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Analysis of virtual power plant performance for voltage stability in distribution networks with high DER penetration using PowerFactory-Python co-simulation: An Aotearoa New Zealand case study

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Abstract

The way power systems operate is being reshaped by the high penetration of distributed energy resources (DERs) such as rooftop solar, batteries and electric vehicles in low-voltage distribution networks. These technologies, although beneficial for decentralization and decarbonization, pose significant technical challenges-including voltage rise, frequency fluctuations and bidirectional power flow. Virtual Power Plants (VPPs) are emerging as a promising framework to aggregate, manage and optimize the operation of DERs through intelligent control and coordination. The objective of this research is to analyse the use of Virtual Power Plants (VPPs) to coordinate DERs and enhance voltage stability in low-voltage distribution networks. The study uses an IEEE 13-bus test feeder, modelled in DIgSILENT PowerFactory, incorporating photovoltaic generation, battery energy storage systems, and electric vehicle loads under varying penetration levels. A PowerFactory-Python co-simulation framework is developed using a supervisory iterative approach, where quasi-dynamic simulations are analysed and used to update the control setpoints across successive runs. The results demonstrate that coordinated control of DERs can significantly improve voltage profiles, with voltage levels reduced from peak values above 1.05 pu within limits of approximately 0.99–1.03 pu. Battery energy storage systems provide effective voltage support, while demand-response flexible loads and photovoltaic curtailment act as a secondary control measure. However, the approach is constrained by limited storage capacity and the lack of real-time control implementation. To address these limitations, a reinforcement learning-based control framework is proposed as a future enhancement for adaptive and scalable VPP operation in New Zealand's evolving distribution networks.

Keywords: Virtual power plants; DERs; PowerFactory; Voltage stability.

1. Introduction

Globalization, population growth and rapid technological advancement have driven a continual rise in energy demand therefore leading to more production and hence emissions (Venegas-Zarama et al., 2022). Renewable energy plays a crucial role in greenhouse gas emission reduction and mitigating climate change (International Energy Agency, 2023). New Zealand has the highest share of renewables amongst all the member countries, with about 80 percent electricity being renewables (International Energy Agency, 2023).

As the world moves away from monopolistic power systems with the rapid penetration of distributed energy resources (DERs), such as solar PV, wind turbines, battery energy storage system (BESS), and electric vehicles, it is also changing the traditional electricity networks. However, the distribution grids are not equipped to accommodate decentralization, resulting in voltage fluctuations, frequency instability, reverse power flows and reduced power quality. Moreover, the renewable DER output is highly dependent on weather and location which makes the energy output inconsistent. The complexity and variability because of this demands innovative solutions and virtual power plants (VPPs) have emerged as a promising solution. The research suggests VPPs are those that provide a unified framework for assimilating distributed generation, augmenting renewable energy adoption, improving operation efficiency and enabling participation in electricity markets (Pawar et al., 2024). Adding on, another research proposes aggregating DERs into VPPs, which coordinate diverse resources to operate as a unified, dispatchable entity (Koraki and Strunz, 2018).

VPPs have emerged as a promising framework to enhance system flexibility by reducing the effect of variability of renewables, optimizing DER utilization and reducing the need for costly grid reinforcements (Naval and Yusta, 2021). Internationally, they are successfully deployed in California, Australia, and Germany. South California Edison (SCE) has adopted an array of measures to integrate more PV, EVs, Battery Storage Systems, and other DERs onto the grid. Tesla Virtual Power Plant in collaboration with SCE aggregates residential solar, Tesla PowerWall fleet to deliver in case of blackout due to extreme weather events and also delivers services such as frequency regulation and demand response for CAISO (California Independent System Operator). Another in the USA, Green Mountain Power (GMP) in Vermont, set up a VPP program in 2017 in collaboration with Tesla using PowerWall batteries 2.0. GMP during peak power times utilizes the energy stored in batteries by sending it back to the grid to meet demand which reduces the transmission and capacity expenses (Jones et al., 2022). Another demonstrated benefit of this system was supplying approximately 2901 hours of backup power using the Powerwall batteries during a major storm in 2018 (Jones et al., 2022). Enabled by advances in data analytics, artificial intelligence, communication technologies, smart grid protocols, VPPs have evolved from theoretical constructs into practical tools for grid operators and market participants.

Aotearoa New Zealand has a high penetration of renewable energy sources, which is also increasing every year as indicated in Figures 1 and 2, which show a clear upward trend for both solar photovoltaic installation at the distribution level and electric vehicles adoption. The pilot projects such as those conducted by Meridian, Genesis, Contact Energy and Wellington Electricity; demonstrate that VPPs can provide cost-effective alternative to network upgrades. A large-scale Virtual Power Plant has the potential to play a lead role in New Zealand's decarbonization journey, increase grid resilience, help the system manage peak loads effectively increase electrification, and also provide financial benefits to customers (Meridian Energy, 2023).

However, there is limited practical application in aggregating high DER at the distribution level. The proven international success in managing distributed resources and maintaining grid stability shows potential application in a New Zealand context. Inspired by these international cases, this study analyse a VPP through a IEEE test distribution system, representative of typical Aotearoa New Zealand feeder characteristics, to simulate VPP performance, and assess its ability to alleviate voltage and peak load management challenges arising from high DER penetration using an iterative control strategy using python scripting. Ultimately, the results from this study aim to provide insights into scalable DER integration and support the development of flexible and resilient electricity networks.

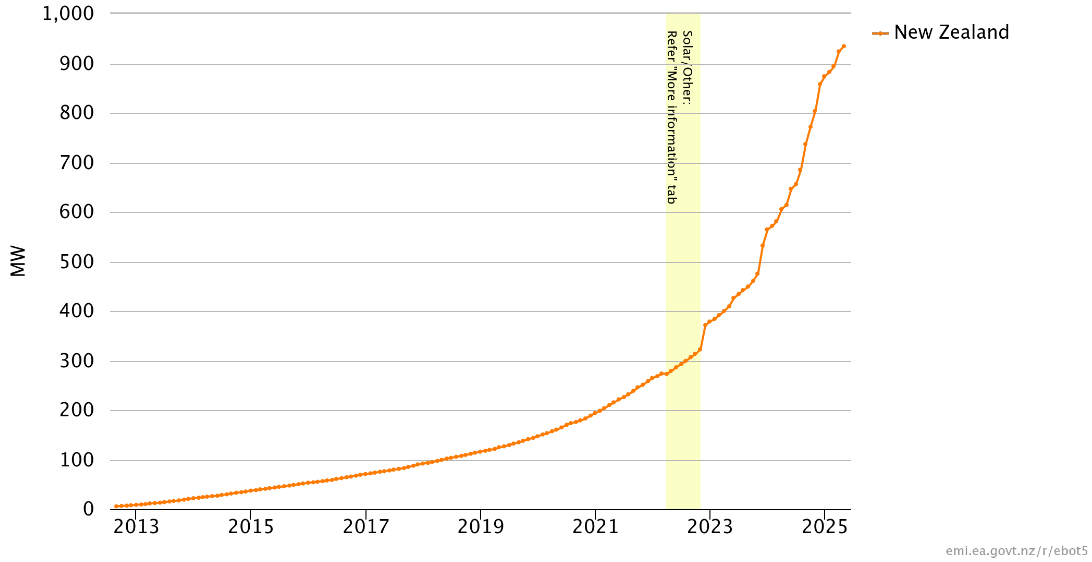

Figure 1. Growth in Solar PV installations in Aotearoa New Zealand
(Source: EMI, 2025)

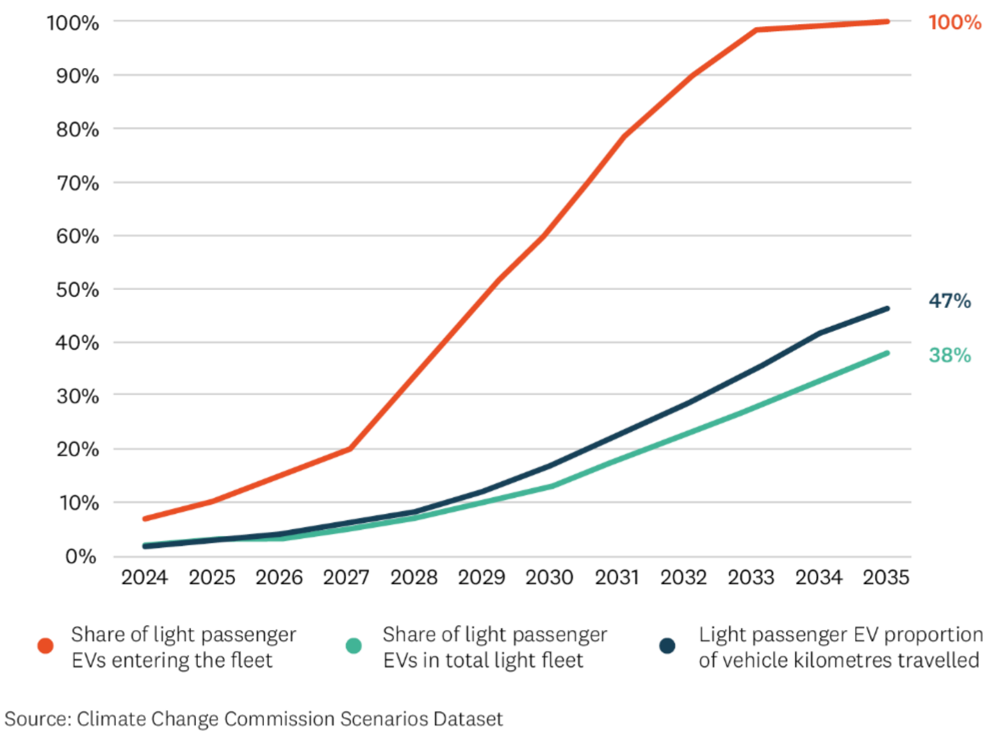

Figure 2. Projected EV adoption in Aotearoa New Zealand
(Source: EECA, 2024)

1.1. Objective of the paper

While VPP and DER technologies are essential for achieving Aotearoa New Zealand's decarbonisation goals, the resulting strain on distribution networks cannot be overlooked. However, the practical application and technical evaluation of VPPs within the country remain limited.

The overall problem this study aims to address is:

Can Virtual Power Plants (VPPs) effectively improve voltage regulation and peak load management in Aotearoa New Zealand's distributed energy networks?

To address this, the study evaluates the effectiveness of a supervisory iterative VPP framework implemented through Python–PowerFactory co-simulation. The analysis is performed on a modified IEEE 13-bus network, representative of New Zealand distribution characteristics, under varying DER penetration levels and seasonal variation to assess the ability of coordinated control to maintain voltage levels to improve overall network performance and asset longevity.

2. Literature review

This literature review explores the concept of VPPs, their evolution from theoretical concepts to basic aggregation of resources, and now sophisticated service-oriented systems. Additionally, the review also includes the operational challenges of the grid with high penetration of DERs like the unreliable power supply nature of renewables. The review covers the voltage stability issues and reduced inertia in distribution networks. The literature analysis then progresses to the role of VPPs as a flexible and decentralized solution capable of local generation (peak demand), load balancing (shaving demand response loads), and hence providing grid stability.

2.1. Virtual power plants: Concept and framework

The concept of VPPs was introduced by Awerbuch and Preston in 1997 and set a transformative change from regulated electricity markets to a deregulated environment (Marzbani et al., 2025). There is no universally accepted definition for a virtual power plant framework in the literature. From the mid-2000s, onwards, the scope of VPP-related steadily expanded in complexity and focused on micro-units distributed generation, and basic market participation (Venegas-Zarama et al., 2022). One perspective of VPP is defined as an autonomous micro-grid in (Naval and Yusta, 2021). Further VPP is defined as a cloud-based platform that integrates distributed energy resources (DERs), flexible loads and storage systems through two-way communication network (Panda et al., 2022). Recent studies conceptualize it as a collection of different types of DERs that are spread across the distributed networks with emphasis on artificial intelligence, blockchain, vehicle-to grid technologies, and multi-agent coordination (Dai et al., 2025).

A VPP is a layered energy management system that aggregates DERs, demand response loads, and BESS, enables coordinated decision-making, and energy trading through communication, infrastructure, and decision layers (Rouzbahani et al., 2021). VPP technology keeps evolving to encompass different types of distributed energy resources that have inherent uncertainty and manage them efficiently as a whole (Lee and Won, 2021).

Figure 3 illustrates the structural framework of a VPP, showing interactions among distributed energy resources, end users, grid operators, and energy markets.

The EU Fenix project and Sattar and Ghaoud (2024) divide VPPs into two different categories: CVPP, and TVPP. The technical virtual power plants (TVPPs), provides the system management, operation, balance and auxiliary service for distribution system operators (DSO) as well as the transmission system operators (TSO) (Wang et al., 2022). TVPPs coordinate organically clustered DERs by collecting static and dynamic operational data, interacting with the DSO for safety regulation, dynamically adjusting controllable outputs to balance RES fluctuations, and forwarding optimized dispatch results to the

CVPP for profit allocation and system-level coordination (Aboelhassan et al., 2024). Overall, while CVPPs emphasize market participation and economic returns, TVPPs extend the framework by ensuring technical stability, system reliability, and secure integration of DERs. This research focuses on TVPP and its contribution to network performance.

