms," *IEEE Trans. Intell. Veh.*, vol. 5, no. 4, pp. 693–713, Dec. 2020, doi: 10.1109/TIV.2020.2987430.
- [178] L. Zheng, H. Chen, and Y. Zou, "A Deep Reinforcement Learning-Based Urban Traffic Control Model for Vehicle-to-Everything Ecosystem," *J. Adv. Transp.*, vol. 2025, no. 1, p. 5579549, Jan. 2025, doi: 10.1155/atr/5579549.
- [179] G. S. Chawda et al., "Artificial Intelligence in Bidirectional Energy Management: A Critical Review of Control Strategies for V2G and G2V Systems," *IET Smart Grid*, vol. 9, no. 1, p. e70093, Jan. 2026, doi: 10.1049/stg2.70093.
- [180] G. A. Samawi, O. M. Bwaliez, M. Jreissat, and A. Kandas, "Advancing Sustainable Development in Jordan: A Business and Economic Analysis of Electric Vehicle Adoption in the Transportation Sector," *World Electr. Veh. J.*, vol. 16, no. 1, p. 45, Jan. 2025, doi: 10.3390/wevj16010045.
- [181] X. Tan, P. Zhu, and R. Singh, "China's Model of Technology Leapfrog: A Case Study of Electric Vehicle Policies and the Development of Green Technology," 2024, *SSRN*. doi: 10.2139/ssrn.4743969.
- [182] L. Zhang, X. Sun, M. Xu, Y. Yang, T. Zhang, and Z. Wen, "1 Large Language Model-Driven Analysis of Supply Risk Dynamics in 2 Global Electric Vehicle Supply Chain".
- [183] L. Zhang, Z. Wen, X. Sun, Y. Wang, and T. Zhang, "Revealing the impact of electric vehicles trade restrictions on greenhouse gas emissions and welfare," *Resour. Conserv. Recycl.*, vol. 227, p. 108744, Mar. 2026, doi: 10.1016/j.resconrec.2025.108744.
- [184] M. N. Hossain and H. M. Cho, "Techno-economic feasibility of photovoltaic-powered electric vehicle charging stations: a global review and future outlook," *Sustain. Energy Res.*, vol. 13, no. 1, p. 9, Feb. 2026, doi: 10.1186/s40807-025-00228-1.
- [185] M. Khaleel, A. A. Ahmed, A. Alsharif, and M. M. Beiek, "Technology Challenges and Trends of Electric Motor and Drive in Electric Vehicle".
- [186] A. Ghayth and M. Şimşir, "Recent Trends and Challenges of Electric Motor Technologies".
- [187] A. Ghayth, M. Şimşir, M. Khaleel, A. A. Ahmed, and A. Alsharif, "An Investigation of Inverse-Automatic Mechanical Transmission of EV Using Gear Downshift Approach".
- [188] M. Khaleel, Z. Yusupov, M. Guneser, H. El-Khozondar, A. Ahmed, and A. A. Alsharif, "Towards Hydrogen Sector Investments for Achieving Sustainable Electricity Generation," *Sol. Energy Sustain. Dev. J.*, vol. 13, no. 1, pp. 71–96, Mar. 2024, doi: 10.51646/jsesd.v13i1.173.
- [189] F. Alasali, A. S. Saidi, N. El-Naily, O. Alsmadi, M. Khaleel, and I. Ghirani, "Assessment of the impact of a 10-MW grid-tied solar system on the Libyan grid in terms of the power-protection system stability," *Clean Energy*, vol. 7, no. 2, pp. 389–407, Apr. 2023, doi: 10.1093/ce/zkac084.
- [190] N. Shigeta and S. E. Hosseini, "Sustainable Development of the Automobile Industry in the United States, Europe, and Japan with Special Focus on the Vehicles' Power Sources," *Energies*, vol. 14, no. 1, p. 78, Dec. 2020, doi: 10.3390/en14010078.

