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MULTI-AGENT AI ORCHESTRATION OF GRID-FORMING VIRTUAL POWER PLANTS FOR BIDIRECTIONAL EV ENERGY NETWORKS

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Abstract
This manuscript proposes a novel AI-based framework that combines Virtual Power Plants (VPPs) with a bidirectional Electric Vehicle (EV) energy network, along with decentralized Multi-Agent System (MAS) orchestration for the future of renewable energy-dominated smart grids. The study addresses important issues of intermittency, low-inertia grid operation, integration of large numbers of EVs, and distributed energy coordination. A holistic Cyber-Physical Smart Grid Architecture is proposed that integrates Renewable Energy Systems, Battery Energy Storage Systems (BESS), Vehicle-to-Grid (V2G) technology, decentralized grid-forming inverter control, and reinforcement learning-based Artificial Intelligence orchestration in a decentralized operational environment. The framework uses autonomous intelligent agents to coordinate renewable generation and EV charging/discharging schedules, storage dispatch, and grid stabilization in real time. The simulation-based evaluation was performed under various operational conditions, including renewable variability stress, high EV penetration, and bidirectional V2G operation. Results show significant improvements in renewable energy use, operational Efficiency, voltage and frequency stability, peak demand reduction, and carbon emissions reduction over traditional central grid systems. The design framework resulted in a renewable utilization rate of>90%, reduced operational costs by up to 29%, and increased grid stability through adaptive grid-forming control mechanisms. In addition, coordinated EV fleets were effectively used as distributed mobile energy storage resources for peak shaving, ancillary services, and balancing renewable energy. The results validate the potential of AI-driven grid-forming VPPs as a scalable, resilient, and economically viable future option for low-carbon smart energy systems with significant renewable energy and EV uptake. The proposed framework offers valuable technical, operational, and policy lessons for utility operators, smart grid planners, and policymakers to support sustainable, intelligent energy transition strategies.

1. Introduction

The energy sector is facing a worldwide paradigm shift driven by growing energy demand, rapid urbanization, environmental concerns, and the rapid development of renewable energy technologies. The aging of the power grid, increased electricity usage variability, and the rise of intermittent renewable energy sources like solar and wind power are creating problems for traditional centralized power systems. The challenges have made it increasingly important that energy management be intelligent, flexible, and sufficiently decentralized to ensure grid stability, reliability, and sustainability under highly dynamic operating conditions (Rathor and Saxena 2020; Rajendran, Raute, and Caruana 2025).

Virtual Power Plant (VPP) has been one of the most promising paradigms for coordinating distributed energy resources (DERs), such as renewable energy systems, battery energy storage systems (BESS), and flexible loads in a coordinated smart grid environment, in recent years (Prakash et al. 2022; Onsomu, Terciyanlı, and Yeşilata 2024). A VPP groups geographically distributed energy resources and controls them as a single, smart energy asset that can compete in electricity markets, participate in frequency regulation, and participate in demand response programs. VPPs also enable a decentralized approach to managing energy assets, which can help increase Efficiency, use of renewable energy sources, and grid resilience (Abdelkader, Amissah, and Abdel-Rahim 2024).

At the same time, the growing adoption of EVs is changing the face of the modern power system. Conversely, the proliferation of EVs is laying the groundwork for the redefinition of modern power systems. The rise in the adoption of EVs globally has been driven by advancements in battery technology, falling manufacturing costs, and global initiatives for carbon neutrality and sustainable transportation (Yang, Huang, and Lin 2022; Lipu et al. 2022). However, due to the large-scale penetration of EVs, there are significant challenges to power system stability, including increased peaks, voltage fluctuations, transformer overloading, and demand uncertainty (Diahovchenko, Chuprun, and Čonka 2023). Smart grid policies and solutions for intelligent charging coordination and advanced energy management strategies are essential to enable the effective integration of EVs in future smart grids (Shopan Ali et al. 2024).

As an innovative strategy to convert EVs from passive electricity consumers into active distributed energy resources (Wu et al. 2022), bidirectional energy exchange, or Vehicle-to-Grid (V2G), has attracted significant attention. A bidirectional charging infrastructure can be used to store surplus renewable energy during low-demand periods and supply electricity to the grid during high-demand periods. This will allow EVs to integrate with the grid to provide ancillary services such as frequency control, voltage support, peak shaving, and emergency backup power (Das et al. 2022). However, deploying large-scale bidirectional EV networks will require advanced coordination systems to manage highly dynamic energy flows across distributed systems (Yu, Yang, and Wang 2025).

At the same time, rising inverter-based renewable energy (IBRE) penetration has introduced new challenges regarding grid inertia and frequency stability. Conventional synchronous generators provide natural inertial support to maintain grid frequency stability, whereas renewable energy systems integrated via power electronic inverters may not (Magdy, Ali, and Xu 2021). To overcome these issues, grid-forming inverter technology has been introduced as a key element in the future smart grid. Unlike grid-following inverters, grid-forming inverters can actively set voltage and frequency references to operate under weak-grid and islanded conditions (Unruh et al. 2020). Grid-forming capability is therefore important for enabling the reliable and resilient operation of renewable-dominated power systems and for VPP architectures (Awad and Bayoumi 2026).

In recent years, Artificial Intelligence (AI) has emerged as a groundbreaking solution to operational challenges that complicate distributed energy resources and EV-integrated smart grids. The framework used in this work has been modeled using AI techniques that can process large amounts of real-time data, forecast energy demand patterns, optimize the dispatch of renewable energy, and coordinate multiple distributed agents under complex operating conditions with uncertainty (Vishnubhatla

2020). Multi-Agent Systems (MAS) have been among the most promising AI techniques for decentralized energy management because they possess features of autonomous decision-making, adaptability, and cooperative coordination (Hammad and Abu-Zaid 2024). Smart energy networks enable multiple intelligent agents to represent EVs, charging stations, renewable generators, batteries, and grid operators, all of which optimize energy systems and orchestrate complex energy interactions in real time, in a distributed manner (Al-Shetwi et al. 2025).

While previous research has investigated various aspects of VPPs, EV integration, AI optimization, and renewable energy coordination separately, several critical areas remain under-researched or inconclusive (Arévalo, Ochoa-Correa, and Villa-Ávila 2024). Most existing studies focus on grid-following VPP architectures, and very few emphasize operational strategies that could enable grid-forming operation in future low-inertia power systems. Second, many EV integration studies focus on unidirectional charging and overlook the dynamic potential of bidirectional V2G energy exchange in large-scale distributed networks. Thirdly, current AI-based energy management systems are typically based on centralized optimization approaches that are complex, difficult to scale, and prone to communication bottlenecks in highly distributed environments (Kermansaravi et al. 2025). In addition, the industry lacks the integration of multi-agent AI orchestration into grid-forming VPPs for coordinated EV energy management in renewable-dominated scenarios. Hence, this work presents a novel framework for incorporating Multi-Agent AI Orchestration into grid-forming Virtual Power Plants (VPPs) for bidirectional EV Energy Networks. The proposed framework is based on an intelligent multi-agent coordination environment for integrating renewable energy systems, battery energy storage, grid-forming inverter control, and bidirectional EV charging. The framework is designed to improve energy grid stability, renewable energy use, operational Efficiency, and energy resilience by implementing adaptive, AI-driven orchestration strategies. Specifically, the study aims to explore the potential for decentralized intelligent agents to dispatch energy sources, coordinate EV charging/discharging behaviors, and enable the stable operation of a future smart grid across different renewable generation and demand scenarios.

This research has made the following major contributions:

(i) An integrated framework of an AI-driven VPP for smart energy grids has been developed,

(ii) Bidirectional energy exchange of EVs has been incorporated into a decentralized smart energy network,

(iii) Multi-agent orchestration strategies for distributed energy optimization have been developed, and

(iv) System reliability, economic performance, and sustainability benefits have been evaluated under various operational scenarios. This study's results will help inform researchers, utility operators, policymakers, and smart grid planners as they strive for resilient and sustainable future energy systems.

2. Literature Review

2.1 Evolution of Virtual Power Plants

The rise of distributed energy resources (DERs), renewables, and smart grid systems has helped drive the shift from centralized energy production to decentralized, flexible power systems. The traditional power grid network was developed around centralized generation facilities using fossil fuels, which deliver electricity in one direction from the generation plant to the consumer along the grid (Liu et al. 2023). The introduction of renewable energy sources, energy storage solutions, and distributed loads, however, has created highly decentralized and dynamic energy systems in today's power systems.

In this transition, Virtual Power Plants (VPPs) have come to the fore as a potential means of creating an aggregated distributed energy resource that can be coordinated into a market-responsive energy entity (Abdelkader, Amissah, and Abdel-Rahim 2024). A VPP integrates renewable energy generation technologies, batteries, dynamic industrial loads, and EVs through advanced communication and control systems. VPPs are not based on a single physical generation source, but rather, they manage geographically distributed resources with the help of intelligent energy management systems

(López Sáez de Argandoña 2020). VPPs are designed primarily to optimize distributed energy operations, increase grid reliability, increase renewable penetration, and enhance market participation.

The first VPP models focused mainly on economic dispatch and demand-side management using central optimization methods (Huang, Li, and Zhang 2025). But today's VPP designs are increasingly built to incorporate distributed intelligence, real-time communication, and decentralized control mechanisms to address the complexity of their operations. The latest research has demonstrated that, in smart grids, advanced VPP frameworks can achieve significantly greater energy flexibility, lower transmission losses, and better integration of renewables (Tang and Wang 2025).

2.2 Grid-Forming and Grid-Following Technologies

The increasing scale of renewable energy systems has posed a significant challenge for the operation of low-inertia power systems. Traditional power generation technology is dominated by synchronous generators, which are known to provide natural rotational inertia and frequency stability during disturbances in the system (Li et al. 2022). However, renewable energy sources such as solar photovoltaic (PV) and wind power are usually interfaced via power electronic converters, which lack inherent inertia support (Meegahapola et al. 2020).

Conventional renewable energy systems are based on grid-following inverters that synchronize with the existing grid voltage and frequency (Aljarrah et al. 2024). Grid-following technologies work well when the grid is strong, but can become unstable when the grid is weak, when renewable energy is high, or when the grid is islanded. For this reason, grid-forming inverters have attracted increasing research interest over the last few years.

In contrast to following grid conditions, grid-forming inverters actively set voltage and frequency references (Mohammed et al. 2024). This enables inverter-based resources to support grid stability, black start, and islanded microgrid operation. (Zhang et al. 2021) showed that grid-forming control strategies can enhance frequency regulation, voltage support, and transient stability performance in power systems dominated by renewable generation. Several studies have shown that grid-forming control strategies can enhance frequency regulation, voltage support, and transient stability performance in power systems dominated by renewables (Zhang et al. 2021). Furthermore, grid-forming technologies are increasingly considered key enablers for future smart grids with high renewable penetration and the coordination of distributed energy sources (Cavus 2025).

Although these benefits are observed, deploying grid-forming technologies in large-scale VPP architectures remains a significant technical challenge. To coordinate multiple distributed grid-forming resources, advanced communication schemes, adaptive control algorithms, and intelligent dispatch mechanisms are required to ensure stable operation of the overall grid under varying demand and renewable energy generation levels (Liu et al. 2023).