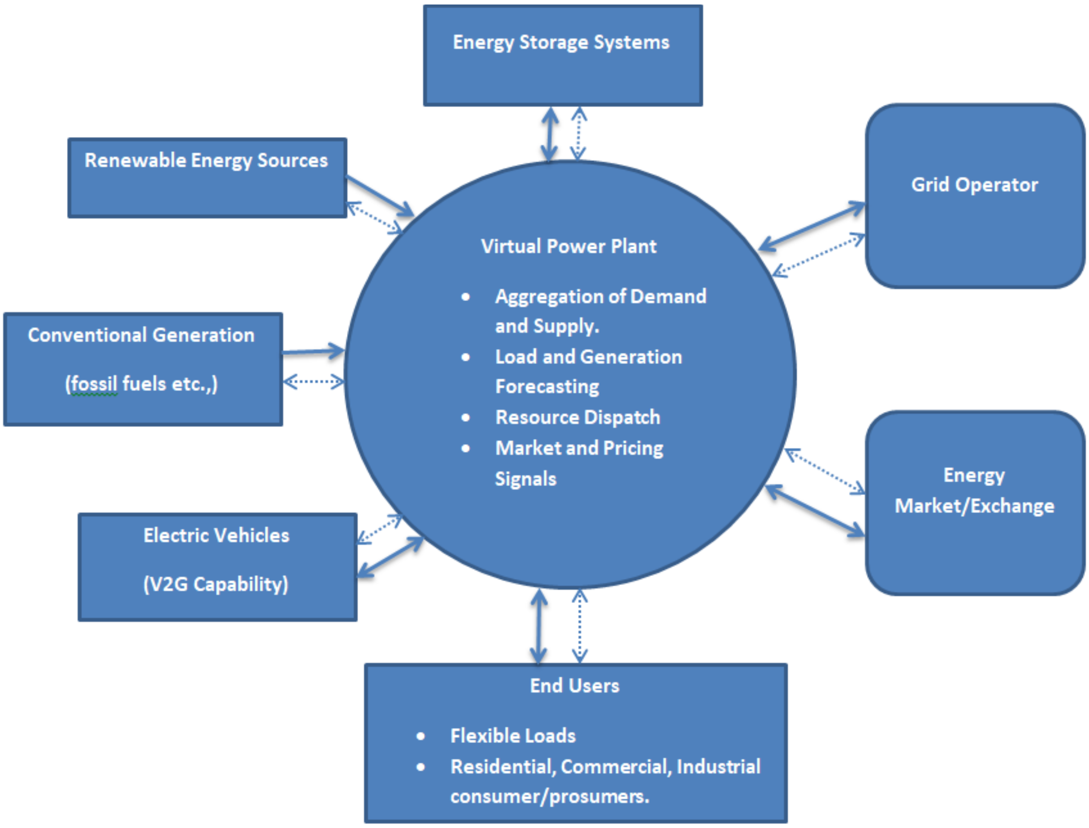

Figure 3. Basic schematic of a VPP; solid iines show the power/energy flow and the dotted lines denote the control, coordination, feedback flow

Generally, a VPP has four fundamental components that enable smooth power flow operations, namely: distributed energy resources (DERs), energy storage systems (ESS), flexible loads, and Information and Communication technologies (ICT) (Bhuiyan et al., 2021).

Distributed Energy Resource (DERs) is the backbone of VPPs and is a broad term that includes both dispatchable sources, such as gas turbines, diesel units, and biogas/diesel units, and non-dispatchable resources, which is predominantly renewable sources whose output is inherently variable and weather-dependent (Wan Abdullah et al., 2021). Flexible loads are those which are capable of adjusting their consumption in response to grid requirements. Therefore, it serves as valuable component of VPPs through demand side participation to enhance grid support and operational flexibility (Ibrar, 2023). Finally, information and communication technology (ICT) acts as the nervous system of VPPs that connects and coordinates its operations for seamless monitoring, control and communication (Yang et al., 2022).

Having outlined the fundamentals of a VPP, the following section examine how these elements interact within a distribution grid facing high DER penetration, with focus on uncertainties.

2.2. Uncertainties and challenges in high DER-networks

VPPs are an aggregation of various energy sources amongst which renewables is an integral part. Renewable energy, especially solar PV and wind,is variable in nature due to its dependency on weather and location. VPPs are employed to manage this variability through robust scheduling and dispatch strategies (Marcelino et al., 2021). The consumption pattern of residential, commercial, and industrial users is both diverse and unpredictable which makes the stochastic nature of load demand more pronounced (Vafa et al., 2025). Variable Renewable Energy (VREs) due to its nature and forecasting constraints also contribute to load uncertainty. The fluctuations in demand, due to Electric Vehicles (EVs) and smart appliance, require VPPs to adapt to changing load profiles (Lin et al., 2020). The presence of cyber threats and the risk of communication link failures further contribute to challenges, posing threats to grid security and stability (Liu et al., 2023). The variability of distributed energy sources also complicates the communication and coordination within the grid (Zhou et al., 2025). Uncertainties in DER-rich distribution networks evolve into operational challenges that require coordinated VPP strategies are mentioned below.

Operating VPPs solely for economic objectives can aggravate technical issues in a distribution network, leading to voltage limit violations and thermal overloading lines and transformers. Traditional voltage regulation methods rely on static points which are inefficient in system high DERs, leading to unwanted reactive power flows and voltage quality issues (Akbari et al., 2024; Padullaparti et al., 2023). These challenges necessitate new control strategies and planning principles that coordinate to maintain network compliance (Chihota and Bekker, 2020). The widespread integration of PV systems, EVs, flexible loads such as heat pumps increase stress on distribution networks, which can lead to current and voltage limit violations, which contribute to congestion (Shahzad and Jasińska, 2024). The displacement of traditional synchronous generators by inverter based DERs affects the system inertia by lowering it, posing frequency stability challenges (Kabir et al., 2024). VPPs must address congestion also provide frequency support, through coordination with DSO (Naughton et al., 2021). The spatio-temporal erraticism of RES, such as different behaviors of solar and wind forecast errors, adds complexity to forecasting. (Nadimi and Goto, 2025) suggests smoothing or accumulating errors based on spatial correlation to improve the accuracy of forecasts.

The ability to mitigate the aforementioned constraints is closely tied to the temporal resolution at which they operate and the performance metrics used to evaluate them. Altogether these time-scale aware strategies and metrics provide a structured basis for balancing reliability, efficiency, and flexibility in DER-dense distribution networks (Akbari et al., 2024; Padullaparti et al., 2023). The flexibility of DERs can be harnessed to mitigate uncertainties, but it requires sophisticated decision-making models that consider inherent nature of loads and operational constraints of the grid (Riaz and Mancarella 2021).

2.3. Role of VPPs in voltage regulation and peak demand

Studies have demonstrated that in unbalanced distribution networks proper management of VPPs can significantly reduce system unbalance by controlling active and reactive power from aggregated DERs and adjustable loads, thereby effectively maintaining voltage stability (Piltan et al., 2022). Moreover, VPPs are capable of regulating distribution network voltage by controlling both active and reactive power from their aggregated resources and adjustable loads, thereby playing an effective role in maintaining voltage stability (Park and Son, 2020).

VPP ensures that supply matches demand conditions by dynamically coordinating energy generation and consumption across diverse energy resources (Oshnoei et al., 2022). This allows excess energy to be stored during low demand and released during peak hours, which eases grid stress and also enhances voltage stability (Zhong et al., 2022). VPP balances energy flows and also delivers a range of ancillary services. For instance, rapid adjustment of DER outputs keeps the grid frequency within acceptable operational bounds (Liu et al., 2023). These functions show that VPPs not only aggregates DERs- they play an active and vital role in maintaining power quality and operational security across modern grids. By aggregating resources such PV systems, BESS and flexible loads, VPPs enable coordinated control that enhances system flexibility reliability and overall network performance. This framework allows DERs to operate as unified system capable of supporting grid operation under varying conditions, thereby improving operational efficiency (Riaz and Mancarella, 2019).

A key contribution of VPPs lies in voltage regulation, particularly in networks with high PV penetration. Zecchino et al. (2019) show reactive power support from BESS can be used to regulate voltage levels by absorbing or injecting reactive power as required. Nakmura et al. (2021) also suggests Battery Energy Storage Systems (BESS) can effectively regulate voltage in low-voltage distribution networks with high PV penetration by mitigating voltage rise and maintaining nodal voltages within safe limits. Building on these capabilities, control strategies within VPP frameworks further enhance voltage regulation performance. Rule-based control strategies within VPP frameworks utilise BESS to perform real-time voltage regulation through coordinated active and reactive power dispatch, offering a deterministic and low-complexity solution that can effectively mitigate voltage deviations and enhance power quality in distribution networks while remaining suitable for practical implementation in embedded energy management systems (Costa et al., 2025). BESS offers dispatchable active and reactive power control which enables compensation for the intermittency and variability of renewable sources (Caretta et al., 2023).

The traditional approach usually treat peak shaving and voltage control separately. However, Zhang et al. (2021) show that peak shaving and voltage regulation are inherently interdependent processes and can reshape load profiles directly influencing voltage behaviour within distribution networks. In addition to DER dispatch, peak demand can be reduced through conservation voltage reduction (CVR), where controlled voltage lowering leads to a proportional reduction in load demand (Padullaparti, 2023). Effective voltage regulation in high penetration DER distribution networks require coordinated control of multiple devices, including transformers, energy storage systems, and distributed generation resources. Rule-based control strategies, implemented through expert systems, provide a practical and interpretable approach to voltage regulation by translating operator knowledge into structured control actions (Dandea and Gheorghe, 2023). Electric vehicles, when integrated within VPPs act as a distributed and flexible energy storage resource capable of providing grid support through controlled charging and vehicle-to-grid (V2G) operation, enabling peak load reduction, voltage regulation, and improved load profile smoothing across distribution networks (Alden et al., 2026).

However, the implementation of VPPs is not without challenges. The effectiveness of coordinated control relies on accurate forecasting of generation and demand, which remains inherently uncertain in systems with high renewable penetration. Artificial intelligence (AI) based approaches, including machine learning and reinforcement learning, have been increasingly applied in VPP control to enable adaptive, data-driven coordination of distributed energy resources; however, their practical deployment is constrained by high computational complexity, extensive data requirements, and challenges in real-time implementation (Zare et al., 2025). Overall, the literature highlights that although VPPs offer significant potential for enhancing grid flexibility and coordinating DERs, their implementation remains constrained by technical and operational challenges. These findings emphasise the need for scalable, interpretable, and computationally efficient control frameworks capable of simultaneously addressing voltage regulation, peak demand management, and system stability, forming the basis for the methodology adopted in this research project.

3. Research methods

The aim of this research is to simulate and analyse a Virtual Power Plant (VPP) in a representative distribution feeder. A modified IEEE 13-bus distribution feeder is used as the test system, adapted to reflect Aotearoa New Zealand distribution characteristics through appropriate load, EV, and PV datasets. This study strategy is shown in Figure 4 and adopts a simulation-based research design to allow controlled and repeatable evaluation of VPP operation under different scenarios.

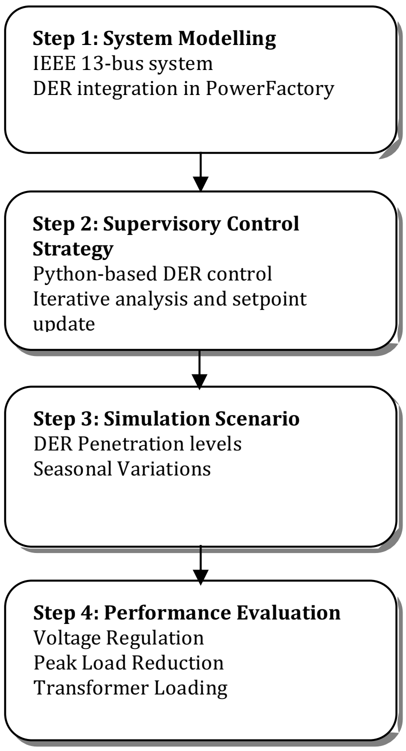

Figure 4. Strategy of the research project

The coordinated operation of DERs as controllable loads is examined in the study to provide services such as voltage regulation, and improved renewable integration. A co-simulation framework links DigSILENT PowerFactory with Python scripting that allows supervisory control and iterative analysis. The control framework follows an iterative run–analyse–update–rerun approach to evaluate the impact of coordinated DER control.

3.1. Network modelling

This section describes the modified IEEE 13-bus feeder as shown in Figure 5 that is adopted as the baseline model because it is a well-established benchmark for distribution-level studies, with sufficient complexity to capture unbalanced loads-combination of single-phase, two-phase, and three-phase loads and short lines, but still is compliant for co-simulation. This characteristic of the model is preserved in the model to reflect realistic low-voltage distribution behaviour. The network is used as an analytical platform to simulate a range of scenarios involving distributed energy resources (DERs), electric vehicle (EV) loads, and time-varying demand, enabling assessment of the VPP's capability in managing voltage regulation and peak load conditions. In the modified model, DERs including photovoltaic (PV) systems, battery energy storage systems (BESS), and EV loads are integrated at selected buses (634, 646, and 671) to represent distributed energy participation within the feeder. The feeder is adapted to represent a realistic distribution network configuration with mixed residential, commercial, and community loads. The system is modelled in DIgSILENT PowerFactory, with Python used to implement a supervisory control framework. This allows an iterative analysis of system behaviour and coordinated DER control under varying operating conditions.

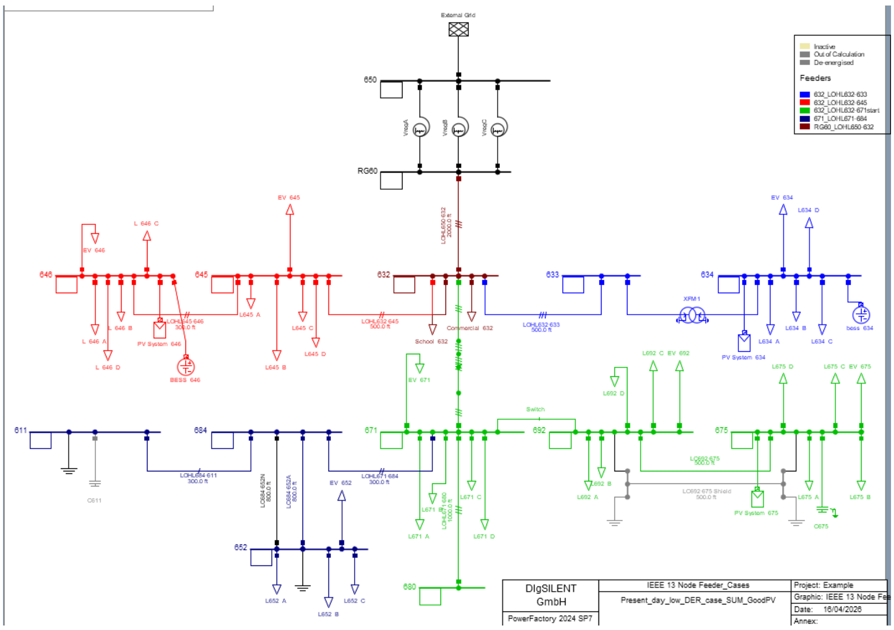

Figure 5. Modified IEEE 13-bus distribution network with integrated PV systems, BESS, and EV loads

In Table 1 the load categories (A–D) represent different demand profiles used to capture diversity in residential consumption patterns. These profiles reflect variations in household behaviour, enabling a more realistic representation of aggregated load across the distribution feeder.