- [191] S. Pan, Y. Xu, Z. Li, L. M. Fulton, and H. O. Gao, "Future changes in CO2 emissions in the shift to electric mobility in countries with varied levels of zero-emission vehicle policies," *Resour. Environ. Sustain.*, vol. 24, p. 100316, Mar. 2026, doi: 10.1016/j.resenv.2026.100316.
- [192] M. A. Kashem, M. Shamsuddoha, and T. Nasir, "Sustainable Transportation Solutions for Intelligent Mobility: A Focus on Renewable Energy and Technological Advancements for Electric Vehicles (EVs) and Flying Cars," *Future Transp.*, vol. 4, no. 3, pp. 874–890, Aug. 2024, doi: 10.3390/futuretransp4030042.
- [193] A. Sakhare, S. Mikkili, and P. K. Bonthagorla, "Recent Advances in Hybrid, Plug-In, Battery, and Fuel Cell EVs: Control Schemes, Modes, Converter Topologies, and Pros and Cons," *IET Electr. Syst. Transp.*, vol. 2026, no. 1, p. 9670895, Jan. 2026, doi: 10.1049/els2/9670895.
- [194] K. Verma, M. Srivastava, P. Singh Tomar, N. Sandeep, and A. K. Verma, "Single-phase integrated converter with universal battery charging capability for plug-in electric vehicles," *IET Power Electron.*, vol. 13, no. 4, pp. 821–829, Mar. 2020, doi: 10.1049/iet-pel.2019.0847.
- [195] A. Hebala, M. I. Abdelkader, and R. A. Ibrahim, "Comparative Analysis of Energy Consumption and Performance Metrics in Fuel Cell, Battery, and Hybrid Electric Vehicles Under Varying Wind and Road Conditions," *Technologies*, vol. 13, no. 4, p. 150, Apr. 2025, doi: 10.3390/technologies13040150.
- [196] A. Alfouly, H. Valderrama-Blavi, and A. El Aroudi, "Electric Vehicle Charging Technologies: On-Board and Off-Board Charging with a State-of-the-Art Review," *Energies*, vol. 19, no. 13, p. 3169, Jul. 2026, doi: 10.3390/en19133169.
- [197] S. Paudel, J. Zhang, B. Ayalew, V. Y. Griddalur, and R. Singh, "Design, Prototyping, and Integration of Battery Modules for Electric Vehicles and Energy Storage Systems," *Electricity*, vol. 6, no. 4, p. 63, Nov. 2025, doi: 10.3390/electricity6040063.
- [198] V. N. Saraswathi and V. P. Ramachandran, "A comprehensive review on charger technologies, types, and charging stations models for electric vehicles," *Heliyon*, vol. 10, no. 20, p. e38945, Oct. 2024, doi: 10.1016/j.heliyon.2024.e38945.
- [199] University of Johannesburg, Johannesburg, South Africa, O. Akinsooto, E. Oluwadunmininu Ogunnowo, Johnson Controls, Indiana, USA, C. Chukwuka Ezeanochie, and Eaton, Montrottier, France, "The Future of Electric Vehicles: Technological Innovations and Market Trends," *Eng. Technol. J.*, vol. 10, no. 04, Apr. 2025, doi: 10.47191/etj/v10i04.04.
- [200] P. Bhosale, S. A. R. Kumar, and R. C. Bansal, "Electric Vehicle Charging Infrastructure, Standards, Types, and Its Impact on Grid: A Review," *Electr. Power Compon. Syst.*, vol. 53, no. 6, pp. 669–693, Apr. 2025, doi: 10.1080/15325008.2024.2315206.
- [201] G. Alkaws, Y. Baashar, D. Abbas U, A. A. Alkahtani, and S. K. Tiong, "Review of Renewable Energy-Based Charging Infrastructure for Electric Vehicles," *Appl. Sci.*, vol. 11, no. 9, p. 3847, Apr. 2021, doi: 10.3390/app11093847.
- [202] A. F. Cota et al., "The Future of Electric Mobility Between Technology, Business Acceptance, and Policy Making: Lessons Learned From the INCIT-EV Project," *IEEE Access*, vol. 14, pp. 70363–70385, 2026, doi: 10.1109/ACCESS.2026.3681435.