2.3 Electric Vehicle Integration and Bidirectional Energy Networks

Electric Vehicles (EVs) are fast becoming one of the most transformative components in the future energy system. Cost reductions in batteries, governmental policies supporting EV adoption, and carbon-emission reduction policies have driven the global shift towards sustainable transportation, resulting in increased EV uptake (Zaino et al. 2024). But the growing share of EVs poses significant challenges to the current electricity grid.

The widespread adoption of large-scale EV charging can lead to transformer overloads, voltage instabilities, and network congestion in the distribution network (Visakh and Selvan 2023). In areas with high EV density, such as urban areas, uncoordinated charging can exacerbate grid instability. Hence, intelligent charging coordination is crucial for achieving stable integration of EVs into smart grids.

Vehicle-to-Grid (V2G) technology has been identified as a potential solution to enable EVs to become active energy sources rather than passive electricity consumers. Bidirectional charging systems enable EV batteries to store power from renewable sources when demand is low and return the electricity to the grid when demand is high. This two-way energy transaction can be used to provide ancillary services such as frequency regulation, spinning reserves, peak shaving, and emergency backup power (Al Kez 2022).

Recent research has shown that integrated V2G can be a major factor in addressing the Utilization of renewable energy and cost reduction in smart grid systems. Moreover, consolidated EV fleets may also serve as distributed battery storage systems to help maintain grid resilience as renewable energy supplies become more intermittent. The bidirectional operation of EVs in these large-scale networks, however, is problematic, as EV mobility patterns and charging regimes are stochastic, and battery availability is also random (Tang et al. 2025).

2.4 Multi-Agent Systems in Smart Energy Networks

Due to the complexity of modern distributed energy systems, there is an increasing interest in decentralized energy systems management using Multi-Agent Systems (MAS). MAS are collections of independent agents that can communicate, cooperate, and make decisions in a distributed manner across dynamic environments (Maldonado et al. 2024). A smart energy system can include agents representing distributed generators, batteries, EVs, consumers, charging stations, and grid operators. Multi-agent systems offer benefits over centralized optimization methods, such as scalability, flexibility, fault tolerance, and real-time adaptability (Binyamin and Ben Slama 2022). All agents work independently, but each agent also needs to interact with other agents regionally to meet global system goals such as energy balancing, cost minimization, and reliability improvement.

The MAS frameworks have been used in several research works, such as smart grid operation, microgrid management, and renewable energy coordination. For instance, distributed agents have been applied to coordinate EV charging scheduling, dispatch renewables, and control distributed battery storage. Multi-agent coordination has also been demonstrated to work well in DEMs and DR applications (Arévalo et al. 2025).

But the use of MAS in grid-forming VPP systems is still relatively scarce. The studies are either on economic optimization or on local microgrid coordination, without a thorough integration of grid-forming features, renewable generation intermittency management, and bidirectional EV orchestration within a single decentralized system.

2.5 Artificial Intelligence in Smart Grid Optimization

In today's smart grid era, the use of Artificial Intelligence (AI) is indispensable due to its ability to handle massive data, recognize operational patterns, and support adaptive decision-making under uncertainty (Arévalo et al. 2025). AI is increasingly used for renewable energy forecasting, load prediction, fault detection, dispatch optimization, and demand response management.

Artificial Intelligence techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Deep Learning (DL) models have shown promising results in renewable generation forecasting and electricity demand prediction (Khan et al. 2022). Reinforcement Learning (RL) has also attracted significant interest for dynamic energy management because it can learn optimal operating policies by interacting with complex environments (Yu et al. 2021).

In smart energy networks, AI can be used to schedule charging for EV fleets, optimize battery storage operations, and optimize the use of renewable energy (Sarker et al. 2025). Under uncertain operating conditions, Deep Reinforcement Learning (DRL) techniques are promising for adaptive control of the microgrid and for optimizing distributed energy resources (Al-Saadi, Al-Greer, and Short 2023).

While significant progress has been made, there are still limitations in the research on smart grids using AI. Various current frameworks suffer from scalability issues in large distributed systems (Ali and Choi 2020). Moreover, the dynamics of the grid required for forming and the current coordination needs of inverter-dominated renewable networks are not always accounted for in AI models (Hakam and Tabaa 2026).

2.6 Renewable Energy Integration and Energy Storage Coordination

One of the most critical goals in realizing the smart grid of the future is integrating renewable energy. Solar and wind energy generators generate electricity in an environmentally friendly way but come with the disadvantages of intermittency and variability (Ahmed et al. 2024). Energy storage systems, especially Battery Energy Storage Systems (BESS), are a key component in reducing the effect of renewable variability and increasing grid flexibility (Santos et al. 2021).

The features of battery storage include energy shifting, peak shaving, voltage support, and smoothing of renewable energy (Datta, Kalam, and Shi 2021). Several studies have demonstrated that BESS can be an effective method for increasing the penetration of renewables and reducing the operational costs of VPPs (Abdullah et al. 2021). Also, integrated storage facilities can enhance grid resiliency when renewable energy sources are variable or when system disturbances occur.

To increase operational stability and maximize the use of renewables, hybrid renewable-storage systems are increasingly being incorporated into VPP architectures (Ochoa-Correa, Arévalo, and Martinez 2025). The coordination of distributed storage resources and EV batteries in decentralized energy networks remains a significant challenge, particularly due to dynamic charging patterns and unpredictable renewable energy profiles.

2.7 Cybersecurity and Communication Challenges

Communication networks, IoT devices, cloud computing, and infrastructures for real-time data exchanges are important components of modern VPPs and smart networks (Abdelkader, Amissah, and Abdel-Rahim 2024). These technologies can facilitate intelligent coordination and distributed optimization, but they also pose cybersecurity risks and communication reliability issues.

Cyberattacks on smart grid communication systems can disrupt energy management operations, violate user privacy, and negatively affect power system operation (Alomari et al. 2025). There are several significant cybersecurity threats to modern energy networks, including Distributed Denial-of-Service attacks, False Data Injection, and communication delays.

To solve these problems, researchers have investigated blockchain technologies, secure communication protocols, and edge computing architectures to improve cybersecurity and decentralized trust management in smart grids (Islam et al. 2025). However, secure communication infrastructure and AI-based multi-agent VPP coordination are not yet mature fields of research, and further investigation is needed (Liu and Gao 2025).

2.8 Identified Research Gaps

While there have been great strides in VPPs, smart grids, renewable integration, and EV energy management, some key research questions remain unanswered. Firstly, there have been limited studies investigating the adoption of grid-forming inverter technologies in AI-driven VPP architectures. Second, most EV integration research has focused mainly on charging optimization rather than large-scale bidirectional energy coordination via V2G. Third, current AI-based frameworks often rely on centralized optimization, which may not be suitable for smart grid systems with a highly distributed, dynamic nature.

In addition, there has been little research integrating multi-agent AI orchestration, grid-forming control, renewable energy coordination, and bidirectional EV integration within a single decentralized framework. Closing the gaps will be crucial to making future smart energy networks resilient, scalable, and sustainable, with high levels of renewable energy and EV penetration.

3. Theoretical and Conceptual Framework

3.1 Systems Theory for Distributed Smart Energy Networks

Today's power system is becoming increasingly decentralized and interconnected, evolving into a smart energy system. The major reason for this transition is the dawning of the distributed energy resources (DERs), renewable energy systems, electric vehicles (EVs), battery storage technologies, and intelligent communication infrastructure (Al-Shetwi et al. 2025). Future energy systems exhibit characteristics of complex adaptive systems because they are composed of many distributed components that continuously interact, leading to system-wide behavior that emerges from these interactions (Fereidunian et al. 2026).

Systems theory offers a thorough analytical framework for describing such interconnected, non-linear energy environments. The interplay between energy generation, storage, consumption, and control in distributed smart grids is highly interdependent and subject to uncertainties arising from renewable intermittency, EV charging patterns, market signals, and grid disturbances. In contrast to conventional centralized power grids, distributed smart grids must provide adaptive mechanisms to coordinate operations in real time to address changing conditions.

In this context, Virtual Power Plants (VPPs) can be seen as cyber-physical energy systems that involve decentralized resources within a coordinated operating system (Raeispour et al. 2026). The systems-theory approach is used to model interactions among renewable generators, battery storage units, EV fleets, charging infrastructure, and grid operators within a decentralized orchestration environment. This theoretical approach allows the study to analyze the energy flow, communication interactions, system resilience, and operational stability among interdependent energy agents.

3.2 Conceptual Architecture of Grid-Forming Virtual Power Plants

The proposed framework's conceptual basis comes from the combination of grid-forming Virtual Power Plants, bidirectional EV energy networks, and AI orchestration mechanisms. Existing VPP architectures are primarily used for economic dispatch and market participation of distributed energy resources (DERs) (Huang, Li, and Zhang 2025). But as the share of inverter-based renewables rises, new operational requirements have emerged for frequency stability, voltage control, and grid resilience.

The suggested framework introduces grid-forming inverter technologies that actively set voltage and frequency references in distributed power systems (Rathnayake et al. 2021) to overcome these challenges. Grid-forming inverters can directly help stabilize the system and enable low-inertia, renewable-dominated networks (Alshahrani et al. 2024), unlike grid-following inverters, which rely on external grid references.

The conceptual architecture consists of four interconnected layers:

(i) Physical Energy Layer

This Layer includes renewable energy systems (solar PV and wind), battery energy storage systems (BESS), EV charging infrastructure, and distributed electrical loads. These physical assets constitute the operational foundation of the VPP network.

(ii) Communication and Data Layer

The communication layer enables real-time information exchange between distributed agents using IoT devices, smart meters, cloud platforms, and edge computing systems (Mehmood et al. 2021). This Layer supports data acquisition, monitoring, and decentralized coordination.

(iii) Multi-Agent AI Coordination Layer

This Layer contains autonomous intelligent agents responsible for distributed decision-making, energy optimization, and adaptive orchestration. Each agent operates independently while coordinating with neighboring agents to achieve global energy management objectives (Stennikov et al. 2022).

(iv) Grid-Forming Control Layer

This Layer manages voltage stabilization, frequency regulation, bidirectional power flow, and grid synchronization using grid-forming inverter control mechanisms.

The integration of these four layers forms a decentralized, adaptive VPP ecosystem capable of supporting large-scale integration of renewable energy and EVs.

3.3 Multi-Agent Coordination Theory

The proposed framework is strongly grounded in Multi-Agent System (MAS) theory, which enables decentralized control and distributed intelligence in complex energy systems. Multi-agent systems consist of autonomous computational entities capable of communication, cooperation, negotiation, and local decision-making within dynamic environments (Jin et al. 2025).

In smart grid applications, each distributed energy component can be represented as an intelligent agent with specific operational objectives and constraints. In the proposed multi-agent framework, the renewable energy agents are to optimize the output of renewable energy generation based on the availability of renewables and operational demand. Storage agents manage the charging and discharging times of batteries, facilitating load balancing and energy flexibility. The bidirectional charging operations of EV agents are controlled under Vehicle-to-Grid (V2G) coordination, whereas the voltage and frequency condition are monitored by the grid agents, aiming to achieve the stability of the distributed smart grid environment.