Table 1. Distribution of residential households across buses in the modified IEEE 13-bus network

Bus	LoadTypeA	LoadTypeB	LoadTypeC	LoadTypeD	Total houses
645	15	13	13	9	50
646	15	13	12	10	50
652	3	2	5	0	10
671	20	16	17	12	65
675	21	18	18	13	70
692	18	14	14	14	60
634	10	15	15	20	60
TOTAL	**115**	**103**	**103**	**89**	**365**

3.2. DER modelling and data inputs

3.2.1. Load modelling

Residential load demand is modelled using half-hourly time-series profiles obtained from Green Grid Study (2019) representing typical daily consumption patterns under New Zealand conditions. The baseline demand profiles are primarily derived from the Green Grid project datasets. Additionally, Transpower and Electricity Authority load curves/peak demand curves are further reviewed to validate and compare overall demand trends, ensuring consistency in peak timing and daily load behaviour.

Four distinct load profiles (A–D) are developed to represent variability in household demand, including differences in peak magnitude and timing. Rather than assuming a single baseline profile to represent all households, these profiles are proportionally distributed and scaled across buses based on the household allocation presented in Table 1. This enables a more realistic representation of spatial demand distribution within the network. This approach reduces potential bias associated with uniform load assumptions and aligns with distribution-level modelling practices.

Furthermore, temporal variation is introduced by applying demand shifting to the base load profile, to account for differences in occupancy patterns and appliance usage that influence peak demand timing. This allows the model to capture both magnitude and timing diversity in residential consumption. The resulting load profiles for summer and winter conditions are illustrated in Figures 6 and 7, respectively, demonstrating variation in demand behaviour across the different load types. This modelling approach ensures that aggregated demand curves accurately reflect realistic operating conditions in modified IEEE 13-bus network.

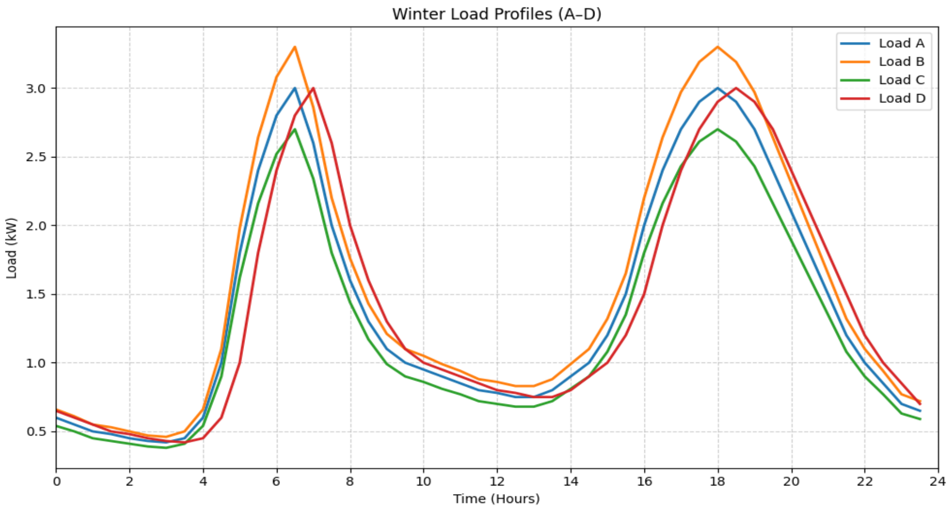

Figure 6. Representative winter load profiles for residential demand (A–D)

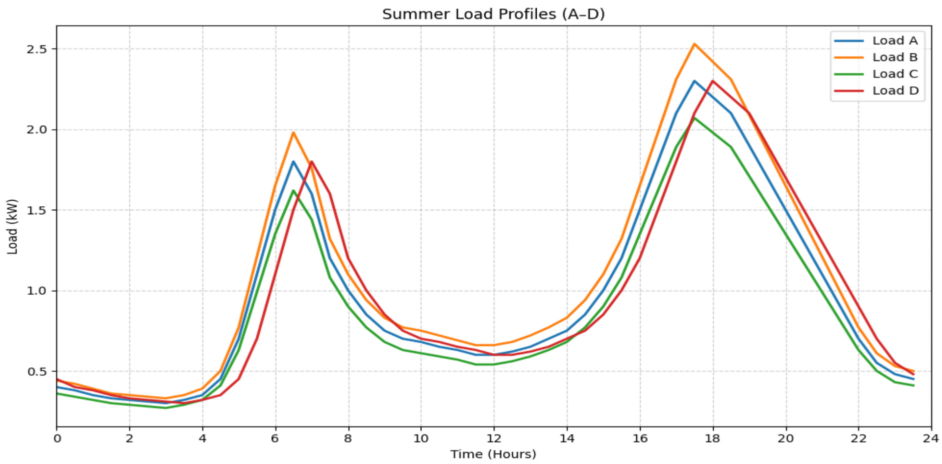

Figure 7. Representative summer load profiles for residential demand (A-D)

3.2.2. School and commercial modelling

The load profiles for the school in Figure 8 are derived from typical daily electricity demand patterns observed in school buildings, based on the study conducted at Remuera Intermediate School, which analysed temporal variations in energy consumption and peak demand behavior (Wong & Byrd, 2011). Commercial electricity demand profile as shown in Figure 9 is informed by Aotearoa New Zealand-specific studies such as the BRANZ Building Energy End-Use Study (BEES), which provides realistic load patterns and operational schedules for commercial buildings, including offices and retail spaces, based on measured energy use data (Cory et al., 2015).

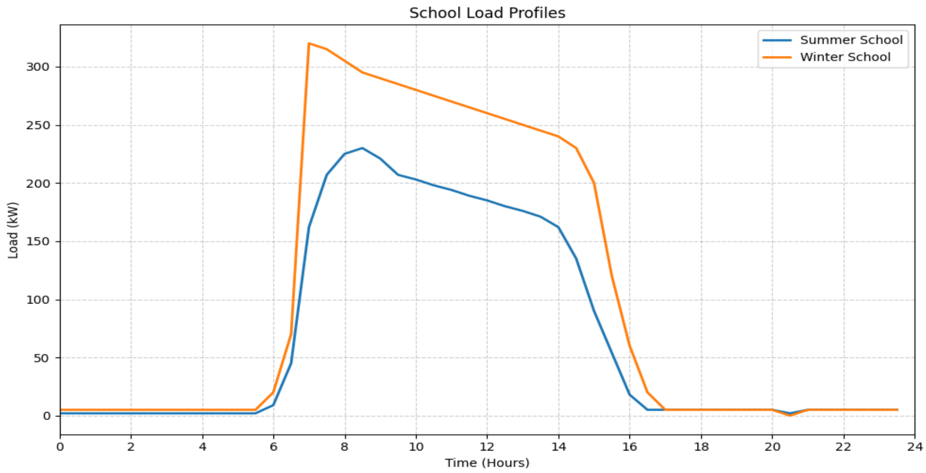

Figure 8. Representative school load profiles for summer and winter conditions

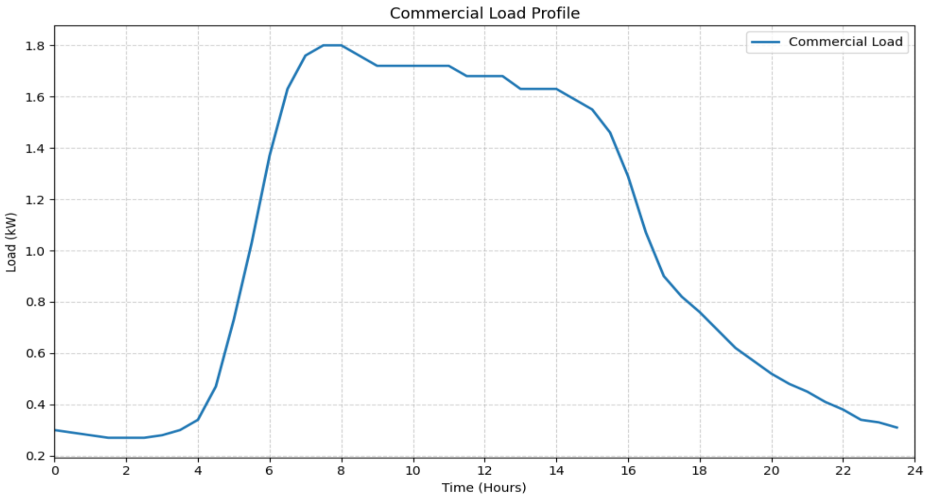

Figure 9. Load curve for small commercial in a distribution network

3.2.3. EV modelling

Electric vehicle (EV) charging demand is strongly influenced by user behaviour, particularly the timing of charging events. A study conducted by University of Canterbury in Aotearoa New Zealand shows that many EV users tend to charge their vehicles upon returning home, typically between 17:00 and 18:00, which coincides with existing residential peak demand periods. This can significantly increase peak loading on distribution networks depending on charging strategies and penetration levels (Williams et al., 2023). A EECA study (2024) on residential EV chargers was also studied to validate the EV load curve which also shows pronounced evening peak to realistically capture their impact (see Figure 10).

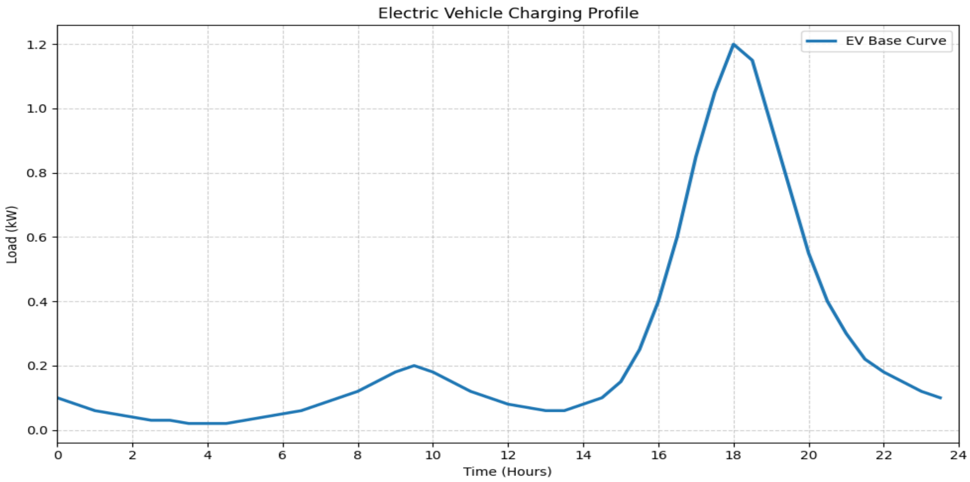

Figure 10. EV base load curve which is also then scaled up for different penetration scenarios

3.2.4. PV modelling

The PV generation time-varying curves were developed using the global irradiance data obtained from NIWA, with location set at Wellington under four representative scenarios: summer good day, summer bad day, winter good day, and winter bad day. As reported by BRANZ (2024), residential PV systems in New Zealand are generally installed with capacities in the range of 5-6 kW per household. The active power output of PV at each time step was calculated by scaling the installed PV capacity at the corresponding bus by the irradiance value and dividing by 1000, as shown in equation (1). This formulation assumes that 1000 W/m^2 represents full solar availability, allowing the irradiance profile to scale the PV output relative to the installed PV system at each bus. Lower PV penetration levels, such as 30% and 50%, were then obtained by proportionally scaling the 100% PV curve.

$$P_{pv}(t) = P_{bus} * \frac{G(t)}{1000} \quad (1)$$

To account for the diversity and spatial distribution of solar installations, an aggregated PV model is used at each bus. Equation (1) ensures that the PV generation scales proportionally to the total connected PV system size, representing a scenario where solar penetration is distributed across the residential clusters (Buses 646,634, 675) relative to their peak demand.

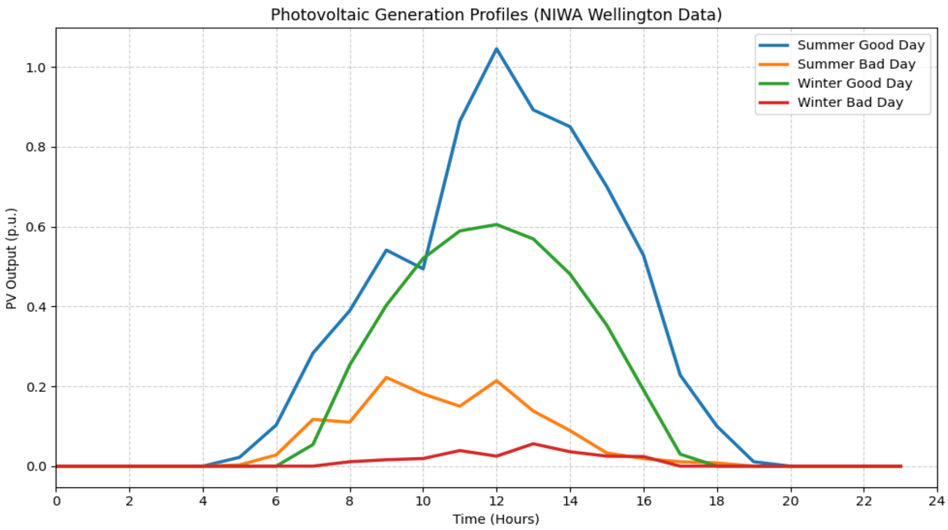

Figure 11. Normalized PV output (p.u.) for Wellington showing representative curves showing seasonal and weather-based variability using SolarView irradiance data.

3.2.5. BESS modelling and assumptions

Presently, there is limited public data available to quantify the adoption of residential battery energy systems in New Zealand. Transpower (2019) highlights the importance of BESS in supporting future grid operations. The reports from Electricity Authority (2023) and EECA (2022) also indicate that the battery deployment is still at an early stage. Although there is increased discussion on the role of BESS there is a lack of clearly defined statistics with existing literature generally describing battery uptake as emerging and in early adoption stage.

Therefore, the battery energy storage system (BESS) capacity is modelled as 0.15 MWh, which represents an aggregated resource across multiple households. This reflects partial adoption of residential battery systems rather than full penetration for the purpose of evaluating VPP performance under increased storage participation.