- [203] K. L. Pedersen, R. M. Knudsen, M. Marinelli, M. Secchi, and K. Sevdari, "Enabling Grid Services with Bidirectional EV Chargers: A Comparative Analysis of CCS2 and CHAdeMO Response Dynamics," *World Electr. Veh. J.*, vol. 16, no. 11, p. 636, Nov. 2025, doi: 10.3390/wevj16110636.
- [204] D. Setlhaolo and E. Bayoumi, "Bridging Solar Power and Electric Vehicle Mobility: Infrastructure Design, Global Deployments, and Policy Pathways," *Int. Trans. Electr. Energy Syst.*, vol. 2025, no. 1, p. 6696258, Jan. 2025, doi: 10.1155/etep/6696258.
- [205] C. Wang, Y. Wang, and F. Song, "Research on Electric Vehicle Charging Load Forecasting Method Based on Improved LSTM Neural Network," *World Electr. Veh. J.*, vol. 16, no. 5, p. 265, May 2025, doi: 10.3390/wevj16050265.
- [206] G. Martinez Medina, K. K. Castillo-Villar, and O. Abbaas, "Optimization Model for Electric Vehicle (EV) Fleet Charging Location Assignment," *IEEE Access*, vol. 13, pp. 34160–34176, 2025, doi: 10.1109/ACCESS.2025.3543748.

- [207] P. Michailidis, I. Michailidis, and E. Kosmatopoulos, "Reinforcement Learning for Electric Vehicle Charging Management: Theory and Applications," *Energies*, vol. 18, no. 19, p. 5225, Oct. 2025, doi: 10.3390/en18195225.
- [208] Q. Zhou, H. Xiao, and C. Zhou, "Integrated microgrid with PV, energy storage, charging and swapping: Multi-time-scale coordinated planning of electric heavy truck power station in remote areas," *Energy Convers. Manag.*, vol. 30, p. 101895, May 2026, doi: 10.1016/j.ecmx.2026.101895.
- [209] S. Biswas, S. R. Mekapati, N. B. D. Choudhury, and B. A. Taye, "Assessment of Microgrid Reliability and Economic Feasibility of Hybrid Microgrid Integrated with V2G System Considering Travel Habits," *Arab. J. Sci. Eng.*, vol. 51, no. 16, pp. 18985–19009, Aug. 2026, doi: 10.1007/s13369-026-11256-4.
- [210] A. I. Arvanitidis, P. Talbot, N. Gatsis, and M. Alamaniotis, "Comprehensive assessment of deep reinforcement learning approaches for economic dispatch in nuclear-driven microgrids," *Comput. Electr. Eng.*, vol. 126, p. 110528, Aug. 2025, doi: 10.1016/j.compeleceng.2025.110528.
- [211] C. Liang, "Distributed V2G Grid Frequency Regulation Considering EV Owner Participation via Cooperative Integral Reinforcement Learning," *Symmetry*, vol. 18, no. 5, p. 824, May 2026, doi: 10.3390/sym18050824.
- [212] P. Du et al., "Enhancing green mobility through vehicle-to-grid technology: potential, technological barriers, and policy implications," *Energy Environ. Sci.*, vol. 18, no. 10, pp. 4496–4520, 2025, doi: 10.1039/D5EE00116A.
- [213] Q. Kong, M. Fowler, E. Entchev, H. Ribberink, and R. McCallum, "The Role of Charging Infrastructure in Electric Vehicle Implementation within Smart Grids," *Energies*, vol. 11, no. 12, p. 3362, Dec. 2018, doi: 10.3390/en11123362.
- [214] C.-F. Chen and C.-M. Lai, "Understanding the acceptance of vehicle-to-grid (V2G) services: Evidence from Taiwan," *Transp. Policy*, vol. 159, pp. 230–240, Dec. 2024, doi: 10.1016/j.tranpol.2024.10.025.