The proposed framework adopts a cooperative MAS structure where agents exchange operational information and collaboratively optimize system-wide energy performance. This decentralized coordination mechanism improves scalability, fault tolerance, and adaptability compared to centralized optimization approaches (Álvarez-López, González-Briones, and Li 2026).

The theoretical foundation for multi-agent coordination is supplemented by distributed optimization, which decomposes complex global optimization problems into subproblems and solves them cooperatively. This method is especially suitable for highly distributed EV-integrated smart grid systems that face significant dynamic operational uncertainty.

3.4 AI-Orchestrated Decision-Making Framework

The overall conceptual framework centers on Artificial Intelligence (AI) as the primary orchestration mechanism. With AI-driven orchestration, distributed energy resources (DER) can be coordinated intelligently, real-time energy dispatch can be optimized, and the intelligent control can adapt to the uncertainty of electricity generation from renewable sources and of electricity demand from EVs (Twaisan and Barışçı 2022).

The framework includes elements of machine learning and reinforcement learning to aid the agents' autonomous behavior and adaptive decision-making (Zhu 2023). Reinforcement learning (RL) is of particular interest because, as agents interact with their surrounding energy environment, they continuously learn optimal operational strategies (Sivamayil et al. 2023).

The AI orchestration process consists of Real-time monitoring of grid conditions and energy demand, forecasting renewable generation and EV charging behavior, dynamic optimization of energy dispatch and storage utilization, adaptive coordination among distributed agents, and continuous learning and operational improvement.

This AI-driven decision-making process enables the VPP to dynamically balance renewable generation, EV charging loads, battery storage operation, and grid-forming stability requirements under uncertain operating conditions.

3.5 Bidirectional EV Energy Exchange Model

In addition, the theoretical framework considers bidirectional energy exchange between vehicles and the grid (Vehicle-to-Grid-V2G) (Mojumder et al. 2022). Standard EV charging infrastructure works on the principle of "one-way" transfer of electricity from the grid to the EV battery. Bidirectional charging, however, presents EVs as mobile energy storage solutions to support grid operations (Adegbohun et al. 2024).

The proposed framework conceptualizes EV fleets as dynamic distributed storage networks capable of absorbing surplus renewable energy during low-demand periods, providing peak shaving during high-demand conditions, supporting frequency regulation and voltage stabilization, and enhancing emergency backup power availability.

This bidirectional energy exchange mechanism significantly improves system flexibility and the Utilization of renewable energy. The aggregation of EV batteries within the VPP architecture effectively creates a large-scale distributed storage ecosystem capable of supporting future renewable-dominant smart grids (Awad and Bayoumi 2026).

3.6 Sustainability and Energy Resilience Framework

The proposed conceptual framework takes a sustainability and resilience perspective in the operation of smart energy systems. Sustainable energy systems focus on reducing carbon emissions, increasing the use of renewable energy, and increasing energy efficiency (Vujanović et al. 2021). At the same time, resilient energy systems should be able to operate stably in the face of various disturbances, including the intermittency of renewable energy sources, network communication failures, and variations in peak demand (Xu et al. 2024).

The framework considers sustainability and resilience in relation to renewable energy penetration, reduction in carbon emissions and overall energy efficiency in the distributed SMG operations. It also evaluates the reliability of the electrical grid, voltage stability, frequency stability, and flexibility in operating coordinated renewable-storage-EV systems. In addition, the framework considers the economic optimization considering improved use of the energy, lower operating costs and better use of distributed energy.

By integrating AI-driven orchestration, grid-forming control, and bidirectional EV coordination, the proposed framework aims to enhance environmental sustainability and operational resilience in future smart energy networks (Anvari et al. 2025).

3.7 Proposed Integrated Conceptual Framework

Based on the theoretical foundations discussed above, this study proposes an integrated conceptual framework for Multi-Agent AI Orchestration of Grid-Forming Virtual Power Plants for Bidirectional EV Energy Networks (Kiasari and Aly 2026).

It integrates distributed renewable energy sources, grid forming inverter technologies and battery energy storage systems into an integrated smart grid architecture. It also incorporates the bidirectional EV charging infrastructure and the multi-agent coordination in AI to support adaptive and decentralized energy management. Furthermore, the real-time communication networks enable the continuous exchange of data, control and coordination of the distributed energy resources.

The conceptual model proposes a decentralized cyber-physical smart grid architecture that enables adaptive energy management, the integration of renewable energy sources, and resilient distributed operation (Aghmadi and Mohammed 2024).

The framework aims to enable future low-carbon energy systems with high shares of renewables, high levels of EV adoption, and intelligent, coordinated distributed energy.

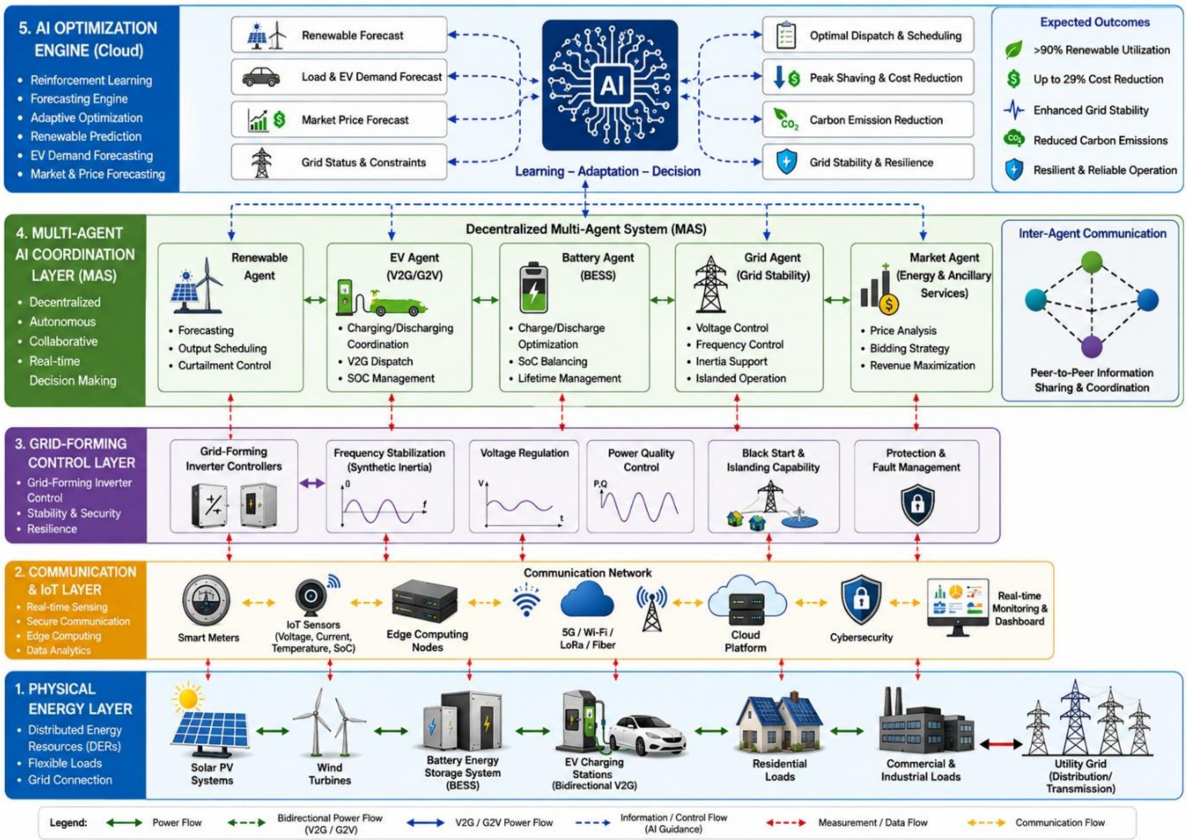


Figure 1. Decentralized Multi-Agent AI-Orchestrated Grid-Forming Virtual Power Plant Architecture for Bidirectional EV-Integrated Smart Energy Networks

4. Methodology

4.1 Research Design and Systems Approach

The focus of this study is to analyze the operational performance of AI-powered grid-forming Virtual Power Plants (VPPs) using a quantitative systems-based research approach when connected to a bidirectional Electric Vehicle (EV) energy network. It integrates distributed energy system modeling, multi-agent artificial intelligence (AI) orchestration, renewable energy optimization, and grid-forming control strategies within a single smart grid framework. The methodology proposed aims to evaluate the reliability of the system, renewable energy exploitation, voltage stability, system efficiency, and bidirectional Vehicle-to-Grid (V2G) power exchange across different operational scenarios.

The systemic methodology adopted in this research is based on a broad spectrum of the distributed energy modeling, multi-agent orchestration, renewable energy optimization, and grid-forming control strategies in a decentralized smart grid. The research process starts with data collection and preprocessing, which are carried out with the renewable generation profiles, EV charging demand patterns, electricity consumption behavior and operational grid parameters. Later a distributed Multi-Agent System (MAS) architecture is designed to facilitate the coordination of renewable generation, battery storage, bidirectional EV charging and grid-forming operational control. It then simulates renewable energy and EV network operations under varying operating conditions such as increasingly renewable intermittency, high EV penetration, and varying load demand conditions.

Further, energy dispatch, adaptive grid stabilization and distributed energy coordination in real-time is optimized using Artificial Intelligence (AI) driven orchestration based on reinforcement learning. Finally, the proposed framework is tested through Technical, Economic, Environmental and operational performance indicators to determine the reliability of the systems, renewable energy usage, operational efficiency and smart grid resilience.

The framework is implemented using distributed smart-grid simulation principles, in which renewable generation systems, EV fleets, battery storage systems, and grid-forming VPPs interact dynamically within a decentralized cyber-physical energy environment.

The proposed smart energy network consists of a grid-forming Virtual Power Plant integrating: Solar photovoltaic (PV) systems; Wind energy generation systems; Battery Energy Storage Systems (BESS); Electric Vehicle charging/discharging stations; Distributed residential and commercial loads; Smart grid communication infrastructure.

The VPP operates as an aggregated distributed energy management platform that coordinates energy generation, storage, and consumption in real time. The network includes bidirectional EV charging systems enabling Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) operation.

Table 1. Technical Configuration and Distributed Energy Capacity Parameters of the Proposed AI-Orchestrated Grid-Forming VPP Network

Component	Capacity
Solar PV	20 MW
Wind Farm	15 MW
Battery Storage	25 MWh
EV Fleet	1000 EVs
Peak Grid Demand	30 MW

The operational simulation is conducted under hourly resolution over a 24-hour and seasonal operational cycle.

4.3 Data Collection and Preprocessing

The study utilizes representative smart grid operational datasets derived from renewable energy profiles, EV charging demand patterns, electricity consumption behavior, and grid operational parameters obtained from publicly available smart grid and renewable energy databases.

4.3.1 Renewable Energy Data

Solar irradiance and wind speed profiles are used to estimate renewable power generation.