3.3. Simulation framework

The simulation framework developed in this study integrates DIgSILENT PowerFactory with Python-based control to evaluate the performance of a Virtual Power Plant (VPP) under varying distributed energy resource (DER) conditions. A quasi-dynamic simulation (QDS) approach was used to capture the time-varying behaviour of loads, photovoltaic (PV) generation, and electric vehicle (EV) charging over a 24-hour period with a 30-minute resolution. The overall workflow follows a supervisory run–analyse–update–rerun approach, as illustrated in Figure 12.

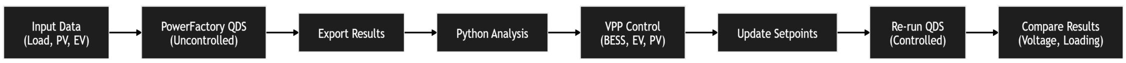

Figure 12. Simulation of the PowerFactory–Python workflow

Time-varying profiles for load, EV charging, and PV generation were implemented in DIgSILENT PowerFactory using time characteristic curves. These profiles were developed externally in Python/Excel based on representative datasets, including residential (A–D), commercial, school, EV, and PV profiles. The half-hourly values were imported into PowerFactory and assigned to the corresponding elements (loads, PV systems, and EV loads), enabling realistic temporal behaviour within the quasi-dynamic simulation framework.

Within each study case, a set of operating scenarios was developed to evaluate the impact of different levels of DER penetration. These scenarios are defined based on varying EV and PV penetration levels, ranging from low to high adoption. The combination of study cases and operating scenarios enables systematic analysis of network behaviour under increasing DER integration and varying generation conditions.

Table 2. Summary of operating scenarios

Scenario	EV Penetration	PV Penetration	Notes
1	10%	10%	Present-day low DER (baseline)
2	10%	30%	Low EV, medium PV
3	10%	50%	Low EV, high PV (overvoltage condition)
4	30%	5%	Medium EV, low PV
5	30%	50%	Medium EV, high PV
6	50%	5%	High EV, low PV (loading stress)
7	50%	30%	High EV, medium PV
8	50%	50%	High EV, high PV (high DER case)
9	10%	10%	Low EV, low-moderate PV
10	100%	100%	Extreme DER stress-test scenario

Table 2 encapsulates the operating scenarios considered in this research. The scenarios range from present-day low DER conditions to high penetration cases, including intermediate combinations to capture low, medium, and high adoption levels of EVs and PV systems. Although multiple scenarios were simulated to capture a wide range of operating conditions, the results discuss the most representative and critical cases. These include scenarios that demonstrate significant voltage deviations and clearly illustrate the impact of increasing DER penetration, as well as the effectiveness of the proposed VPP control strategy. Particularly, scenarios with high PV penetration analyse potential overvoltage conditions, while higher EV penetration levels provide insight into demand-side impacts and load variability. Together, these scenarios form the basis for evaluating the effectiveness of coordinated VPP control strategy.

The Battery Energy Storage Systems (BESS) were included within the simulation framework as locally controlled resources rather than predefined time-varying profiles. Unlike load, EV, and PV models, which were implemented using time characteristic curves, the operation of BESS in the uncontrolled case, was a built-in QDSL-based BESS model available in DIgSILENT PowerFactory was used to represent baseline battery behaviour. Alternatively, for the controlled case, BESS active and reactive power outputs were generated externally from Python-based VPP controller based on network conditions identified from the simulation results. These outputs were then converted into time-dependent setpoint curves and applied in PowerFactory for subsequent simulation runs.

3.4. VPP Control Strategy

The operational behavior of the VPP control strategy is governed by a supervisory, rule-based framework built on the results of quasi-dynamic simulations in DIgSILENT

PowerFactory. Rather than acting within each simulation time step, the controller evaluates system-wide voltage conditions after an initial simulation run and determines coordinated control actions for distributed energy resources (DERs), which are then applied in subsequent simulation to observe the effect.

The control process begins by extracting bus voltage profiles over the 24-hour simulation horizon- 48 setpoints. For each time step, the controller identifies the bus with the highest voltage magnitude, representing the most critical overvoltage condition in the network. Control actions are first applied at this location to ensure that the most severe violations are addressed before considering the remaining buses. The controller then sequentially evaluates other buses and applies additional control actions where required, based on their local voltage conditions. A hierarchical control structure is adopted to utilise available DER flexibility efficiently. Battery Energy Systems are prioritised as the primary control resource due to their ability to absorb excess generation i.e., provide both active and reactive power support. During periods of high voltage, the BESS operates in charging mode to reduce net power injection at the corresponding bus. The battery state of charge (SOC) is updated at each time step according to equation 2.

$$\mathrm{SOC(t+1)} = \mathrm{SOC(t)} + \frac{(P_{BESS}(\mathrm{t}) \times \Delta\mathrm{t})}{E_{rated}} \tag{2}$$

Where, $P_{BESS}(t)$ represents the battery power (charging is indicated with –ve sign), Δt is the simulation time step (0.5 hours), and E_{rated} is the battery energy capacity.

The active power of the BESS is controlled based on local voltage conditions using a rule-based formulation mentioned in equation 3.

$$P_{BESS}(\mathrm{t}) = \begin{cases} -P_{max}, & V(t) > V_{upper} \\ 0, & otherwise \end{cases} \tag{3}$$

Where, $V(t)$ is the bus voltage and V_{upper} is the upper voltage threshold.

If the available BESS capacity is insufficient to improve/mitigate the voltage level, the controller utilises demand-side flexibility through EV charging by increasing local consumption during high-voltage periods. As a final measure, photovoltaic (PV) curtailment is applied when necessary due to its intermittent nature, expressed as equation 4.

$$P_{PV,controlled}(t) = \alpha(\mathrm{t}) \times P_{PV}(t) \tag{4}$$

Where, α(t) is a time-dependent curtailment factor bounded between 0 and 1.

The operation of the BESS is constrained by both power and energy limits to ensure realistic behaviour within the simulation. Equation 5, 6 and 7 show the constraints that ensure the battery operates within its physical limits while responding to voltage conditions identified by the control strategy.

$$-P_{min} \leq P_{BESS}(t) \leq P_{max} \tag{5}$$

$$-Q_{min} \leq Q_{BESS}(t) \leq Q_{max} \tag{6}$$

$$-SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{7}$$

The control actions determined for BESS, EV, and PV are translated into time-dependent active and reactive power setpoints and implemented in PowerFactory as updated time characteristic curves. The simulation is then re-executed to evaluate the impact of coordinated control on network voltage performance.

It is noted that the control strategy is implemented as a supervisory iterative approach rather than real-time closed-loop control. This is mainly due to limitations in directly integrating step-by-step Python control within the quasi-dynamic simulation environment in DIgSILENT PowerFactory. As a result, control actions are applied through an external run–analyse–update–rerun process. While this approach does not represent fully real-time operation, it provides a scalable, practical and computationally efficient framework for evaluating coordinated DER control and its impact on efficient network performance.

4. Results and discussion

This section presents the results of quasi-dynamic simulations for both uncontrolled and controlled scenarios, representing system operation before and after implementing the VPP control strategy. The results are used to evaluate the impact of DER penetration and the effectiveness of the proposed Virtual Power Plant (VPP) control strategy. The analysis is structured in a systematic manner. The base case in Figure 13 represents the bus voltages for the load-only scenario, and Figure 14 shows the effect of introducing PV and BESS. This is followed by additional scenarios with increasing PV generation and EV adoption levels, and finally the implementation of coordinated VPP control. This structured approach demonstrates how the proposed control strategy enhances performance in terms of voltage regulation and transformer loading.

To maintain clarity and avoid redundancy, only representative scenarios are presented in this section. While multiple combinations of PV and EV penetration under different seasonal and solar generation profiles were simulated, the results exhibited consistent trends across cases. Therefore, selected scenarios are used to highlight key system behaviours, including a high PV–high EV scenario and a low PV–high EV scenario in winter, representing a more critical, grid-stressed condition.

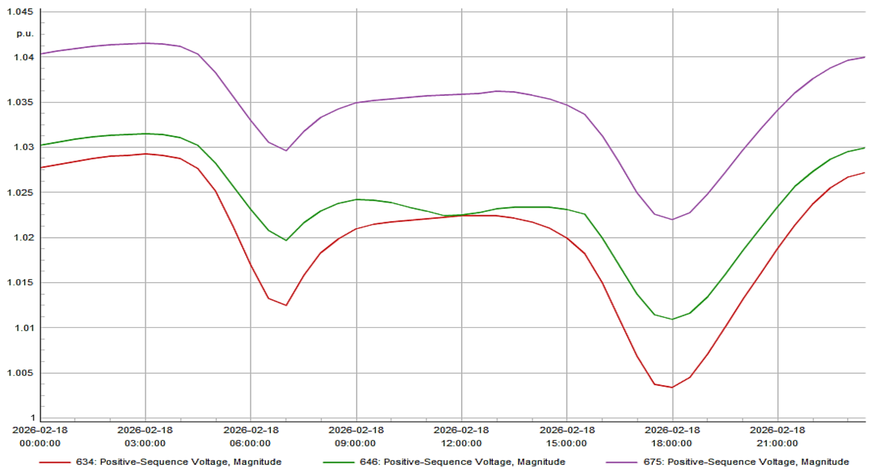

Figure 13. Voltage profiles of selected buses (634, 646, and 675) under the base case load-only scenario with minimal distributed energy resource (DER) penetration

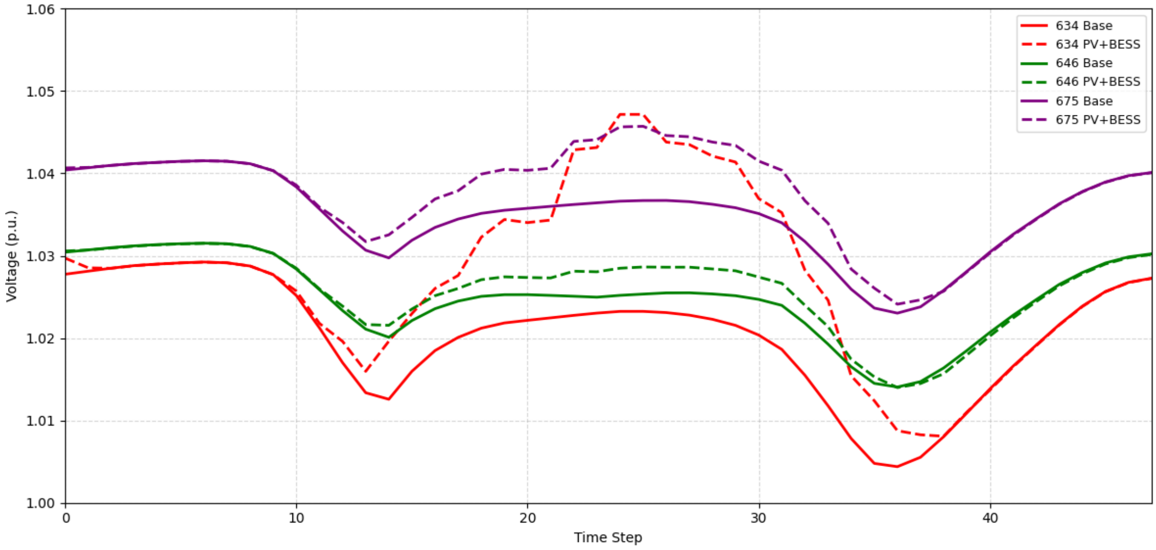

Figure 14. Comparison of bus voltage profiles under load-only (solid) and PV+BESS (dashed) conditions

The voltage profile across the selected buses is observed to remain relatively high, within the range of 1.025 – 1.045 p.u. This is due to the default voltage regulator settings in the IEEE 13-node feeder. The default regulator settings have not been changed, as they ensure that the voltage at the end of the feeder remain within acceptable limits under varying conditions. Additionally, the use of line drop compensation results in the regulator maintaining a higher upstream voltage to compensate for expected voltage drops along the feeder. This characteristic baseline behaviour is therefore considered when interpreting the impact of DER integration and the effectiveness of the proposed VPP control strategy.

However, despite the influence of the voltage regulator on the absolute voltage levels, the relative trends in the voltage profile remain clearly interpretable, allowing meaningful comparison between different scenarios as discussed in this section.

4.1. Scenario 1: High EV, high PV

In the uncontrolled case, voltage levels show larger fluctuations and approach operational limits during both peak demand and high generation periods, as observed in Figures 15.

Figures 15 to 18 depict the system behaviour observed under uncontrolled operation for both good and bad PV conditions in summer. The bus voltages show influence of PV generation on voltage levels, with higher midday voltages observed under stronger solar irradiance. The transformer loadings and active power flow further highlight this impact, where consistent high solar irradiance reduces midday loading but leads to reverse power flow. Furthermore, reduced PV availability results in higher reliance on the grid, which leads to lower midday loading relief and a more pronounced evening peak. These graphs collectively demonstrate the direct influence of PV variability on voltage profiles, and power flow within the network.