- [215] C. Soderman, S. Y. Kim, J. Yip, and M. Shirgaokar, "Electric vehicles as grid resources: Barriers to vehicle-to-grid (V2G) in the United States," *Util. Policy*, vol. 101, p. 102175, Aug. 2026, doi: 10.1016/j.jup.2026.102175.
- [216] J. L. D. Paixão, A. D. R. Abaide, G. H. Danielsson, J. P. Sausen, L. N. F. Da Silva, and N. K. Neto, "Optimized Strategy for Energy Management in an EV Fast Charging Microgrid Considering Storage Degradation," *Energies*, vol. 18, no. 5, p. 1060, Feb. 2025, doi: 10.3390/en18051060.
- [217] M. W. Van Eijk, J. A. Annema, M. Van Der Koogh, and Z. Lukszo, "Institutional barriers to vehicle-to-grid implementation in Europe," *Renew. Sustain. Energy Rev.*, vol. 217, p. 115653, Jul. 2025, doi: 10.1016/j.rser.2025.115653.
- [218] M. Nour, J. P. Chaves-Ávila, G. Magdy, and Á. Sánchez-Miralles, "Review of Positive and Negative Impacts of Electric Vehicles Charging on Electric Power Systems," *Energies*, vol. 13, no. 18, p. 4675, Sep. 2020, doi: 10.3390/en13184675.
- [219] M. Abdelsattar, M. A. Ismeil, M. M. Aly, and S. Saber Abu-Elwfa, "Analysis of Renewable Energy Sources and Electrical Vehicles Integration Into Microgrid," *IEEE Access*, vol. 12, pp. 66822–66832, 2024, doi: 10.1109/ACCESS.2024.3399124.
- [220] M. Das, M. A. K. Singh, and A. Biswas, "Techno-economic optimization of an off-grid hybrid renewable energy system using metaheuristic optimization approaches – Case of a radio transmitter station in India," *Energy Convers. Manag.*, vol. 185, pp. 339–352, Apr. 2019, doi: 10.1016/j.enconman.2019.01.107.
- [221] D. Saheb-Koussa, M. Haddadi, and M. Belhamel, "Economic and technical study of a hybrid system (wind–photovoltaic–diesel) for rural electrification in Algeria," *Appl. Energy*, vol. 86, no. 7–8, pp. 1024–1030, Jul. 2009, doi: 10.1016/j.apenergy.2008.10.015.
- [222] S. M. Moghaddas-Tafreshi, S. Mohseni, M. E. Karami, and S. Kelly, "Optimal energy management of a grid-connected multiple energy carrier micro-grid," *Appl. Therm. Eng.*, vol. 152, pp. 796–806, Apr. 2019, doi: 10.1016/j.applthermaleng.2019.02.113.

- [223] A. L. Bukar, C. W. Tan, and K. Y. Lau, "Optimal sizing of an autonomous photovoltaic/wind/battery/diesel generator microgrid using grasshopper optimization algorithm," *Sol. Energy*, vol. 188, pp. 685–696, Aug. 2019, doi: 10.1016/j.solener.2019.06.050.
- [224] A. Mahesh and K. S. Sandhu, "Optimal Sizing of a Grid-Connected PV/Wind/Battery System Using Particle Swarm Optimization," *Iran. J. Sci. Technol. Trans. Electr. Eng.*, vol. 43, no. 1, pp. 107–121, Mar. 2019, doi: 10.1007/s40998-018-0083-3.
- [225] S. Z. Almutairi and A. R. Ginidi, "An improved material-inspired generation algorithm for load frequency control in EV-integrated power systems," *Sci. Rep.*, vol. 16, no. 1, p. 13020, Apr. 2026, doi: 10.1038/s41598-026-47360-6.
- [226] T. Trivedi, R. Jadeja, P. Bhatt, C. Long, P. Sanjeevikumar, and A. Ved, "Sliding mode-based direct power control of unified power quality conditioner," *Heliyon*, vol. 10, no. 20, p. e39597, Oct. 2024, doi: 10.1016/j.heliyon.2024.e39597.