Solar PV generation is modelled as:

$$P_{PV}(t) = \eta_{PV} \times A \times G(t) \times [1 - \beta(T_t - T_{ref})]$$

Where:

- $P_{PV}(t)$= PV power output
- η_{PV}= PV efficiency
- A= panel area
- $G(t)$= solar irradiance
- β= temperature coefficient

Wind power generation is estimated using:

$$P_{wind}(t) = \frac{1}{2}\rho A v_t^3 C_p$$

Where:

- ρ= air density
- A= rotor swept area
- v_t= wind speed
- C_p= power coefficient

4.3.2 EV Charging Demand Data

EV charging demand is modeled using stochastic charging behavior, accounting for arrival and departure times, battery state of

Charge (SOC), charging preferences, and daily mobility patterns.
The EV charging load profile is generated using probabilistic distribution methods to simulate realistic urban charging behavior.

4.3.3 Grid Operational Data

Grid operational data includes voltage and frequency limits, load demand profiles, electricity pricing signals, transformer loading limits, and renewable penetration targets.
The data preprocessing involves removing the missing values, eliminating outlier data, normalizing time series and adjusting load balancing to ensure consistency and accuracy of the model.
Normalized input data are expressed as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

4.3.4 Benchmark Dataset Validation

To validate the operational reliability and generalizability of the proposed AI-driven grid-forming Virtual Power Plant (VPP) framework, benchmark datasets from publicly available smart grid and renewable energy repositories were integrated into the simulation environment. Solar irradiance and wind generation profiles were obtained from the National Renewable Energy Laboratory renewable integration datasets, while Electric Vehicle (EV) charging demand behavior was modeled using the ACN-Data charging dataset developed by the California Institute of Technology Adaptive Charging Network project. Grid operational demand profiles and electricity pricing signals were incorporated using benchmark smart-grid operational datasets commonly adopted in distributed energy system studies.
The integrated dataset consisted of approximately 52,560 hourly operational data samples collected over one year of simulated smart-grid operation. The dataset included renewable generation variability, EV charging demand uncertainty, electricity load fluctuations, battery storage operational states, voltage-frequency deviations, and distributed grid operational conditions under seasonal variations.
Data preprocessing involved missing value handling, outlier removal, temporal normalization, and load balancing to ensure consistency and simulation reliability. Approximately 94.2% of the collected data samples were validated and retained after preprocessing and quality assessment, while inconsistent and incomplete records were excluded from the final simulation dataset.
For AI model development, the processed dataset was divided into:

- 70% training dataset
- 15% validation dataset
- 15% testing dataset

The proposed reinforcement learning-based orchestration framework was validated using comparative performance analysis between conventional grid operation and AI-orchestrated decentralized operation under identical operational datasets. Validation metrics included renewable energy utilization, frequency stability, voltage regulation performance, operational cost reduction, peak demand mitigation, and carbon emission reduction

4.4 Multi-Agent System Modeling

The proposed framework utilizes a decentralized Multi-Agent System (MAS) architecture where each distributed energy component is represented by an autonomous intelligent agent.

Agent Categories

Table 2. Decentralized Multi-Agent Operational Architecture and Functional Roles within the AI-Driven Smart Grid Framework

Agent Type	Operational Role
Renewable Agent	Renewable generation optimization

EV Agent	Charging/discharging coordination
Battery Agent	Storage scheduling
Grid Agent	Frequency and voltage monitoring
Market Agent	Energy pricing optimization

Each agent operates independently while exchanging information with neighboring agents using decentralized communication protocols.

The multi-agent coordination objective is:

$$\min\ F = w_1 C_{cost} + w_2 E_{CO_2} - w_3 R_{reliability}$$

Where:

- C_{cost}= operational cost
- E_{CO_2}= carbon emissions
- $R_{reliability}$= system reliability

4.5 AI-Driven Orchestration Framework

Artificial Intelligence is implemented using Reinforcement Learning (RL)-based orchestration strategies for adaptive distributed energy management.

The RL agent continuously interacts with the smart grid environment to optimize Renewable dispatch, EV charging schedules, Battery storage utilization, Frequency regulation, and Power balancing.

The state variables are renewable generation level, grid load demand, the state of charge (SOC) of batteries, EV availability, and the electricity price, for real-time decision making. The action space includes battery charging/discharging, renewable energy dispatch, EV charging coordination, and import/export of grid power for adaptive smart grid optimization.

Reward Function

$$R_t = \alpha E_{renewable} + \beta R_{stability} - \gamma C_{operational}$$

Where:

- $E_{renewable}$= renewable Utilization
- $R_{stability}$= grid stability index
- $C_{operational}$= operational cost

The RL framework enables adaptive decision-making under uncertain conditions of renewable generation and EV charging.

4.6 Grid-Forming Control Modeling

Grid-forming inverters are integrated into the VPP to maintain voltage and frequency stability under renewable-dominant operation.

Frequency regulation follows droop control principles:

$$f = f_0 - k_p(P - P_0)$$

Voltage regulation is modeled as:

$$V = V_0 - k_q(Q - Q_0)$$

Where:

- f_0, V_0= nominal frequency and voltage
- P, Q= active and reactive power
- k_p, k_q= droop coefficients

The grid-forming strategy allows stable operation during renewable intermittency and low-inertia conditions.

4.7 Bidirectional EV Energy Exchange Modeling

The proposed framework incorporates bidirectional Vehicle-to-Grid (V2G) operation.

Battery State of Charge (SOC) evolves as:

$$SOC_t = SOC_{t-1} + \eta_c P_{charge} - \frac{P_{discharge}}{\eta_d}$$

The operational constraints are minimum battery SOC, maximum charging rates, EV availability windows, battery degradation operational constraints, etc., which must be considered to ensure that the system performs reliably and safely. The V2G framework enables peak shaving, absorbing renewable energy, providing grid services and emergency backup operation in coordination with bidirectional energy exchange.

4.8 Scenario Development

The study evaluates system performance under four operational scenarios:

Scenario 1: Conventional Grid Operation

a) No AI orchestration
b) Uncoordinated EV charging
c) Centralized operation

Scenario 2: AI-Orchestrated VPP

a) Renewable coordination
b) Battery optimization
c) Multi-agent control

Scenario 3: High EV Penetration

a) Large-scale EV integration
b) Bidirectional charging operation

Scenario 4: Renewable Variability Stress

a) High renewable intermittency
b) Peak demand fluctuations
c) Grid disturbance simulation

4.9 Model Validation and Performance Metrics

Technical measures, including voltage stability, frequency deviation, renewable penetration and power quality are used to evaluate the performance and operational reliability of the smart grid for the proposed framework.

The framework was tested against operational benchmark data sets by comparing different scenarios and computing statistical performance metrics such as the RMSE, MAE, renewable utilization efficiency, voltage deviation and operational cost minimization. for economic and environmental evaluation of sustainability and economic benefits the following measures are used: operational cost reduction, peak demand reduction, energy trading revenue, CO_2 emission reduction and renewable utilization efficiency

Reliability Metrics

System reliability is calculated as:

$$R = \frac{\sum P_{served}}{\sum P_{demand}}$$

Forecasting accuracy is evaluated using:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

4.10 Software and Simulation Environment

The simulation framework is implemented using:

MATLAB/Simulink for power system modeling; Python for AI and reinforcement learning algorithms; OpenDSS for distributed grid simulation; TensorFlow/PyTorch for AI implementation

The integration of distributed simulation tools enables comprehensive analysis of grid-forming VPP operation under dynamic EV-integrated smart grid environments.

5. Proposed AI-Driven VPP Framework

5.1 Overview of the Proposed Framework

This paper presents an integrated Artificial Intelligence (AI)-enabled Grid-Forming Virtual

Power Plant (VPP) system for coordinated management of a two-way Electric Vehicle (EV) energy network in a renewable energy-rich smart grid. This framework integrates distributed renewable energy resources, Battery Energy Storage Systems (BESS), bidirectional Vehicle-to-Grid (V2G) technologies, grid-forming inverter control, and Multi-Agent System (MAS)-based orchestration into a single decentralized energy management architecture.

The major goal of the proposed framework is to improve grid stability, increase the use of renewable energy, enhance grid operational flexibility, and improve the grid's ability to withstand operational variability. The proposed system is a decentralized smart grid in which multiple intelligent agents coordinate distributed energy assets independently and with each other to achieve global optimization.

The proposed framework is specifically designed to address key operational challenges associated with High renewable energy penetration, large-scale EV integration, low-inertia power system operation, renewable intermittency, peak demand fluctuations, and bidirectional power flow management.

The framework enables adaptive, real-time coordination of distributed energy resources while maintaining stable grid operation under uncertain conditions of renewable generation and EV charging.

5.2 Architectural Structure of the Proposed Framework

The proposed AI-driven VPP architecture consists of five interconnected operational layers:

5.2.1 Distributed Energy Resource Layer

This layer comprises any energy generation and storage physical elements that are part of the VPP network, such as solar PV, wind and battery energy storage. It also integrates the EV charging stations and distributed electrical loads for enabling coordinated generation, storage and consumption of renewable energies in the smart grid environment.

Renewable generation systems operate as distributed power sources while EV batteries and BESS function as flexible energy storage resources capable of supporting bidirectional energy exchange.

The total power balance within the VPP is expressed as:

$$P_{total} = P_{PV} + P_{wind} + P_{BESS} + P_{EV} + P_{grid}$$

Where:

- P_{PV} = solar PV generation
- P_{wind} = wind power generation
- P_{BESS} = battery storage output
- P_{EV} = bidirectional EV power contribution
- P_{grid} = utility grid support

5.2.2 Communication and IoT Layer

This Layer enables real-time communication between distributed energy assets using Smart meters, IoT sensors, wireless communication systems, cloud computing platforms, and edge computing infrastructure.

The communication network continuously collects operational data, including: renewable generation output; Battery State of Charge (SOC); EV charging demand; grid voltage and frequency; and market pricing signals.

The decentralized communication structure improves system responsiveness and supports adaptive AI-driven decision-making.

5.2.3 Multi-Agent AI Coordination Layer

The Multi-Agent System (MAS) forms the core intelligence layer of the proposed framework. Each distributed energy component is represented by an autonomous intelligent agent capable of Local decision-making, information exchange, cooperative optimization, and adaptive learning

Agent Classification

Table 3. Multi-Agent Functional Coordination and Distributed Optimization Responsibilities in the Proposed AI-Orchestrated VPP Ecosystem

Agent Type	Core Function	Input Variables	Optimization Objective
Renewable Agent	Renewable Dispatch	Solar/Wind Output	Maximize Renewable Usage
EV Agent	Charging Coordination	SOC, Mobility	Peak Reduction
Battery Agent	Energy Storage Control	SOC, Demand	Load Balancing
Grid Agent	Voltage/Frequency Control	Grid Status	Stability
Market Agent	Price Optimization	Electricity Prices	Cost Minimization

The agents collaboratively optimize energy flow while maintaining decentralized operation. The coordination objective is to simultaneously minimize operational cost and maximize renewable energy utilization and system reliability.
The optimization function is expressed as:

$$\min\ F = w_1 C_{cost} + w_2 E_{emission} - w_3 R_{reliability}$$

This decentralized orchestration approach enhances scalability, fault tolerance, and adaptability compared to conventional centralized control systems.