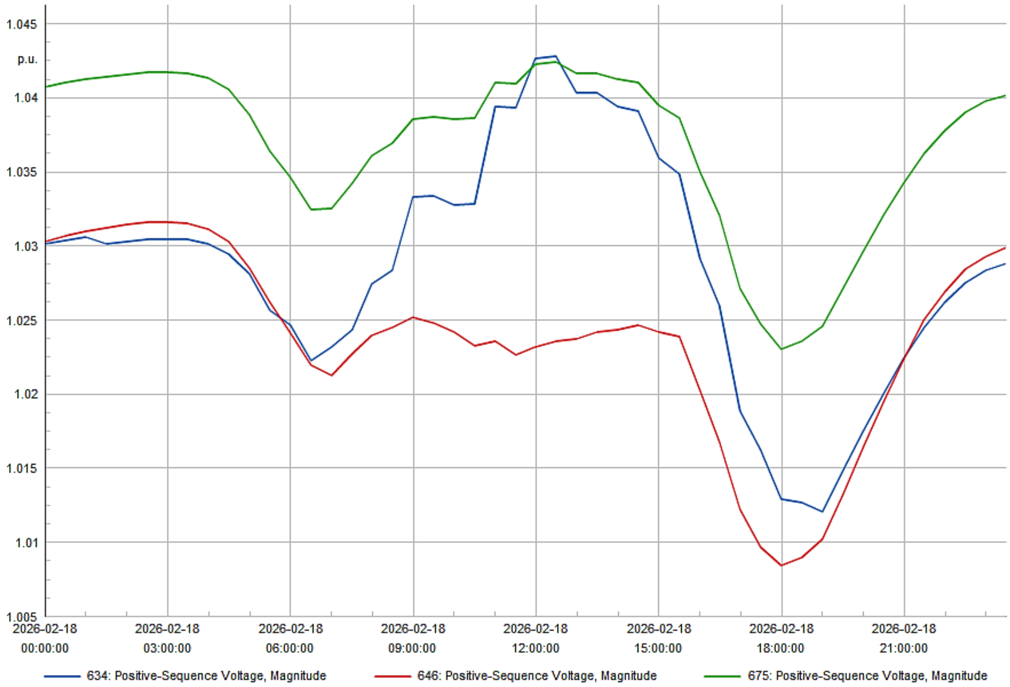

Figure 15. Uncontrolled bus voltage profiles at buses 634, 646, and 675 under summer good PV conditions

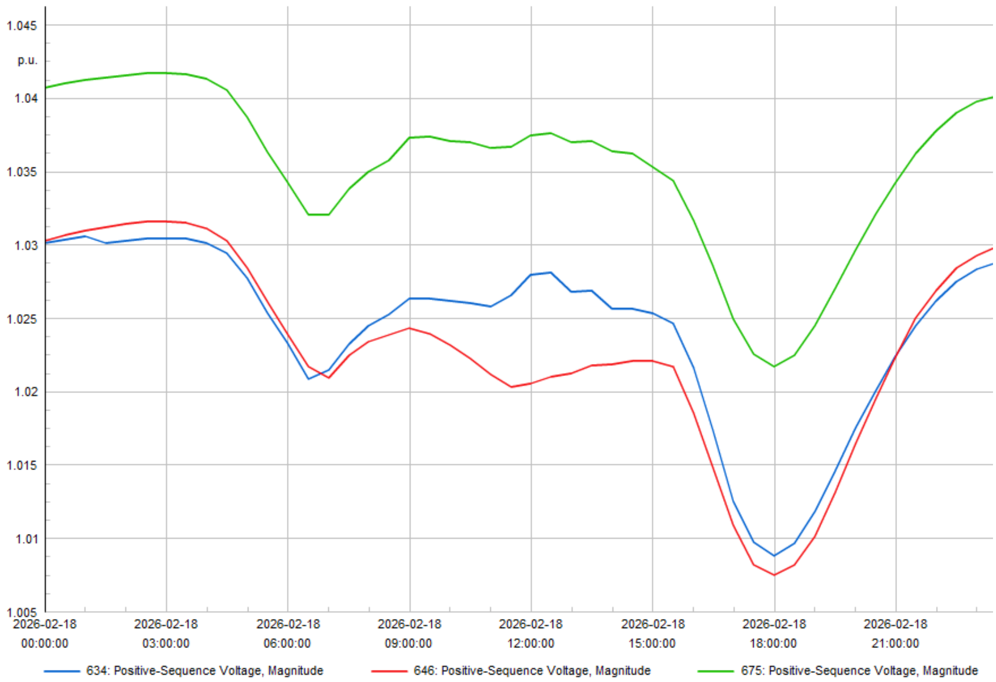

Figure 16. Uncontrolled bus voltage profiles at buses 634, 646, and 675 under summer bad PV conditions

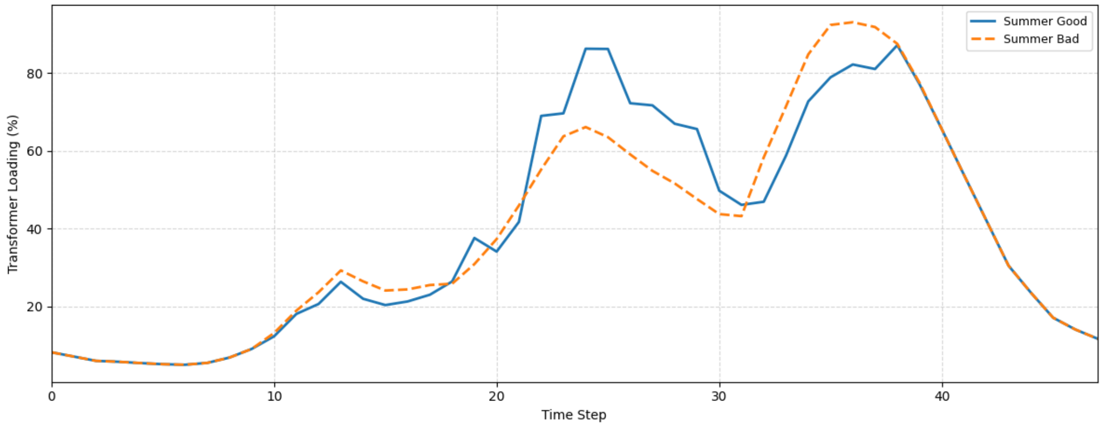

Figure 17. Transformer loading profile under uncontrolled operation for summer good and summer poor solar conditions

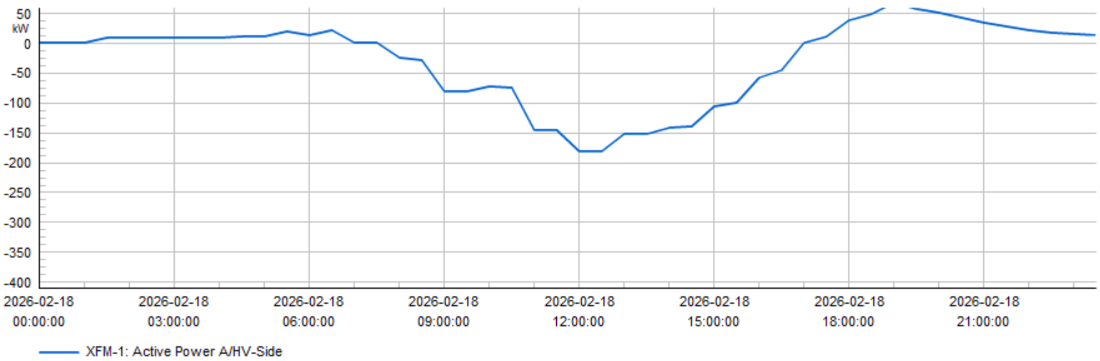

Figure 18. Reverse power flow observed in summer good PV conditions

4.1.1. VPP- controlled operation

The uncontrolled scenario exhibit periods of reverse power flow during high PV generation, contributing to increased transformer loading and voltage rise, as shown in Figures 17 and 18. Under VPP control, this effect is mitigated through coordinated BESS charging and demand-side flexibility. By absorbing excess generation locally, the VPP reduces both the magnitude and duration of reverse power flow, during midday in this case, where loading peaks are effectively flattened.

The VPP-controlled results maintain voltages closer to nominal values (around 1.02-1.03 p.u.), with reduced voltage deviations and improved stability. Another important observation, as illustrated in Figure 19, is the unequal impact of the VPP controller across the buses, which is consistent with the characteristics of the IEEE 13-bus feeder, where voltage sensitivity depends on bus location, line impedance, and local loading conditions.

In this scenario, the uncontrolled case exhibits peak loading close to 88–90% (Figure 17), while the controlled case reduces this significantly (Figure 20), achieving an approximate 20% reduction. In addition to peak reduction, the controlled loading profile is visibly smoother, indicating improved load distribution and enhanced network stability. The uncontrolled case exhibits higher loading levels, particularly during peak demand periods, reaching value 90.73%. With the implementation of the VPP control strategy, the loading is significantly reduced, demonstrating effective peak shaving and improved utilisation of network capacity.

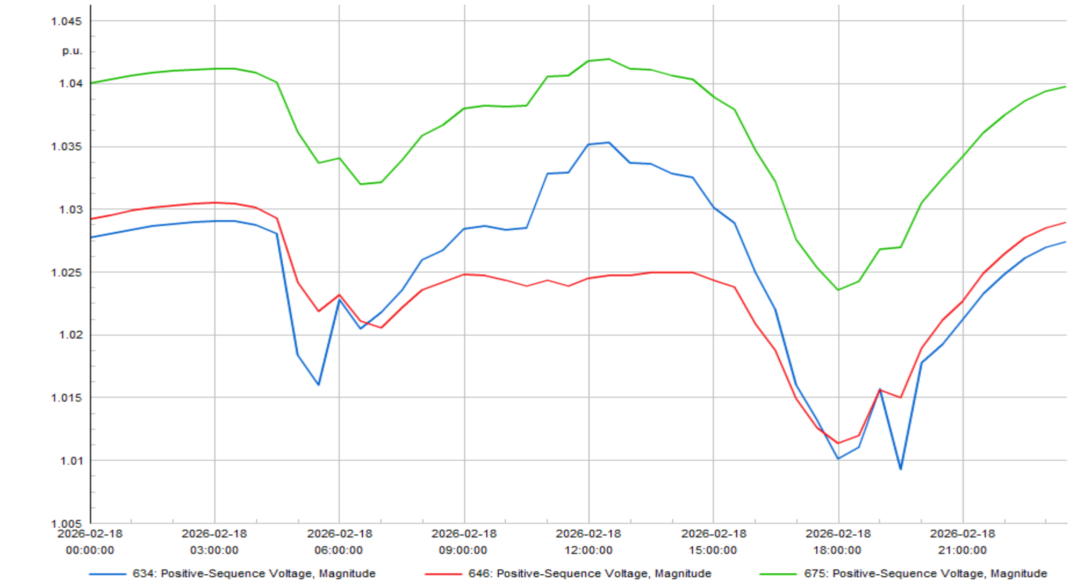

Figure 19. Selected bus voltage profiles under VPP control demonstrating reduced voltage variations and improved stability (summer good day)

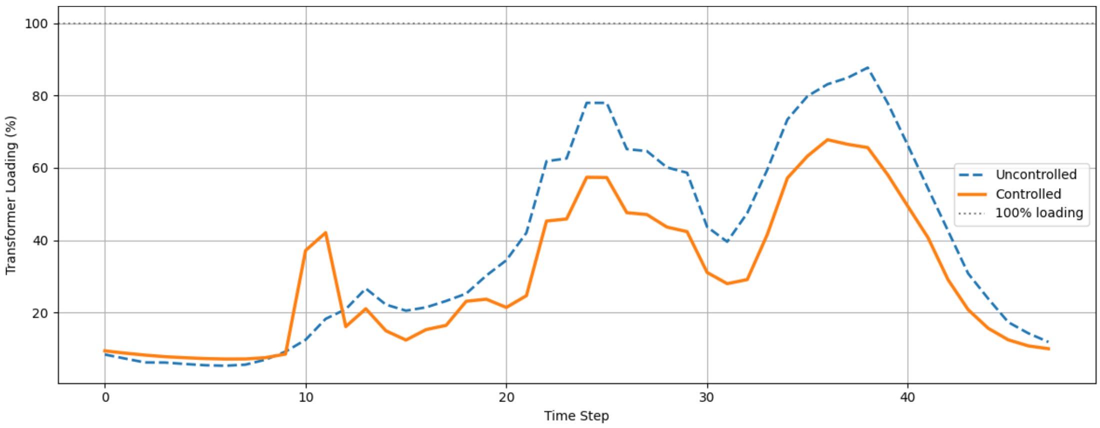

Figure 20. Comparison of transformer loading under uncontrolled and controlled conditions

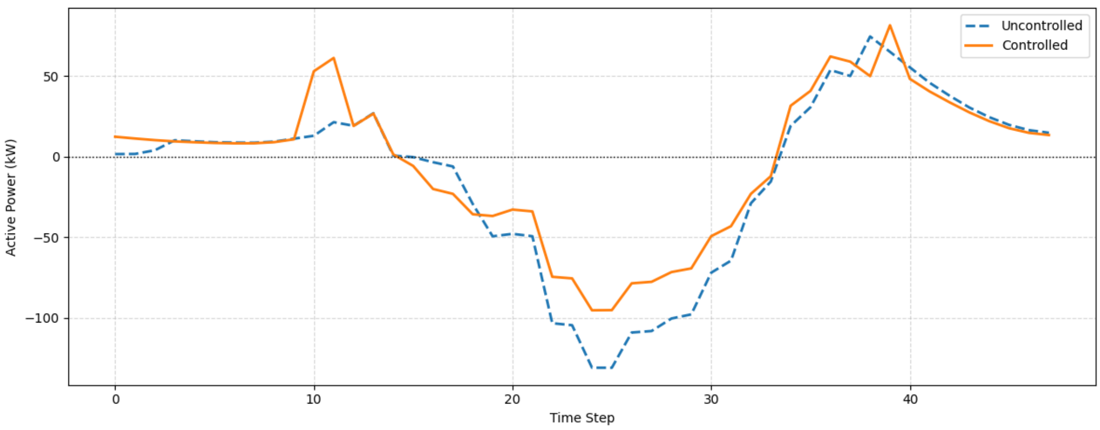

Figure 21. Active power flow through transformer XFM -1 under both controlled and uncontrolled condition

The observed improvements are due to the rule-based control logic implemented in the VPP controller. The strategy prioritises reactive power support and BESS charging under elevated voltage conditions, while PV curtailment is only applied as a last-resort action when voltage exceeds 1.035 p.u. Similarly, BESS discharge is prioritised during evening peak periods when transformer loading exceeds 85%, with EV demand reduction applied only as a secondary measure. These thresholds ensure that flexibility resources are used before curtailing renewable generation or reducing demand. The resultant effect demonstrates that coordinated control through a Virtual Power Plant (VPP) framework significantly improves the operational performance of distribution networks with high distributed energy resource (DER) penetration