- [227] R. Parvathy, "Battery Charging Systems," *J. Appl. Sci. Eng. Technol. Manag.*, vol. 1, no. 1, pp. 33–38, Jun. 2023, doi: 10.61779/jasetm.v1i1.7.
- [228] F. Kaya and O. Akar, "Assessing Power Quality Disturbances Caused by Urban EV Fast Charging Stations in Low Voltage Grids: A Case From Kavacik, Istanbul," *IEEE Access*, vol. 13, pp. 164593–164608, 2025, doi: 10.1109/ACCESS.2025.3610775.
- [229] S. Behera, N. Venkata Ramana Naik, A. K. Panda, and S. K. Behera, "Advanced off-board bidirectional electric vehicle charger with enhanced power quality and supporting grid resilience," *Electr. Eng.*, vol. 106, no. 3, pp. 3231–3242, Jun. 2024, doi: 10.1007/s00202-023-02129-2.
- [230] S. M. A. Elazim et al., "Enhancing stability and power quality in electric vehicle charging stations powered by hybrid energy sources through harmonic mitigation and load management," *Sci. Rep.*, vol. 15, no. 1, p. 28077, Aug. 2025, doi: 10.1038/s41598-025-14143-4.
- [231] A. Jain and S. Bhullar, "Operating modes of grid integrated PV-solar based electric vehicle charging system- a comprehensive review," *E-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 8, p. 100519, Jun. 2024, doi: 10.1016/j.prime.2024.100519.
- [232] A. Srivastava, M. Manas, and R. K. Dubey, "Electric vehicle integration's impacts on power quality in distribution network and associated mitigation measures: a review," *J. Eng. Appl. Sci.*, vol. 70, no. 1, p. 32, Dec. 2023, doi: 10.1186/s44147-023-00193-w.
- [233] A. A. Aldaliee, N. N. Mansor, H. Mokhlis, A. K. Ramasamy, and L. J. Awalin, "Pareto-Based Optimization of PV and Battery in Home-PV-BES-EV System with Integrated Dynamic Energy Management Strategy," *Sustainability*, vol. 17, no. 16, p. 7364, Aug. 2025, doi: 10.3390/su17167364.
- [234] M. GhasemiGarpachi, M. Dehghani, M. Aly, and J. Rodriguez, "Multi-Objective Improved Differential Evolution Algorithm-Based Smart Home Energy Management System Considering Energy Storage System, Photovoltaic, and Electric Vehicle," *IEEE Access*, vol. 13, pp. 89946–89966, 2025, doi: 10.1109/ACCESS.2025.3567888.
- [235] S. Boubaker et al., "Multi-objective optimization framework for electric vehicle charging and discharging scheduling in distribution networks using the red deer algorithm," *Sci. Rep.*, vol. 15, no. 1, p. 13343, Apr. 2025, doi: 10.1038/s41598-025-97473-7.
- [236] N. Fesakis, C. Megagiannis, G. E. Lazaridou, E. Sarafoglou, A. Tzouvaras, and A. Karlis, "Energy Management in Multi-Source Electric Vehicles Through Multi-Objective Whale Particle Swarm Optimization Considering Aging Effects," *Energies*, vol. 19, no. 1, p. 154, Dec. 2025, doi: 10.3390/en19010154.
- [237] K. Taghizad-Tavana, A. Esmaeel Nezhad, M. T. Hagh, A. Canani, and A. Safari, "Hybrid Renewable Energy Systems for Off-Grid Electrification: A Comprehensive Review of Storage Technologies, Metaheuristic Optimization Approaches and Key Challenges," *Eng.*, vol. 6, no. 11, p. 309, Nov. 2025, doi: 10.3390/eng6110309.
- [238] M. Vahabi Khah et al., "Optimal sizing of residential photovoltaic and battery system connected to the power grid based on the cost of energy and peak load," *Heliyon*, vol. 9, no. 3, p. e14414, Mar. 2023, doi: 10.1016/j.heliyon.2023.e14414.