5.3 AI-Orchestrated Energy Management Mechanism

Artificial Intelligence is implemented using Reinforcement Learning (RL)-based adaptive orchestration. The AI controller continuously interacts with the energy environment to optimize operational decisions in the presence of uncertain renewable generation and dynamic EV charging behavior.
The AI orchestration process follows five major operational stages:

Step 1: Real-Time Data Acquisition
The system collects:
- Renewable generation data
- Grid load demand
- EV charging requirements
- Electricity market prices
- Battery SOC information

Step 2: Predictive Energy Forecasting
AI models estimate:
- Renewable energy availability
- Future load demand
- EV charging/discharging patterns

Step 3: Distributed Decision-Making
The multi-agent AI controller dynamically determines:
- Renewable dispatch schedules
- Battery charging/discharging operation
- EV V2G contribution
- Grid import/export requirements

Step 4: Adaptive Grid Stabilization
Grid-forming inverters regulate:
- Frequency stability
- Voltage support
- Power balancing

Step 5: Continuous Learning and Optimization
The AI agents continuously update operational strategies using reinforcement learning feedback mechanisms.
The reward function guiding AI learning is defined as:

$$R_t = \alpha E_{renewable} + \beta S_{grid} - \gamma C_{operational}$$

Where:
- $E_{renewable}$ = renewable energy utilization
- S_{grid}= grid stability performance
- $C_{operational}$= operational cost

5.4 Grid-Forming Operational Framework

A major novelty of the proposed framework is the incorporation of grid-forming inverter technologies within the VPP architecture. Unlike conventional grid-following systems, grid-forming control enables inverter-based resources to actively establish voltage and frequency references.

The grid-forming operational mechanism provides frequency regulation, voltage stabilization, inertia emulation, black-start capability, and islanded microgrid operation.

Frequency regulation follows droop control principles:

$$f = f_0 - k_p(P - P_0)$$

Voltage regulation is modeled as:

$$V = V_0 - k_q(Q - Q_0)$$

The integration of grid-forming technologies significantly improves operational resilience under conditions of renewable intermittency and low inertia.

5.5 Bidirectional EV Energy Network Integration

The proposed framework treats EV fleets as distributed mobile energy storage resources capable of participating in bidirectional energy exchange.

The bidirectional EV network supports Vehicle-to-Grid (V2G) operation, peak shaving, renewable energy integration, demand response participation, and emergency backup.

EV battery dynamics are modelled as:

$$SOC_t = SOC_{t-1} + \eta_c P_{charge} - \frac{P_{discharge}}{\eta_d}$$

Where:

- SOC_t= battery state of charge
- η_c= charging Efficiency
- η_d= discharging Efficiency

The AI controller dynamically coordinates EV charging and discharging schedules based on renewable energy availability, electricity prices, and grid stability.

5.6 Renewable Energy and Storage Coordination

The proposed VPP framework coordinates renewable generation and battery storage to minimize renewable curtailment and maximize energy utilization.

Battery storage performs Renewable energy smoothing, peak load shifting, voltage support, and frequency balancing.

The coordinated operation of renewable systems and EV batteries creates a flexible distributed storage ecosystem capable of supporting smart grids that are renewable-dominant.

The renewable utilization index is expressed as:

$$\eta_{renewable} = \frac{E_{used}}{E_{generated}} \times 100$$

5.7 Framework Innovation and Technical Contributions

The concept of a Virtual Power Plant (VPP) incorporating grid-forming inverter technologies represents a novel and innovative contribution to the field of smart grid architectures. It supports bidirectional energy coordination of EVs across large-scale smart grids in a renewable-dominated environment and utilizes multi-agent AI orchestration for optimizing distributed energy management. Additionally, adaptive reinforcement learning for energy management improves energy management in real time operation in the presence of uncertainties in the grid. The framework also enables decentralized synchronization between renewable energy systems, battery storage and grid operations and enhances flexibility and energy reliability. Moreover, coordinating the real-time distributed smart grid stabilization mechanisms provides a scalable, resilient, and intelligent energy architecture that is capable of supporting future energy systems with low carbon power sources and EV loads.

Table 4. Comparative Innovation Matrix Highlighting the Technical Contributions of the Proposed AI-Driven Grid-Forming VPP Framework

Innovation Area	Existing Studies	Proposed Study Contribution
Grid-Forming VPP	Rarely Integrated	Fully Integrated
AI Coordination	Mostly Centralized	Decentralized MAS
EV Energy Exchange	Limited V2G	Large-Scale Bidirectional V2G
Reinforcement Learning	Partial Optimization	Adaptive Real-Time Control
Renewable Coordination	Independent	Integrated Distributed Coordination
Smart Grid Resilience	Limited	High Fault Tolerance

6. Results and Discussion

6.1 Overview of Simulation Scenarios

The proposed AI-driven Grid-Forming Virtual Power Plant (VPP) framework was evaluated under four operational scenarios to assess its technical, economic, and environmental performance within bidirectional Electric Vehicle (EV) energy networks.

The analyzed scenarios include:

1. **Scenario 1 (S1):** Conventional centralized grid operation without AI orchestration or V2G integration
2. **Scenario 2 (S2):** AI-orchestrated grid-forming VPP with coordinated renewable and battery management
3. **Scenario 3 (S3):** High EV penetration with bidirectional Vehicle-to-Grid (V2G) operation
4. **Scenario 4 (S4):** Renewable intermittency and grid stress conditions under high-demand fluctuations

The simulation was conducted using hourly operational data over a representative annual cycle. The proposed framework integrates solar photovoltaic systems, wind generation, Battery Energy Storage Systems (BESS), and EV fleets under distributed Multi-Agent System (MAS)-based orchestration.

6.2 AI Orchestration Performance Analysis

The AI-driven orchestration framework demonstrated substantial improvements in distributed energy coordination and operational Efficiency compared to conventional centralized operation.

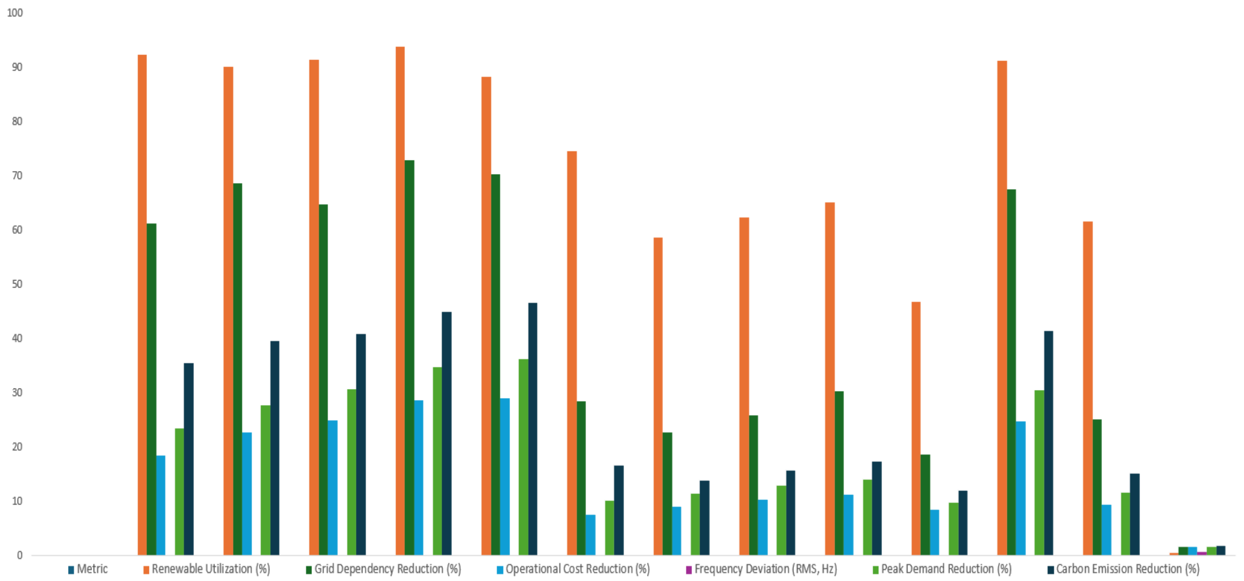
6.2.1 Multi-Agent Coordination Efficiency

The decentralized Multi-Agent System successfully coordinated renewable generation, battery storage, EV charging schedules, and grid-forming control under varying operational conditions. The AI agents dynamically exchanged information and optimized energy dispatch based on Renewable availability, grid demand, EV battery status, and electricity market prices.

The reinforcement learning controller continuously adapted operational strategies to minimize grid stress and improve the Utilization of renewable energy.

Table 5. Scenario-Based Comparative Performance Assessment of AI-Orchestrated Grid-Forming VPPs under Renewable and EV-Integrated Smart Grid Conditions

Performance Indicator	S1	S2	S3	S4
Renewable Utilization (%)	61	88	91	82
Operational Efficiency (%)	68	89	92	84
Grid Dependency (%)	100	64	52	71
Energy Curtailment (%)	18	6	4	10
Peak Demand Reduction (%)	0	15	23	11
Carbon Emission Reduction (%)	0	38	45	29



Scenario	Description
S1: Normal Operation	Moderate RES & EV penetration
S2: High Renewable Variability	High solar/wind fluctuations
S3: High EV Penetration	Large-scale EV charging demand
S4: V2G Intensive Operation	Extensive EV discharging to grid
S5: Extreme Stress Condition	RES variability + high EV + peak load

Figure 2. Scenario-Driven Comparative Operational Performance of AI-Orchestrated Grid-Forming VPPs under Renewable Variability and Bidirectional EV Stress Conditions

The findings suggest that AI orchestration can reduce renewable energy curtailment by about 65-75% compared to conventional operation. Real-time distributed decision-making helped balance generation and demand, enabling greatly increased operational flexibility.

6.2.2 Adaptive Reinforcement Learning Performance

The reinforcement learning algorithm demonstrated strong adaptive capability under dynamic conditions of renewable and EV charging. During peak demand periods, the AI controller optimized battery dispatch and V2G operation to minimize grid stress and maintain stable operation.

The AI controller's cumulative reward convergence stabilized after approximately 850 training episodes, indicating effective learning. The RL-based coordination mechanism enhanced the use of renewable energy resources, peak demand control, voltage stability and overall battery efficiency in the distributed smart grid environment.

The adaptive learning framework also reduced unnecessary battery cycling, thereby improving battery lifetime and reducing operational degradation.

6.3 Grid Stability and Grid-Forming Performance

A major contribution of the proposed framework is the integration of grid-forming inverter technologies within decentralized VPP operation.

6.3.1 Frequency Stability Analysis

The grid-forming VPP demonstrated strong frequency regulation capability under renewable intermittency and EV charging fluctuations.