4.2. Scenario 2: High EV, low PV

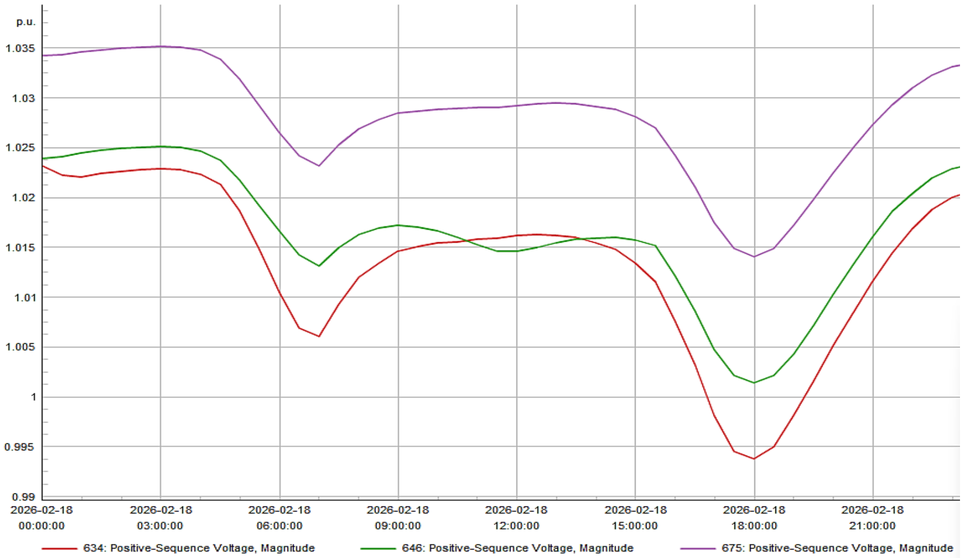

Figure 22. Uncontrolled bus voltage profiles at buses 634, 646, and 675 under winter low-PV conditions

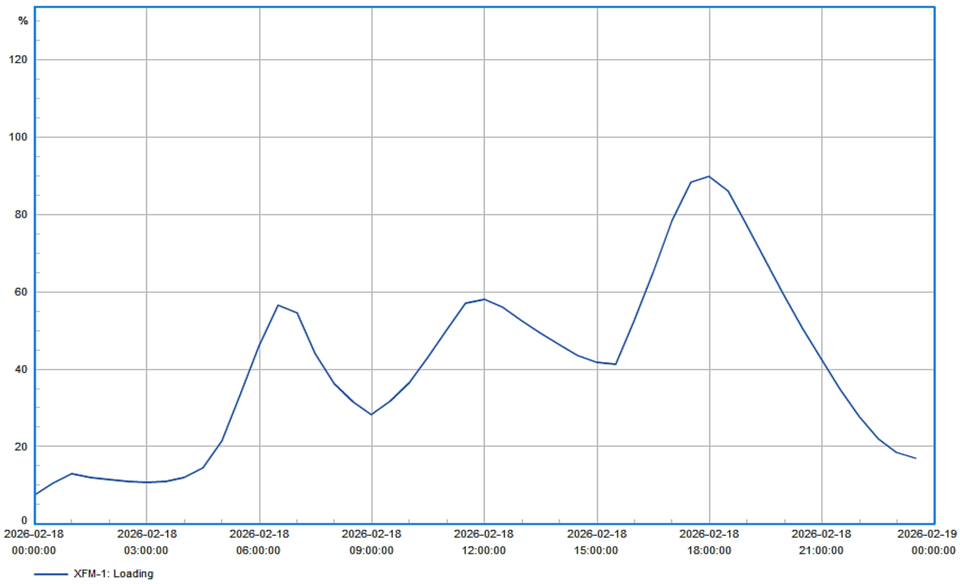

Figure 23. Uncontrolled transformer loading percentage for a winter day with low PV generation

4.2.1. VPP-controlled operation

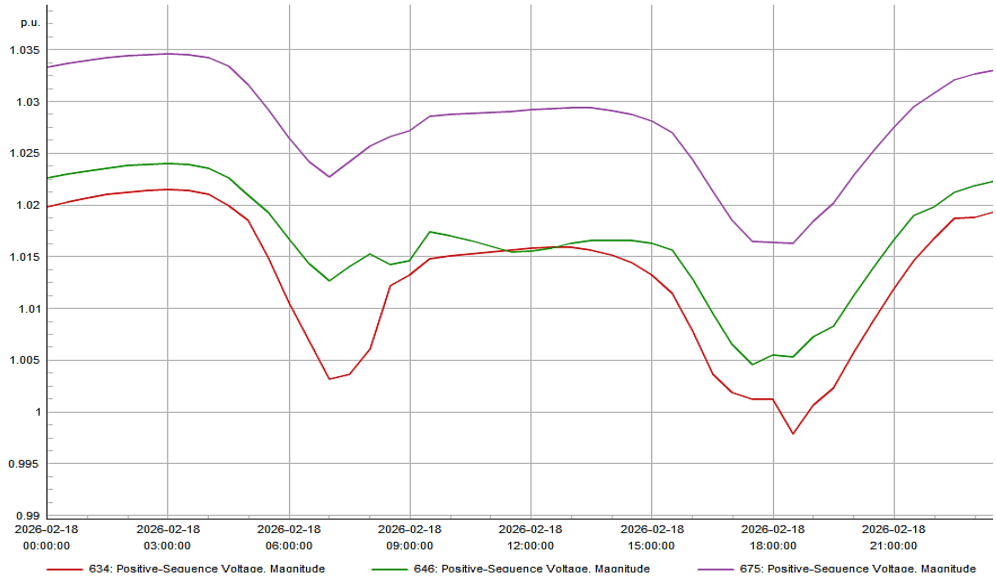

Figure 24. Under VPP-controlled operation, the voltage profile across the selected buses show improved regulation, with reduced voltage dips compared to the uncontrolled case

As seen in Figure 22, in the winter low PV scenario, the uncontrolled voltage drops to approximately 0.995 p.u., whereas under VPP control the minimum voltage remains higher, indicating improved voltage regulation as seen in Figure 24.

A key outcome of the VPP control strategy is the reduction in transformer loading, particularly during peak periods. In the winter high EV and low PV scenario, the uncontrolled transformer loading reaches approximately 88–90%, as shown in Figure 23, whereas the controlled case reduces this to around 80%, as illustrated in Figure 25, corresponding to an absolute reduction of approximately 8–10%.

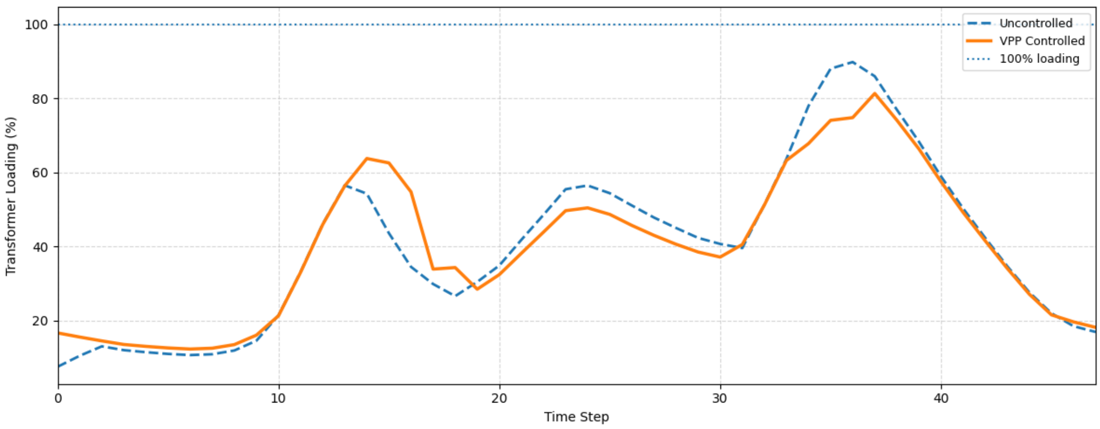

Figure 25. The comparison of transformer loading indicates that the VPP-controlled case reduces peak loading compared to the uncontrolled scenario, particularly during the evening demand period

The role of BESS is significantly enhanced under VPP coordination. In the uncontrolled case, BESS operation is largely passive and dependent on local conditions, resulting in minimal charging during periods of low PV availability and limited contribution during peak demand. In contrast, the VPP-controlled case demonstrates active and strategic operation, where the BESS charges also during periods of elevated voltage and not only excess PV generation and discharges during peak demand periods. This coordinated behaviour enables effective energy shifting across time and improves the utilisation of storage capacity. The VPP enables implicit energy transfer across the network by coordinating DER operation, allowing surplus generation at one node to be absorbed by flexible resources at another.

An important observation is that coordinated control reduces the need for PV curtailment. In local or uncoordinated control, PV systems respond to local bus voltage only, often resulting in premature and excessive curtailment. In contrast, the VPP strategy delays curtailment by first utilising available flexibility such as BESS charging and EV load adjustment throughout the network. As illustrated in Figure 26, the centralised VPP approach reduces curtailment compared to local control, particularly during later time steps, allowing greater utilisation of available solar generation. While peak curtailment values may appear similar in some instances, the overall duration and magnitude of curtailment are reduced, indicating more efficient use of renewable energy.

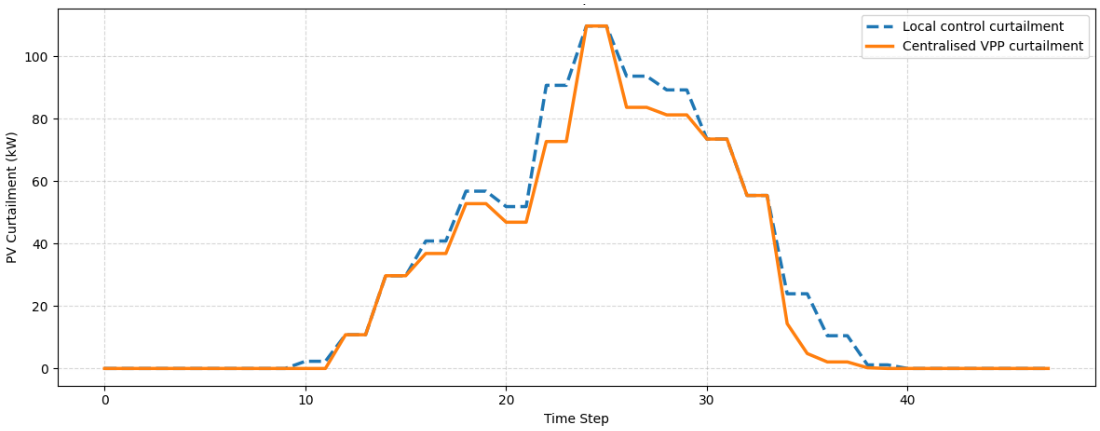

Figure 26. PV curtailment comparison at Bus 675 under local and centralised VPP control, showing reduced curtailment during peak generation periods with centralized coordinated operation

Additionally, EV load control is applied selectively based on system conditions rather than uniformly. In comparison with the summer scenario, the winter case (low PV) is more strongly influenced by evening demand peaks due to reduced generation from PV panels; this increases the reliance on coordinated BESS discharge and EV load management. By reducing EV charging only when transformer loading exceeds defined thresholds, the strategy avoids unnecessary demand reduction during periods such as midday, where high loading may be driven by reverse power flow rather than actual demand stress. This ensures that EV flexibility is utilised efficiently without compromising user demand unnecessarily.

5. Conclusion

The simulations confirm that the proposed rule-based supervisory VPP control strategy successfully meets the research objective of enhancing distribution network performance under high DER penetration. By enabling coordinated operation of PV, BESS, and EV loads, the VPP framework effectively improves voltage regulation, reduces transformer loading, and mitigates reverse power flow while ensuring optimum utilisation of available renewable energy. The findings demonstrate that even a rule-based control approach can deliver meaningful operational benefits, particularly through strategic BESS utilisation and system-wide coordination. While these results highlight the effectiveness of the proposed approach, certain assumptions have been made. Forecast uncertainty for PV and EV behaviour is not explicitly modelled, and communication delays or data latency in real-world VPP deployment are also not considered. In addition, BESS models are simplified with fixed efficiency and power limits, and economic factors such as market signals and operating costs are outside the scope of this work.

Overall, this study shows that VPP-based control provides a practical and effective solution for managing future distribution networks with increasing levels of renewable integration, supporting both network reliability and efficient energy use. Building on the rule-based framework developed in this work, future research could explore more advanced control approaches, such as the reinforcement learning (RL)-based framework proposed in the recommendations, to enable adaptive and data-driven decision-making under uncertain and dynamic operating conditions.

5.1. Recommendations

As highlighted in several studies (Zare et al., 2026) the implementation of Artificial Intelligence for VPP control requires large volumes of data and significant computational resources for training and convergence. These requirements, along with integration complexity within the PowerFactory–Python environment, limit its practical implementation within the scope of this study. While the proposed rule-based VPP control strategy provides a structured and transparent approach for coordinating DERs, its reliance on predefined thresholds and sequential decision logic limits its ability to adapt dynamically to highly variable and uncertain operating conditions.

As a potential enhancement, future work could explore the integration of reinforcement learning (RL) for adaptive VPP control. A framework is recommended, that makes use of a suitable simulation environment, while the RL agent observes system states and determines optimal control actions through continuous interaction. The state space include key network variables such as bus voltages, load demand, photovoltaic (PV) generation, battery state of charge (SOC), and line loading levels. Based on the observed state, the RL agent selects control actions, including battery charge/discharge decisions, flexible load shifting of EV demand, and PV curtailment. A reward function is defined to guide the learning process, where improved DER utilisation is encouraged, and penalties are applied for voltage deviations, thermal overloads, and constraint violations.

Over repeated an interaction with the simulation environment, the agent updates its control policy to maximise cumulative reward, enabling more adaptive and coordinated DER operation compared to fixed rule-based strategies.

Figure 27 illustrates the interaction between the PowerFactory simulation environment and the RL agent. The agent observes system states, takes control actions, receives feedback through the reward signal, and updates its policy iteratively. This closed-loop learning process enables the controller to adapt to changing system conditions and improve decision-making over time. Compared to the rule-based approach, RL has the potential to provide more flexible, scalable, and optimal control strategies, particularly in distribution networks with high penetration of distributed energy resources.