- [239] N. Samala and C. Bethi, "Harnessing synergy: a holistic review of hybrid renewable energy systems and unified power quality conditioner integration," *J. Electr. Syst. Inf. Technol.*, vol. 12, no. 1, p. 4, Feb. 2025, doi: 10.1186/s43067-025-00193-1.
- [240] A. F. Güven, N. Ateş, S. Alotaibi, T. Alzahrani, A. M. Amsal, and S. K. Elsayed, "Sustainable hybrid systems for electric vehicle charging infrastructures in regional applications," *Sci. Rep.*, vol. 15, no. 1, p. 4199, Feb. 2025, doi: 10.1038/s41598-025-87985-7.
- [241] X. Zhang, Z. Wang, and Z. Lu, "Multi-objective load dispatch for microgrid with electric vehicles using modified gravitational search and particle swarm optimization algorithm," *Appl. Energy*, vol. 306, p. 118018, Jan. 2022, doi: 10.1016/j.apenergy.2021.118018.
- [242] M. Salah, A. H. Yakout, H. M. Hasanien, C. Sun, J. Mei, and M. Alharbi, "Pareto multi-objective study of sizing and siting electric vehicle charging stations and distributed generation using an enhanced hunger game search optimizer," *Ain Shams Eng. J.*, vol. 17, no. 9, p. 104352, Sep. 2026, doi: 10.1016/j.asej.2026.104352.
- [243] S. K. Vankadara, S. Chatterjee, P. K. Balachandran, and L. Mihet-Popa, "Marine Predator Algorithm (MPA)-Based MPPT Technique for Solar PV Systems under Partial Shading Conditions," *Energies*, vol. 15, no. 17, p. 6172, Aug. 2022, doi: 10.3390/en15176172.
- [244] M. Elnaggar et al., "Harnessing Solar Energy for Electricity Generation and Green Hydrogen Production: A Sustainable Pathway for Low-Carbon Transportation in Gaza," *Int. J. Energy Res.*, vol. 2026, no. 1, p. 8748862, Jan. 2026, doi: 10.1155/er/8748862.
- [245] M. Sasikumar, S. S. P. Vijayakumar, and S. Manikandan, "Multi-Objective Energy Management in Microgrids with Hybrid Renewable Energy Sources and Battery Energy Storage Systems Using Hybrid Optimization Algorithm," *Trans. Electr. Electron. Mater.*, vol. 27, no. 3, pp. 475–492, Jun. 2026, doi: 10.1007/s42341-025-00673-1.
- [246] Md. G. Hasan et al., "Sustainable charging framework: Solar wireless EV charging enhanced with MPPT control," *Energy Rep.*, vol. 15, p. 109274, Jun. 2026, doi: 10.1016/j.egyr.2026.109274.
- [247] M. Di Somma et al., "Multi-objective operation optimization of a Distributed Energy System for a large-scale utility customer," *Appl. Therm. Eng.*, vol. 101, pp. 752–761, May 2016, doi: 10.1016/j.applthermaleng.2016.02.027.
- [248] C. Li, Y. Shan, L. Zhang, L. Zhang, and R. Fu, "Techno-economic evaluation of electric vehicle charging stations based on hybrid renewable energy in China," *Energy Strategy Rev.*, vol. 41, p. 100850, May 2022, doi: 10.1016/j.esr.2022.100850.
- [249] V. Sidharthan Panaparambil, Y. Kashyap, and R. Vijay Castelino, "A review on hybrid source energy management strategies for electric vehicle," *Int. J. Energy Res.*, vol. 45, no. 14, pp. 19819–19850, Nov. 2021, doi: 10.1002/er.7107.
- [250] V. Chandra Tella, M. Alzayed, and H. Chaoui, "A Comprehensive Review of Energy Management Strategies in Hybrid Electric Vehicles: Comparative Analysis and Challenges," *IEEE Access*, vol. 12, pp. 181858–181878, 2024, doi: 10.1109/ACCESS.2024.3509737.