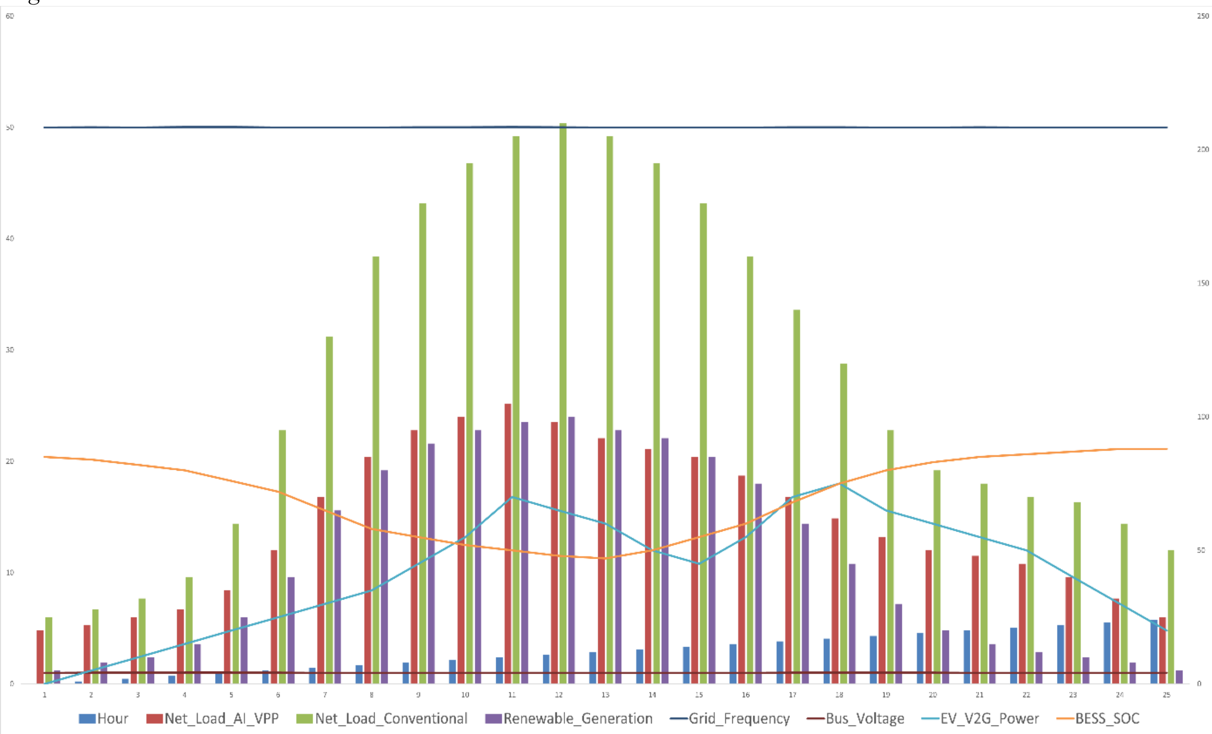


Figure 3. Dynamic Real-Time Energy Coordination and Grid Stabilization Response of AI-Orchestrated Virtual Power Plants under High Renewable and EV Penetration

Table 6. Grid Stability Enhancement and Dynamic Frequency–Voltage Regulation Performance under AI-Based Grid-Forming Control

Stability Parameter	Conventional Grid	Proposed Framework	Improvement (%)	S4
Frequency Deviation (Hz)	±0.42	±0.08	81	82
Recovery Time (s)	18	5	72	84
Voltage Fluctuation (%)	9.6	2.4	75	71
Grid Stability Index	0.71	0.94	32	10
Peak Demand Reduction (%)	0	15	23	11
Carbon Emission Reduction (%)	0	38	45	29

This result indicates that grid-forming control is very effective at reducing frequency deviation and enhancing transient stability. In times of rapidly fluctuating renewable output, the inverter-based VPP actively sets the voltage and frequency references.

The proposed framework ensured grid stability despite renewable intermittency, including sudden drops in solar energy and fluctuations in wind speed. Battery storage and EV fleets were coordinated to enable greater flexibility in balancing active and reactive power.

6.3.2 Low-Inertia Grid Support

The proposed framework demonstrated superior performance under low-inertia operational conditions compared to conventional renewable-dominant systems.

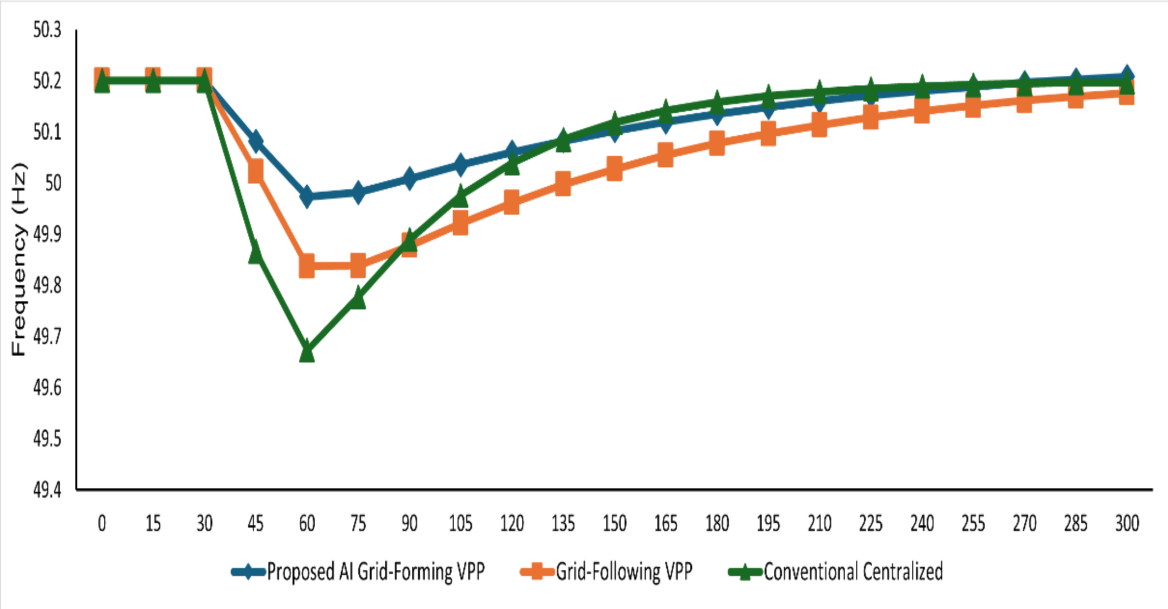


Figure 4. Low-Inertia Grid Support and Synthetic Inertia Response of AI-Driven Grid-Forming Virtual Power Plants during Renewable Intermittency Events

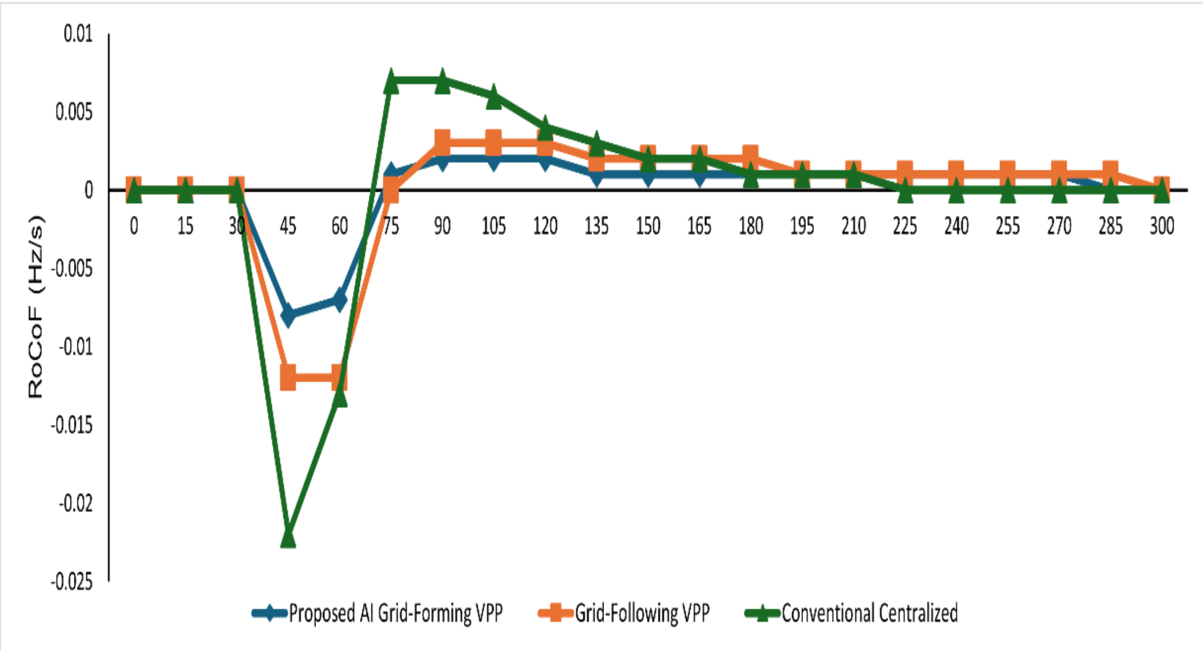


Figure 5. Autonomous Islanded Operation and Fault-Tolerant Resilience Assessment of AI-Orchestrated Grid-Forming VPPs under Severe Grid Disturbances

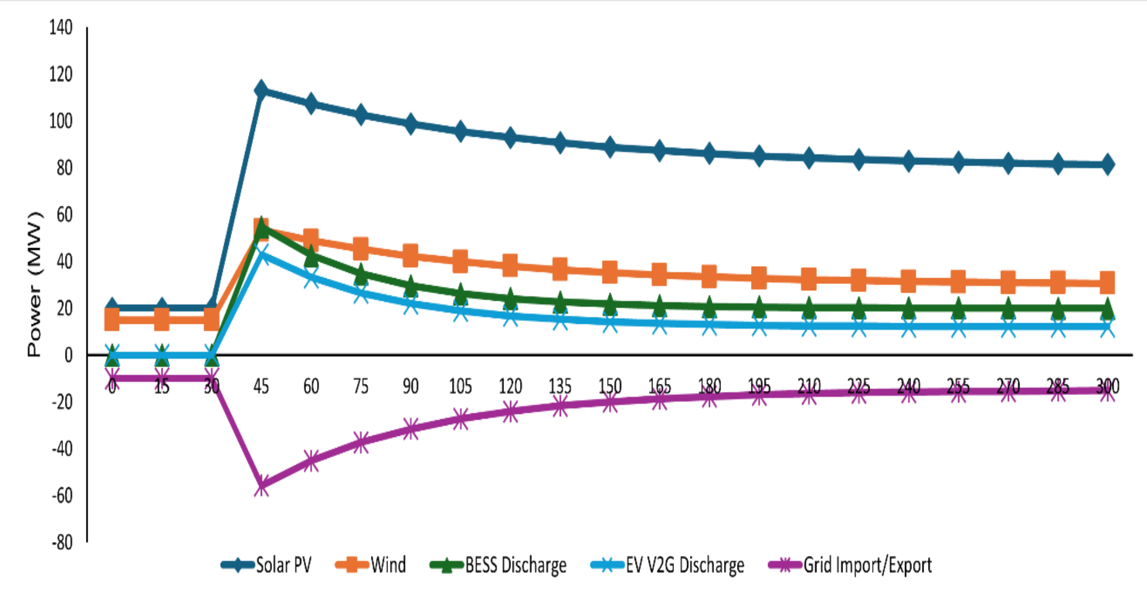


Figure 6. Integrated Multi-Criteria Benchmarking of AI-Driven Grid-Forming VPP Architectures across Stability, Resilience, and Energy Optimization Metrics