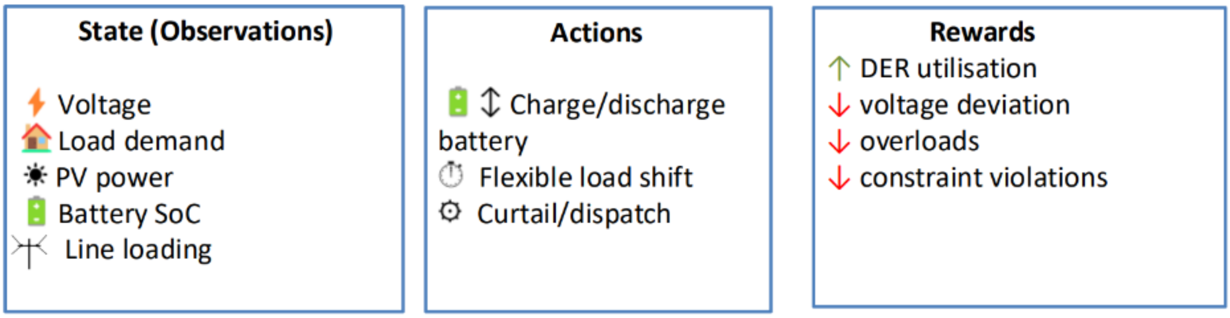

Figure 27. Conceptual reinforcement learning (RL) framework for VPP control

References

Abdelkader SM, Amissah J, Abdel-Rahim O, 2024. Virtual power plants: An in-depth analysis of their advancements and importance as crucial players in modern power systems. Energy, Sustainability and Society, 14, 52, doi:10.1186/s13705-024-00483-y.

Abdolrasol MGM, Mohamed R, Hannan MA, Al-Shetwi AQ, Mansor M, Blaabjerg F, 2021. Artificial neural network based particle swarm optimization for microgrid optimal energy scheduling. IEEE Transactions on Power Electronics, 36 (11), 12151-12157, doi:10.1109/TPEL.2021.3074964.

Aboelhassan I, Almetwally R, Cardenas-Barrera JL, Chang L, 2024. Review on virtual power plant for hierarchical control techniques. IEEE 12th International Conference on Smart Energy Grid Engineering (SEGE), 115-122, doi:10.1109/SEGE62220.2024.10739617.

Aftab MA, Hussain SMS, Ustun TS, Kalam A, 2021. IEC 61850 communication and XMPP based design of virtual power plant. Proceedings of the 31st Australasian Universities Power Engineering Conference (AUPEC 2021), 1-6, doi:10.1109/AUPEC52110.2021.9597719.

Ahmadian A, Ponnambalam K, Almansoori A, Elkamel A, 2023. Optimal management of a virtual power plant consisting of renewable energy resources and electric vehicles using mixed-integer linear programming and deep learning. Energies, 16 (2), 1000, doi:10.3390/en16021000.

Akbari E, Faraji Naghibi A, Veisi M, Shahparnia A, Pirouzi S, 2024. Multi-objective economic operation of smart distribution network with renewable-flexible virtual power plants considering voltage security index. Scientific Reports, 14 (1), 19136, doi:10.1038/s41598-024-70095-1.

Akram U, Mithulananthan N, Shah R, Milano F, 2020. A review on rapid responsive energy storage technologies for frequency regulation in modern power systems. Renewable and Sustainable Energy Reviews, 120, 109626, doi:10.1016/j.rser.2019.109626.

Al Sumarmad KA, Sulaiman N, Wahab NIA, Hizam H, 2022. Energy management and voltage control in microgrids using artificial neural networks, PID, and fuzzy logic controllers. Energies, 15 (1), 303, doi:10.3390/en15010303.

Alajlan R, Hafizur Rahman MM, Al-Naeem M, Almaiah MA, 2024. A literature review on cybersecurity risks and challenges assessments in virtual power plants: Current landscape and future research directions. IEEE Access, 12, 188813-188827, doi:10.1109/ACCESS.2024.3515635.

Al-Gabalawy M, 2021. Reinforcement learning for the optimization of electric vehicle virtual power plants. International Transactions on Electrical Energy Systems, 31 (8), e12951, doi:10.1002/2050-7038.12951.

Alshamasi RZ, Ibrahim DM, 2025. Federated intelligence for smart grids: a comprehensive review of security and privacy strategies. Journal of Electrical Systems and Information Technology, 12, 43, doi:10.1186/s43067-025-00235-8.

Australian Renewable Energy Agency (ARENA), 2021. Tesla virtual power plant lessons learnt report 1. Canberra, ACT, Australia, accessed 25 October 2025 from: https://arena.gov.au/assets/2021/08/tesla-virtual-power-plant-lessons-learnt-1.pdf.

Bedi A, Ramprabhakar J, Anand R, Meena VP, Hameed IA, 2025. Empowering net zero energy grids: a comprehensive review of virtual power plants, challenges, applications, and blockchain integration. Discover Applied Sciences, 7, 252, doi:10.1007/s42452-025-06691-1.

Bhuiyan EA, Hossain MZ, Muyeen SM, Fahim SR, Sarker SK, Das SK, 2021. Towards next generation virtual power plant: Technology review and frameworks. Renewable and Sustainable Energy Reviews, 150, 111358, doi:10.1016/j.rser.2021.111358.

Cabrane Z, Kim J, Yoo K, Lee SH, 2022. Fuzzy logic supervisor-based novel energy management strategy reflecting different virtual power plants. Electric Power Systems Research, 205, 107731, doi:10.1016/j.epsr.2021.107731.

Cambambi CAC, Canha LN, Ramos LF, Adeyanju OM, 2022. Optimization of the virtual power plants through evolutionary algorithms. 2022 IEEE Power & Energy Society General Meeting (PESGM), 1-5, doi:10.1109/PESGM48719.2022.9916985.

Chang W, Dong W, Zhao L, Yang Q, 2020. Model predictive control based energy collaborative optimization management for energy storage system of virtual power plant. 19th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), 112-115, doi:10.1109/DCABES50732.2020.00037.

Chaudhari K, Kandasamy NK, Krishnan A, Ukil A, Gooi HB, 2019. Agent-based aggregated behavior modeling for electric vehicle charging load. IEEE Transactions on Industrial Informatics, 15 (2), 856-868, doi:10.1109/TII.2018.2823321.

Chen C, Xu X, Zhao J, Wen F. 2021 Jan. A two-stage robust optimization for joint energy and reserve dispatch of virtual power plants in electricity markets. Applied Energy, 280, 115, doi: 10.1016/j.apenergy.2020.115981.

Chen J, Liu M, Milano F, 2021. Aggregated model of virtual power plants for transient frequency and voltage stability analysis. IEEE Transactions on Power Systems, 36 (5), 4366-4375, doi:10.1109/TPWRS.2021.3063280.

Chihota MJ, Bekker B, 2020. Modelling and simulation of uncertainty in the placement of distributed energy resources for planning applications. International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 1-6, doi:10.1109/PMAPS47429.2020.9183657.

Chung KH, Park MG, Hur D, 2016. A study on the participation of virtual power plant based technology utilizing distributed generation resources in electricity market. The Transactions of the Korean Institute of Electrical Engineers, 65 (2), 94-100, doi:10.5370/KIEEP.2016.65.2.094.

Dai Z, Tan M, Yang Y, Liu X, Wang R, Su Y, 2025. Massive coordination of distributed energy resources in VPP: a mean field RL-based bi-level optimization approach. IEEE Transactions on Cybernetics, 55 (3), 1332-1346, doi:10.1109/TCYB.2024.3525121.

Dandea V, Grigoras G, 2023. Expert system integrating rule-based reasoning to voltage control in photovoltaic-systems-rich low voltage electric distribution networks: A review and results of a case study. Applied Sciences, 13 (10), 6158, doi:10.3390/app13106158.

Datta MK, 2024. Looking beyond demand response: barriers and opportunities to deploying virtual power plants among rural electric cooperatives in the United States. Master's dissertation, University of Minnesota, accessed 25 November 2025 from: https://conservancy.umn.edu/items/9d313832-a0e3-4588-9049-d6373997f553.

De K, Badar AQH, 2022. Virtual power plant profit maximization in day ahead market using different evolutionary optimization techniques. 4th International Conference on Energy, Power and Environment (ICEPE), 1-6, doi:10.1109/ICEPE55035.2022.9797939.

Ding Y, Zhang S, Chen Y, Zhoa L, Chen H, Sun W, 2024. Optimal scheduling of the virtual power plant with electric vehicles using dueling DDQN. 4th International Conference on Energy, Power and Electrical Engineering (EPEE), 1065-1070, doi:10.1109/EPEE63731.2024.10875393.

Dortans C, Anderson B, Jack M, 2019. NZ GREEN Grid Household Electricity Demand Data: EECA Data Analysis (Part B) Report v2.1. University of Otago, accessed 21 October 2025 from: https://hdl.handle.net/10523/9821.

Fang F, Yu S, Xin X, 2022. Data-driven-based stochastic robust optimization for a virtual power plant with multiple uncertainties. IEEE Transactions on Power Systems, 37 (1), 456-466, doi:10.1109/TPWRS.2021.3091879.

Fernández-Muñoz D, Pérez-Díaz JI, 2022. Optimisation models for the day-ahead energy and reserve scheduling of a hybrid wind-battery virtual power plant. arXiv preprint, doi:10.48550/arXiv.2206.13784.

Guo J, Dou C, Yue D, Zhang B, Zhang Z, Zhang Z, 2025. Multiagent system-based VPPs cooperative power control for frequency regulation considering diverse communication issues. IEEE Transactions on Smart Grid, 16 (4), 2846-2857, doi:10.1109/TSG.2025.3557436.

Guo J, Dou C, Yue D, Zhang Z, Zhang Z, Zhang B, 2025. Co-design of power dispatch with dynamic power regulation and communication transmission optimization for frequency control in VPPs. Journal of Modern Power Systems and Clean Energy, 13 (4), 1383-1394, doi:10.35833/MPCE.2024.000604.

Guo Y, Zhang Q, Wang Z, 2021. Cooperative peak shaving and voltage regulation in unbalanced distribution feeders. IEEE Transactions on Power Systems, 36 (6), 5235-5244, doi:10.1109/TPWRS.2021.3069781.

Howorth G, Kockar I, 2024. VPP implementations: Different types of services developed, experiences and platforms. 7th European Grid Services Market Symposium, accessed 24 November 2025 from https://strathprints.strath.ac.uk/89925/1/Howorth-Kockar-2024-GSM-2024-VPP-implementations-different-types-of-services-developed.pdf.

Huang J, Li H, Zhang Z, 2025. Review of virtual power plant response capability assessment and optimization dispatch. Technologies, 13 (6), 216, doi:10.3390/technologies13060216.

Hwang JO, Lee JO, Kim GH, Jeon JH, 2023. A novel evaluation method of virtual power plant effect on distribution networks using fuzzy logic. 27th International Conference on Electricity Distribution (CIRED 2023), 1050-1053, doi:10.1049/icp.2023.0625.

Hyun S, Kim G, Park J, Choi Y, 2025. Optimal virtual power plant control algorithm considering the electrical characteristics of distributed energy resources. Applied Sciences, 15 (1), 127, doi:10.3390/app15010127.

Ibrar M, 2023. Enhancing grid resilience: Leveraging power from flexible load in modern power systems. 18th International Conference on Emerging Technologies (ICET), doi:10.1109/ICET59753.2023.10374732.

Idrisov I, Veretennikov I, Vasilev S, Gutierrez S, Ibanez F, 2023. Microgrid digital twin application for future virtual power plants. IECON 2023 – 49th Annual Conference of the IEEE Industrial Electronics Society, 16-19, doi:10.1109/IECON51785.2023.10311709.

International Energy Agency, 2023. World energy outlook, OECD Publishing, Paris, doi:10.1787/827374a6-en.

Jafari S, Byun YC, 2025. AI-driven state of power prediction in battery systems: A PSO-optimized deep learning approach with XAI. Energy, 331, 136764, doi:10.1016/j.energy.2025.136764.

Jin Y, Gao C, 2025. Market applications and uncertainty handling for virtual power plants. Energies, 18 (14), 3743, doi:10.3390/en18143743.

Kabir MH, Newaz SMS, Kabir T, Howlader AS, 2024. Integrating solar power with existing grids: strategies, technologies, and challenges – a review. EPJ Photovoltaics, 15, 21, doi:10.1051/epjpv/2024018.

Khan I, Jayaweera D, Alvarez-Alvarado MS, 2021. A comprehensive review on virtual power plant: components, functions, challenges, and future trends. Energy Reports, 7, 8429-8457, doi:10.1016/j.egyr.2021.08.158.

Kolenc M, Ihle N, Gutschi C, Zajc M, 2019. Virtual power plant architecture using OpenADR 2.0b for dynamic charging of automated guided vehicles. International Journal of Electrical Power and Energy Systems, 104, 415-425.

Koraki D, Strunz K, 2018. Wind and solar power integration in electricity markets and distribution networks through service-centric virtual power plants. IEEE Transactions on Power Systems, 33 (1), 473-485, doi:10.1109/TPWRS.2017.2684918.

Lee J, Won D, 2021. Optimal operation strategy of virtual power plant considering real-time dispatch uncertainty of distributed energy resource aggregation. IEEE Access, 9, 56965-56978, doi:10.1109/ACCESS.2021.3072550.

Li H, Qian S, Zhang X, Hu M, Wand N, Chen W, 2024. Optimized scheduling of virtual power plant based on multiple target particle swarm. 4th International Conference on Smart Grid and Energy Internet (SGEI), 45-49, doi:10.1109/SGEI63936.2024.10914240.

Li X, Luo F, Li C, 2024. Multi-agent deep reinforcement learning-based autonomous decision-making framework for community virtual power plants. Applied Energy, 360, 122813, doi:10.1016/j.apenergy.2024.122813.

Li Z, Xu L, Cheng J, 2023. Secondary frequency regulation strategy of multi-agent virtual power plant based on scenery storage. China Automation Congress (CAC), 1755-1760, doi:10.1109/CAC59555.2023.10451397.

Lin H, Guo Y, Zhou J, Xu M, Wu W, Sun H, Mao T, Zhao W, 2023. A review on virtual power plants: development progress and market participation mechanisms. IEEE 7th Conference on Energy Internet and Energy System Integration (EI2), 2359-2364, doi:10.1109/EI259745.2023.10512817.

Lin L, Guan X, Peng Y, Wang N, Maharjan S, Ohtsuki T, 2020. Deep reinforcement learning for economic dispatch of virtual power plant in Internet of Energy. IEEE Internet of Things Journal, 7 (7), 6288-6297, doi:10.1109/JIOT.2020.2966232.

Liu C, Yang RJ, Yu X, Sun C, Wong PSP, Zhao H, 2020. Virtual power plants for a sustainable urban future. Sustainable Cities and Society, 63, 102640, doi:10.1016/j.scs.2020.102640.