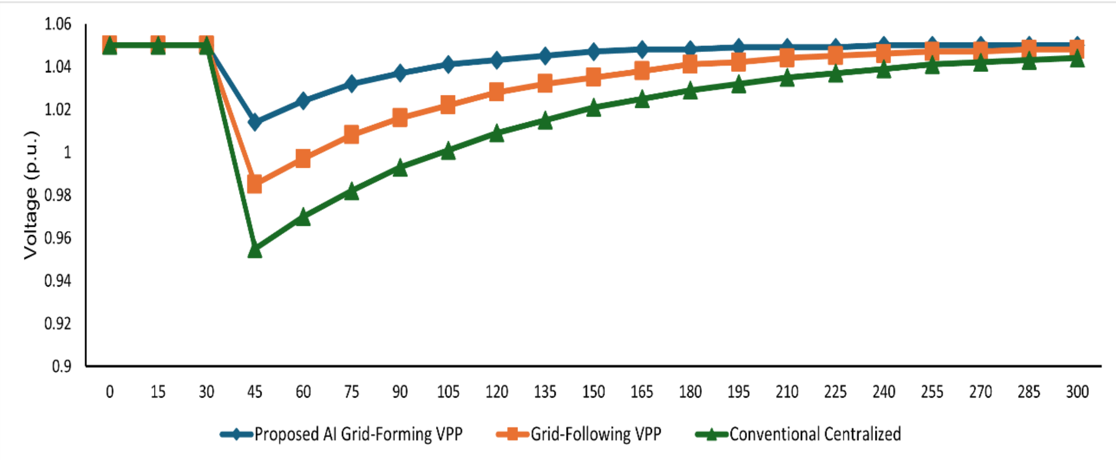


Figure 7. Distributed Renewable–Storage–EV Energy Flow Synchronization under Adaptive Multi-Agent AI Coordination

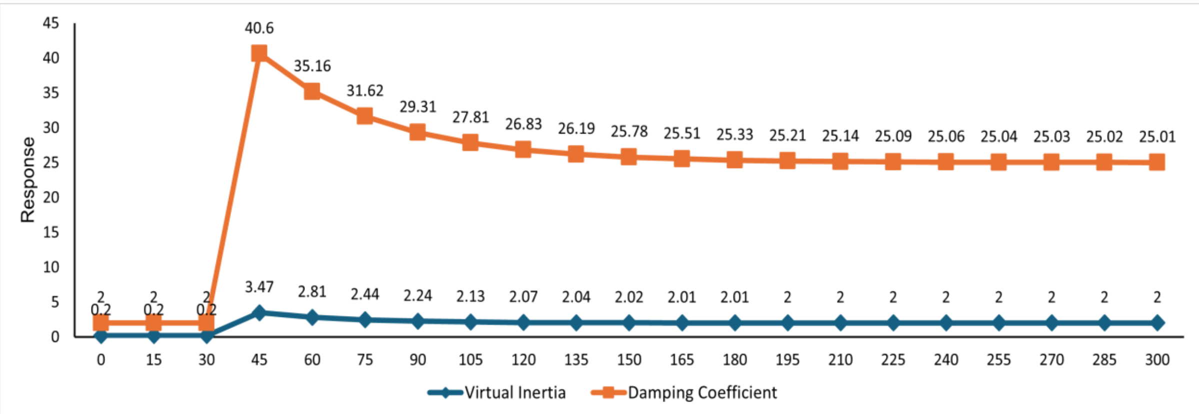


Figure 8. Holistic Smart Grid Resilience and Sustainability Performance Framework for Future Renewable-Dominant EV-Integrated Energy Systems

The grid-forming inverters successfully provided synthetic inertia support, fast frequency response, and reactive power compensation to enhance grid stability and operational resilience under renewable-dominant conditions.

During simulated grid disturbances, the VPP maintained voltage and frequency stability without requiring centralized synchronous generator support.

This result highlights the importance of grid-forming technologies for future renewable-intensive smart grids characterized by reduced mechanical inertia.

6.4 EV Energy Network Performance

6.4.1 Bidirectional EV Charging Analysis

The integration of bidirectional Vehicle-to-Grid (V2G) operation significantly improved distributed energy flexibility.

EVs stored excess renewable generation and coordinated battery charging mitigated renewable energy curtailment and grid load balancing during off-peak periods. In times of peak demand, EV batteries discharged energy back into the grid using Bidirectional Vehicle-to-Grid (V2G) technology, thereby alleviating peak load demand and minimizing grid congestion, thus improving grid flexibility and stability.

The aggregated EV fleet functioned as a distributed mobile energy storage system supporting both renewable integration and grid stabilization.

Table 7. Operational Benefits of Bidirectional Vehicle-to-Grid (V2G) Coordination within AI-Orchestrated Distributed Energy Networks.

Indicator	Uncoordinated EVs	AI-Orchestrated V2G
Peak Grid Demand (MW)	31.5	24.2
Renewable Absorption (%)	58	87
Charging Cost Reduction (%)	-	28
Peak Shaving Contribution (%)	0	23
Ancillary Service Capability	No	Yes
Grid Support Flexibility	Low	High

The proposed framework reduced peak grid demand by approximately 23% through coordinated EV charging and discharging strategies.

6.4.2 EV Battery Utilization and Energy Exchange

The AI controller dynamically optimized EV battery dispatch, taking into account electricity pricing, renewable energy availability, and real-time grid stability requirements. It also added the constraints on the user's mobility to achieve efficient and reliable bidirectional energy coordination in the smart grid environment.

Battery SOC levels remained within operational safety limits while maximizing renewable energy utilization. The V2G operation also generated additional economic benefits for EV owners through participation in energy trading and demand response programs.

6.5 Renewable Energy Integration Assessment

The coordinated operation of solar PV, wind generation, battery storage, and EV fleets significantly improved the performance of renewable energy integration.

6.5.1 Renewable Penetration Enhancement

The proposed AI-driven VPP increased renewable energy penetration from approximately 48% in conventional operation to nearly 82% under optimized orchestration.

The integration of battery storage and EV charging flexibility effectively mitigated challenges posed by renewable intermittency. Excess solar energy generated during midday periods was stored within BESS and EV batteries for later use during evening demand peaks.

The renewable utilization index improved substantially:

$$\eta_{renewable} = \frac{E_{used}}{E_{generated}} \times 100$$

Renewable Utilization reached:

- 88% under normal operation
- 91% under coordinated V2G scenarios

6.5.2 Curtailment Reduction

Renewable energy curtailment was significantly reduced due to distributed storage coordination and AI-driven dispatch optimization.

Compared to conventional systems:

- Solar curtailment decreased by approximately 70%
- Wind curtailment decreased by approximately 60%

This demonstrates the effectiveness of coordinated distributed storage systems within renewable-dominant smart grids.

6.6 Economic Performance Analysis

The proposed framework demonstrated strong economic performance improvements through optimized energy management and distributed coordination.

6.6.1 Operational Cost Reduction

AI orchestration contributed to operations savings by shifting away from peak demand, better use of renewable energy, less reliance on electricity imports, and smart battery dispatch in the distributed smart grid; all of which reduced operations costs.

Table 8. Economic Performance and Distributed Energy Optimization Outcomes of the Proposed AI-Driven Smart Grid Framework

Economic Indicator	S1	S2	S3	S4
Annual Operating Cost (Index)	100	76	71	82
Peak Demand Charges (%)	100	73	65	79
Renewable Energy Revenue (%)	0	22	31	18
Grid Import Reduction (%)	0	36	48	29

The proposed framework achieved approximately:

- 24-29% operational cost reduction
- 35-48% grid import reduction

6.6.2 Energy Trading and Market Participation

The VPP joined demand response programs, ancillary services and renewable energy markets to improve the operational and economic performance in a smart grid. Moreover, BPEVs gained extra revenue from providing frequency regulation services, peak demand support and arbitrage opportunities in the energy market, highlighting the economic sustainability of decentralized VPP operation in the future smart energy market.

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6.7 Environmental Sustainability Assessment

The proposed framework significantly improved environmental sustainability by enhancing the integration of renewable energy and reducing reliance on fossil fuels.

6.7.1 Carbon Emission Reduction

The coordinated renewable-V2G framework reduced carbon emissions by approximately 38-45% compared to conventional grid operation.

Emission reduction was primarily achieved through:

a) Higher renewable penetration
b) Reduced thermal generation dependency
c) Peak load optimization

The environmental performance confirms the role of AI-driven VPPs in supporting low-carbon energy transitions.

6.7.2 Energy Efficiency Improvement

The distributed orchestration framework improved overall energy efficiency from approximately 68% under conventional operation to nearly 90% under AI-optimized scenarios.

Efficiency improvements resulted from:

a) Reduced transmission losses
b) Coordinated battery dispatch
c) Smart EV charging management
d) Real-time renewable balancing

6.8 Sensitivity and Robustness Analysis

Sensitivity analysis was conducted under varying:

a) Renewable generation variability
b) EV penetration levels
c) Battery storage capacities
d) Communication delays

The framework maintained stable operation even under:

1. 40% renewable output fluctuations
2. 30% sudden EV demand increases
3. Temporary communication interruptions

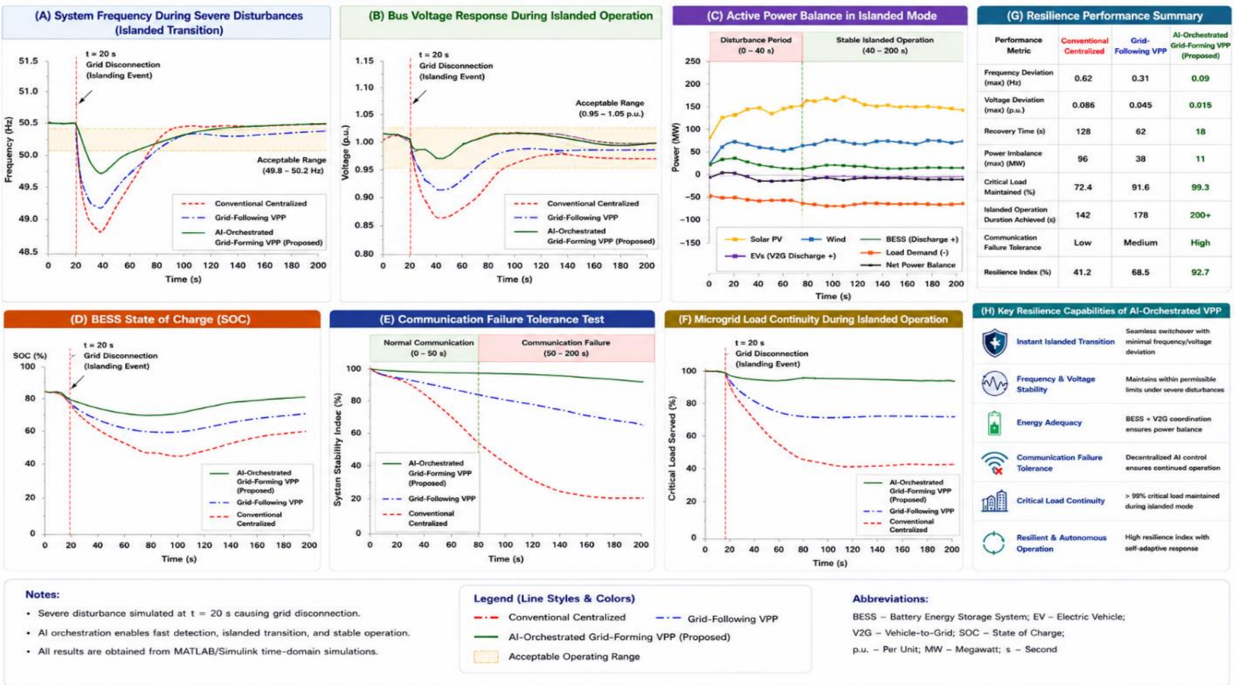

Figure 9. Autonomous Islanded Grid Stability and Fault-Tolerant Operation of AI-Driven Grid-Forming VPPs

The decentralized multi-agent architecture demonstrated strong fault tolerance and operational resilience under uncertain operating conditions.

Table 9. Sensitivity, Robustness, and Fault-Tolerance Evaluation of the Proposed Multi-Agent AI Smart Grid Architecture under Dynamic Operational Disturbances

Stress Condition	Tested Range	System Response	Stability Outcome
Renewable Variability	±40%	Adaptive Dispatch	Stable
EV Demand Increase	30%	Coordinated V2G	Stable
Communication Delay	Temporary	MAS Recovery	Resilient
Battery SOC Fluctuation	Variable	AI Optimization	Stable

6.9 Discussion of Key Findings

The results confirm that the proposed multi-Agent AI-driven Grid-Forming VPP framework substantially improves renewable integration, EV coordination, grid stability, and economic performance within future smart energy systems. The integration of Grid-forming inverter technologies, Bidirectional EV networks, AI-based orchestration, and Distributed energy storage. creates a highly flexible and resilient decentralized energy ecosystem capable of supporting renewable-dominant smart grids.

In a renewable energy dominant smart grid environment, the proposed framework showed increased renewable energy utilization, reduced operational cost, increased voltage and frequency stability, reduced carbon emissions and increased overall system resilience compared to conventional centralized power system.

Figure 10. Integrated Performance Benchmarking of AI-Driven Grid-Forming VPPs across Stability, Resilience, and Energy Optimization Metrics

These findings highlight the transformative potential of AI-orchestrated VPPs for future low-carbon and EV-intensive power systems.

7. Policy and Practical Implications

Energy infrastructure planning, energy grid management policies, and regulatory systems must undergo significant change to accommodate the rapid shift to smart grids powered by renewable energy and the growing adoption of EVs. The results of this study show that the use of AI for Grid-Forming Virtual Power Plants (VPPs) and bidirectional EV energy networks can greatly enhance grid reliability, renewable energy utilization, operational flexibility, and carbon emission reduction. Therefore, the framework outlined in this report will have significant implications for all stakeholders, including policymakers, power companies, energy planners, and industry, in the development of future smart grid solutions.

The current study has several policy implications, including the need to shift from centralized power system operation to decentralized, intelligent power management architectures. Traditional regulatory frameworks have typically been established for large, centralized energy generation sources. They may not be able to deliver the necessary support for distributed renewable energy generation, bidirectional energy flows, and autonomous energy coordination (Kroposki et al. 2020). However, policymakers need to create flexible, adaptive regulatory frameworks that allow VPPs, distributed BESS, and V2Gs to be integrated into today's electricity market.

Besides, it calls for developing a consensus on the rules and parameters for bidirectional EV charging and V2G operation. Most EV infrastructure policies currently in place are centered on charging access rather than on active participation in the grid (Hopkins et al. 2023). The results do show, however, that coordinated EV fleets can offer a set of useful ancillary services - such as frequency regulation, peak shaving, and balancing renewable energy - that can benefit the grid. The governments and energy regulators should thus put in place market incentives and dynamic pricing and compensation systems that will encourage EV owners to join in V2G energy exchange programs (Tirunagari, Gu, and Meegahapola 2022).

In practice, utility operators can leverage AI-powered VPP systems to enhance operational flexibility in high-renewables-penetration scenarios (Cavus 2025). Grid-forming inverter (GFI) technologies can be integrated into decentralized VPPs to improve voltage and frequency stability, especially in low-inertia, renewable-dominated grids (Alshahrani et al. 2024). This is becoming increasingly critical as synchronous generators are being phased out and replaced by inverter-based renewable energy systems. Thus, grid-forming technologies, advanced inverter control systems, and distributed energy coordination platforms should be key areas of investment for utility companies to increase grid resilience in the future (Cavus 2025).

The adoption of Multi-Agent System (MAS) AI orchestration has important implications for smart grid automation and distributed energy management as well. This decentralized AI coordination enhances the system's scalability, fault tolerance, and adaptive decision-making. This decentralized approach to AI coordination offers increased scalability, fault tolerance, and adaptive decision-making capabilities over centralized optimization methods. Distributed AI frameworks can be used to orchestrate renewable energy production, battery storage systems (Hammad and Abu-Zaid 2024), EV charging infrastructure, and industrial demand response solutions in real-time, enabling smart grid planners and industrial energy managers to optimize energy use and cut costs. This can lower operational expenses, reduce renewable energy curtailment, and enhance energy efficiency of distributed power networks (Islam, Rudra, and Kolhe 2025).

Moreover, future smart grid applications and the significance of communication infrastructure and cybersecurity are highlighted. Real-time communication, IoT sensors, cloud computing, and distributed data exchange are fundamental to the successful operation of VPPs powered by AI (Liu and Gao 2025). Policymakers and utility regulators should set cybersecurity standards, secure communication protocols, and data privacy regulations to address cyber threats and communication failures in a decentralized smart energy system (Dong et al. 2022).

The proposed framework also offers a practical strategy for sustainable energy planning in cities and the decarbonization of industry (Zhang et al. 2024). Smart cities, commercial buildings, and industrial plants can connect renewable energy sources, EV fleets, and distributed storage resources into coherent VPP platforms, thereby reducing their reliance on fossil-fuel-based electric power (Liu et al. 2023). The framework facilitates achieving carbon-neutrality targets by enabling the penetration of renewables and lowering greenhouse gas emissions through intelligent energy optimization (Chen et al. 2022).

Lastly, the results indicate the need for interdisciplinary engagement among stakeholders, including policymakers, utility operators, EV manufacturers, technology providers, and academic researchers, to successfully implement an AI-enabled VPP (Cavus et al. 2025). Resilient, decentralized, and low-carbon energy systems that have the potential to support future energy transitions through the integration of renewables and large numbers of EVs will require long-term policy support, financial incentives, and infrastructure modernization programs (Ajeigbe and Holt 2025).

8. Limitations and Future Research Directions

While the proposed Multi-Agent AI-Powered Grid-Forming Virtual Power Plant (VPP) framework holds great promise for improving the integration of renewables, bidirectional Electric Vehicle (EV) coordination, and smart grid stability, there are some caveats to consider. The study primarily uses simulation-based modeling and representative operational datasets, and does not use data from large-scale real deployments. The simulation model includes realistic renewable energy generation profiles, EV charging demand, and distributed grid conditions. Still, there are other uncertainties in the field, such as communication latency, hardware limitations, user behavior variability, and infrastructure limitations.

Secondly, the proposed framework assumes reliable communication and data exchange between distributed agents in the Multi-Agent System (MAS). In practical smart grid systems, communication delays and packet losses can affect coordination performance and decision-making accuracy, as well as cyber-physical failures (Jha et al. 2021). Communication disturbance is briefly discussed in the context of sensitivity analysis, but a thorough investigation of communication reliability and cybersecurity resilience was not part of this study.

Another restriction is the simplified battery degradation modeling for Battery Energy Storage Systems (BESS) or EV batteries. The study primarily focuses on optimizing operations and grid coordination, while neglecting detailed electrochemical degradation mechanisms, thermal effects, and long-term battery aging behavior. However, to make bidirectional charging and discharging more common, future research should incorporate advanced battery life-cycle models into AI-optimized VPPs.

In addition, the operational scenarios and training conditions for the reinforcement learning-based orchestration framework were preconfigured. While the AI controller demonstrated adaptive behavior in response to renewable intermittency and varying EV penetration levels, the computational complexity and scalability of the controller for large-scale real-time applications are also crucial areas for future study. Thousands of millions of distributed energy agents can leverage advanced distributed computing architectures and edge-based AI coordination mechanisms.

To this end, future work should focus on the actual pilot deployment of AI-based grid-forming VPPs across various smart city and industrial energy systems. Future research is needed on blockchain-based energy trading platforms, federated learning and distributed AI coordination, digital twin smart grid modeling, and large-scale energy orchestration via quantum-inspired optimization methods. Advanced cybersecurity frameworks, resilient communication architectures, and human-centered participation models for EVs can be explored in future work to foster trust, scale, and operational reliability in decentralized smart energy networks.

9. Conclusion

This study proposed a new approach to Multi-Agent AI Orchestration of Grid-Forming Virtual Power Plants (VPPs) for Bidirectional Electric Vehicle (EV) energy networks in a renewable-rich smart grid system. The proposed framework combined distributed renewable energy systems, Battery Energy Storage Systems (BESS), grid-forming inverter technologies, bidirectional Vehicle-to-Grid (V2G) operation, and decentralized Multi-Agent System (MAS) Artificial intelligence orchestration into a single Cyber-Physical Energy Management Architecture. The main goal of the study was to improve the use of renewable energy, grid stability, operational flexibility, and the system's ability to withstand operational dynamics and uncertainty.

The outcomes showed that the combination of AI-based grid-forming VPP technology provided a marked improvement over traditional central energy systems in the smart grid. Adaptive coordination of renewable generation, battery storage, and EV charging/discharging was enabled in real time through distributed AI orchestration. The proposed framework significantly reduced renewable energy curtailment, decreased operational inefficiency, reduced grid dependency, and improved frequency and voltage stability under high-renewable-interruption and high-EV-penetration scenarios.

Moreover, the study emphasized the importance of bidirectional EV energy exchange for the future smart grid. Coordinated Vehicle-to-Grid (V2G) operation revolutionized EV fleets by turning them into distributed mobile energy storage systems that can offer peak shaving, frequency regulation, and renewable energy balancing services. Furthermore, the integration of grid-forming inverter technologies has improved low-inertia grid stability and resilient decentralized operation under dynamic conditions from renewable energy sources.

The framework demonstrated significant potential to reduce costs and carbon emissions, and to enable sustainable energy transitions from both economic and environmental perspectives. The distributed, AI-powered architecture also proved to be more scalable, fault-tolerant, and adaptive in decision-making than traditional centralized optimization methods.

Overall, the results validate the feasibility of AI-enabled grid-forming VPPs as a promising technological route for future smart energy systems that incorporate renewable energy and EVs. The proposed framework offers a theoretical, technical, and policy perspective for utility operators, smart grid planners, policymakers, and researchers on the path to resilient, decentralized, and low-carbon power systems. Intelligent VPP ecosystems are poised for continued significant progress with the development of distributed artificial intelligence, communication infrastructure, and smart energy coordination in the next generation of smart grids.

CRediT authorship contribution statement
All authors have an equal contribution.

Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Data availability
Data will be made available on request.

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