Liu J, Yu SS, Hu H, Zhao J, Trinh HM, 2023. Demand side regulation provision of virtual power plants consisting of interconnected microgrids through double stage double layer optimization. IEEE Transactions on Smart Grid, 14 (3), 1946-1958, doi:10.1109/TSG.2022.3203466.

Lu C, Chen S, 2022. Distributed scheduling strategy of virtual power plant using the particle swarm optimization neural network under blockchain background. Computational Intelligence and Neuroscience, 2022, 3222249, doi:10.1155/2022/3222249.

Maldonato F, Hadachi I, 2024. Towards a resilient and sustainable energy system: Reinforcement learning for virtual power plants. arXiv preprint, accessed 25 May 2026 from: https://arxiv.org/abs/2405.01889.

Marcelino CG, Avancini JVC, Delgado CADM, Wanner EF, Jiménez-Fernández S, Salcedo-Sanz S, 2021. Dynamic electric dispatch for wind power plants: A new automatic controller system using evolutionary algorithms. Sustainability, 13 (21), 11924, doi:10.3390/su132111924.

Marzbani F, Osman AH, Hassan MS, 2025. Advances in virtual power plant operations: a review of optimization models. IEEE Access, 13, 131525-131548, doi:10.1109/ACCESS.2025.3591697.

Meridian Energy, 2023. Trial takes Meridian closer to virtual power plant. Meridian Energy News, 19 October, accessed 26 June 2026 from: https://www.meridianenergy.co.nz/news-and-events/trial-takes-meridian-closer-to-virtual-power-plant.

Mirza H, Bellalem F, Mirza C, 2023. Ethical considerations in qualitative research: summary guidelines for novice social science researchers. Social Studies and Research Journal, 11 (1), 441-449.

Mishra N, Choubey S, 2024. Machine learning based power regulation for smart multi storage building. E3S Web of Conferences, 540, 11006, doi:10.1051/e3sconf/202454011006.

Mnatsakanyan A, Albeshr H, Almarzooqi A, Iraklis C, Bilbao E, 2022. Blockchain mediated virtual power plant: from concept to demonstration. Journal of Engineering, 2022 (7), 732-738, doi:10.1049/tje2.12158.

Mo L, Lan J, Chen Z, Yang H, Liao X, Chen H, 2025. Multi-time scale frequency regulation control of virtual power plant based on fuzzy sets. IEEE Transactions on Smart Grid, 16 (3), 2361-2374, doi:10.1109/TSG.2025.3541544.

Mohseni S, Brent AC, Kelly S, Browne WN, 2022. Demand response-integrated investment and operational planning of renewable and sustainable energy systems considering forecast uncertainties: a systematic review. Renewable and Sustainable Energy Reviews, 158, 112095, doi:10.1016/j.rser.2022.112095.

Mondal S, Azmain AM, Mollah L, Reza MS, 2022. Aggregation of distributed energy resources to form a virtual power plant. Proceedings of the 12th International Conference on Electrical and Computer Engineering (ICECE), 21-23, doi:10.1109/ICECE57408.2022.10088589.

Nadimi R, Goto M, 2024. Uncertainty reduction in power forecasting of virtual power plant: from day ahead to balancing markets. Renewable Energy, 238, 121875, doi:10.1016/j.renene.2024.121875.

Nafkha-Tayari W, Ben Elghali S, Heydarian-Forushani E, Benbouzid M, 2022. Virtual power plants optimization issue: A comprehensive review on methods, solutions, and prospects. Energies, 15 (10), 3607, doi:10.3390/en15103607.

Naughton J, Wang H, Cantoni M, Mancarella P, 2021. Co-optimizing virtual power plant services under uncertainty: A robust scheduling and receding horizon dispatch approach. IEEE Transactions on Power Systems, 36 (5), 3960-3972, doi:10.1109/TPWRS.2021.3062582.

Naval N, Yusta JM, 2021. Virtual power plant models and electricity markets – a review. Renewable and Sustainable Energy Reviews, 149, 111393, doi:10.1016/j.rser.2021.111393.

Nemati H, Sánchez-Martín P, Baringo A, Ortega Á, 2024. Single-level robust bidding of renewable-only virtual power plant in energy and ancillary service markets for worst-case profit. arXiv preprint, doi:10.48550/arXiv.2403.02953.

NIWA, 2026. SolarView. Wellington, accessed 15 February 2026 from: https://data.niwa.co.nz/solarview.

O'Neil L, Reedman L, Braslavsky J, Brinsmead T, McDonald C, Ward A, Williams B, 2021. Analysis of the VPP dynamic network constraint management – Advanced VPP grid integration project. CSIRO, accessed 13 February 2026 from: https://arena.gov.au/assets/2021/01/analysis-of-the-vpp-dynamic-network-constraint-management.pdf.

Oshnoei A, Kheradmandi M, Blaabjerg F, Hatziargyriou ND, Muyeen SM, Anvari-Moghaddam A, 2022. Coordinated control scheme for provision of frequency regulation service by virtual power plants. Applied Energy, 325, 119734, doi:10.1016/j.apenergy.2022.119734.

Padullaparti HV, Pratt A, Mendoza Carrillo I, Tiwari S, Baggu M, Bilby C, Ngo Y, 2023. Peak demand management and voltage regulation using coordinated virtual power plant controls. IEEE Access, 11, 130674-130687, doi:10.1109/ACCESS.2023.3334607.

Panda S, Mohanty S, Rout PK, Sahu BK, 2022. A conceptual review on transformation of micro-grid to virtual power plant: issues, modeling, solutions, and future prospects. International Journal of Energy Research, 46 (6), 7492-7520, doi:10.1002/er.7671.

Park SW, Son SY, 2020. Interaction-based virtual power plant operation methodology for distribution system operator's voltage management. Applied Energy, 271, 115222, doi:10.1016/j.apenergy.2020.115222.

Pawar A, Viral RK, Asija D, Bansal M, 2024. Mechanism of virtual power plant with emphasis on distributed generation integration. Asian Conference on Intelligent Technologies (ACOIT), 1-5, doi:10.1109/ACOIT62457.2024.10941371.

Peiris S, Filizadeh S, Muthumuni D, 2024. Modular dynamic phasor modeling and simulation of renewable integrated power systems. Energies, 17 (11), 2480, doi:10.3390/en17112480.

Pettersson F, Batti R, 2023. Swedish consumers' perception of virtual power plants: a mixed-method study of VPPs. Umeå School of Business and Economics (USBE), Umeå University, Sweden, diva2:1770231.

Piltan G, Pirouzi S, Azarhooshang A, Rezaee Jordehi A, Paeizi A, Ghadamyari M, 2022. Storage-integrated virtual power plants for resiliency enhancement of smart distribution systems. Journal of Energy Storage, 55 (Part B), 105563, doi:10.1016/j.est.2022.105563.

Pincelli IP, Hinkley J, Brent AC, 2024. Life cycle assessment of a virtual power plant: Evaluating the environmental performance of a system utilising solar photovoltaic generation and batteries. Renewable Energies, 2(2), doi:10.1177/27533735241285428.

Qais M, 2025. A virtual power plant for coordinating batteries and electric vehicles. Energy Reports, 22, 1644-1654, doi:10.1016/j.egyr.2025.01.189.

Restrepo M, Cañizares CA, Simpson-Porco JW, Su P, Taruc J, 2021. Optimization and rule-based energy management systems at the Canadian Renewable Energy Laboratory

microgrid facility. Applied Energy, 290, 116760, doi:10.1016/j.apenergy.2021.116760.
Riaz S, Mancarella P, 2021. Modelling and characterisation of flexibility from distributed energy resources. arXiv preprint, doi:10.48550/arXiv.2107.05144.
Rouzbahani HM, Karimipour H, Lei L, 2021. A review on virtual power plant for energy management. Sustainable Energy Technologies and Assessments, 47, 101370, doi:10.1016/j.seta.2021.101370.
Salehi MH, Moradian M, Moazzami M, Shahgholian G, 2023. Distributed energy technologies planning and sizing in a sample virtual power plant using speedy particle swarm optimization algorithm. International Journal of Smart Electrical Engineering, 12 (4), 253-266, doi: 10.30495/ijsee.2022.1964937.1219.
Sattar F, Husnain A, Ghaoud T, 2023. Integration of distributed energy resources into a virtual power plant – a pilot project in Dubai. 2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), 526-531, doi:10.1109/ICPSAsia58343.2023.10294691.
Setiawan A, Jufri FH, Dzulfiqar F, Samual MG, Arifin Z, Angkasa FF, Aryani DR, Garniwa I, Sudiarto B, 2024. Opportunity assessment of virtual power plant implementation for sustainable renewable energy development in Indonesia power system network. Sustainability, 16 (5), 1721, doi:10.3390/su16051721.
Shahzad S, Jasińska E, 2024. Renewable revolution: a review of strategic flexibility in future power systems. Sustainability, 16 (13), 5454, doi:10.3390/su16135454.
Shinde P, Kouveliotis-Lysikatos I, Amelin M, 2022. Multistage stochastic programming for VPP trading in continuous intraday electricity markets. IEEE Transactions on Sustainable Energy, 13 (2), 1037-1048, doi:10.1109/TSTE.2022.3144022.
Snyder H, 2019. Literature review as a research methodology: An overview and guidelines. Journal of Business Research, 104, 333-339, doi:10.1016/j.jbusres.2019.07.039.
Speetles B, Lockhart E, Warren A, 2023. Virtual power plants and energy justice. NREL Technical Report NREL/TP-7A40-86607, doi:10.2172/2008456.
Stephenson J, Ford R, Nair NKC, Watson N, Wood A, Miller A, 2018. Smart grid research in New Zealand: A review from the GREEN Grid research programme. Renewable and Sustainable Energy Reviews, 82, 1636-1645, doi:10.1016/j.rser.2017.06.093.
Taheri SI, Davoodi MR, Ali MH. 2A modified modeling approach of virtual power plant via improved federated learning. International Journal of Electrical Power and Energy Systems, 158, 109, doi:10.1016/j.ijepes.2024.109905.
Tan Z, Wang S, Zhong H, Xia Q, Kang C, 2022. Enlarging flexibility region of virtual power plant via dynamic line rating. IET Renewable Power Generation, 16 (2), 751-760, doi:10.1049/rpg2.12419.
Ullah Z, Arshad A, Nekahi A, 2024. Virtual power plants: challenges, opportunities, and profitability assessment in current energy markets. Electricity, 5 (2), 370-384, doi:10.3390/electricity5020019.
Vafa M, Ershadi MH, Arandian B, 2025. Robust operation of renewable virtual power plant in intelligent distribution system considering active and reactive ancillary services markets. Scientific Reports, 15 (1), 22693, doi:10.1038/s41598-025-06501-z.
Venegas-Zarama JF, Muñoz-Hernandez JI, Baringo L, Diaz-Cachinero P, De Domingo-Mondejar I, 2022. A review of the evolution and main roles of virtual power plants as key stakeholders in power systems. IEEE Access, 10, 47937 – 47964, doi:10. 10.1109/ACCESS.2022.3171823.
Wan Abdullah WS, Osman M, Ab Kadir MZA, Verayiah R, Ab Aziz NF, Abdul Rasheed M. 2021. Techno-economics analysis of battery energy storage system (BESS) design for

virtual power plant (VPP) – a case study in Malaysia. Journal of Energy Storage, 44, 102, doi:10.1016/j.est.2021.102568.
Wang S, Jia R, Shi X, Luo C, An Y, Huang Q, Guo P, Wang X, Lei X, 2022. Research on capacity allocation optimization of commercial virtual power plant (CVPP). Energies, 15 (4), 1303, doi:10.3390/en15041303.
Wen M, He H, Qin K, Song B, Teng X, 2025. Optimal scheduling strategy for hierarchical VPP participation in frequency regulation ancillary services based on reinforcement learning. 2025 4th International Conference on Energy, Power and Electrical Technology (ICEPET), 59-67, doi:10.1109/ICEPET65469.2025.11047291.
Yang X, Hu XL, Sun G, Fang C, Tian YJ, Du N, 2022. Coordinated optimization scheduling of building virtual power plant considering power sharing. Journal of Electric Power Science and Technology, 37 (1), 96-105, doi:10.19781/j.issn.1673-9140.2022.01.012.
Yoon SJ, Ryu KS, Kim C, Nam YH, Kim DJ, Kim B, 2024. Optimal bidding scheduling of virtual power plants using a dual-MILP approach under a real-time energy market. Energies, 17 (15), 3773, doi:10.3390/en17153773.
Yu D, Zhao X, Wang Y, Jiang L, Liu H, 2022. Research on energy management of a virtual power plant based on the improved cooperative particle swarm optimization algorithm. Frontiers in Energy Research, 10, 785569, doi:10.3389/fenrg.2022.785569.
Yzzogh H, Kandil H, Benaboud H, 2024. A comprehensive overview of AI-driven behavioral analysis for security in Internet of Things. In: The Art of Cyber Defense. Boca Raton, doi:10.1201/9781032714806.
Zhang T, Gooi HB, 2014. Hierarchical MPC-based energy management and frequency regulation participation of a virtual power plant. IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), 1-5, doi:10.1109/ISGTEurope.2014.7028751.
Zhang Y, Wen M, Li W, Niu B, Qiu W, Li F, 2024. ADP-VFL: an adaptive differential privacy scheme for VPP based on federated learning. ICC 2024 – IEEE International Conference on Communications, 5184-5189, doi:10.1109/ICC51166.2024.10622636.
Zhong Y, Ji L, Li J, Wang Z, Wu J, Li H, 2024. Role and value embodiments, application challenges and system design suggestions of VPP in the context of new type power systems. 2024 IEEE 7th International Electrical and Energy Conference (CIEEC), 1299-1303, doi:10.1109/CIEEC60922.2024.10583469.
Zhou K, Peng N, Yin H, Hu R, 2023. Urban virtual power plant operation optimization with incentive-based demand response. Energy, 282, 128700, doi:10.1016/j.energy.2023.128700.
Zhou Y, Wu S, Deng Y, Jiang M, Fu Y, 2025. Enhancing virtual power plant efficiency: three-stage optimization with energy storage integration. Energy Informatics, 8, 23, doi:10.1186/s42162-025-00477-w.