

Article

Increasing Renewable Energy Penetration on Low-Voltage Networks: An Expert Knowledge Approach

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Abstract: While South Africa is deemed one of the countries with the highest irradiation levels, it still utilises coal as its primary energy source due to its abundance. Due to the world-wide drive towards carbon neutrality, residential, commercial, agricultural, and industrial consumers are considering small-scale embedded generation systems. The National Rationalised Specifications 097-2-3 document specifies the scale of the embedded generation capacity a consumer is allowed to install. However, specifications do not yet make the required provisions for the addition of energy storage. The effective collective management of the grouped small-scale embedded generation systems could provide a high level of energy security and increase the percentage of renewable energy generation in the total energy mix. Potential challenges come into play when considering the stochastic nature of photovoltaic generation and its effect on the storage capacity and the dispersion in load profiles of the residential units typically present on a low-voltage network. This paper contributes by investigating the utilisation of photovoltaic generation in conjunction with storage as the basis for virtual power plant control, with the aim to safely increase renewable energy penetration and improve energy security, all while remaining within the South African low-voltage regulatory limits. A two-level virtual power plant controller is proposed with the dispersed energy storage units as the primary controllable resources and the dispersed photovoltaic generation as the secondary controllable resources. The objective of the controller is to achieve nodal energy management, energy sharing, and ancillary service provision and finally to increase renewable energy penetration. A representative single-feeder low-voltage network is simulated, and test cases of 50% and 75% renewable energy penetration are investigated as the basis for evaluation. The proposed controller architecture proved to maintain network integrity for both test cases. The adaptability of the controller architecture was also confirmed for a changed feeder topology; in this case, it was a multi-feeder topology. Future work is warranted to inform policy on the allowed levels of renewable energy penetration to be based not only on demand but also on the level of energy storage present in a network.

Keywords: virtual power plant; distributed generation; renewable energy aggregation



Citation: Jansen, L.A.; Botha, M.G.; van Schoor, G.; Uren, K.R. Increasing Renewable Energy Penetration on Low-Voltage Networks: An Expert Knowledge Approach. *Electricity* **2024**, *5*, 804–825. <https://doi.org/10.3390/electricity5040040>

Academic Editor: Pavlos S. Georgilakis and Pedro Manuel Soares Moura

Received: 29 July 2024

Revised: 24 October 2024

Accepted: 27 October 2024

Published: 31 October 2024



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1. Introduction

The popularity of distributed energy resources (DERs) is rising worldwide mainly due to the need for more sustainable energy generation with a decreasing impact on the environment [1–3]. The expansion of DERs poses a threat to network integrity, as the intermittent nature of photovoltaic (PV) and wind-based generation affects their reliability due to their dependence on the weather [4]. DERs are generally standalone units that work in isolation as a result of their independent owners. This results in neighbouring DERs often lacking cooperation and coordination, limiting the system's service to the local needs as opposed to the needs of the entire grid [3,5,6]. This is where virtual power plants (VPPs) can help improve both energy security and the level of renewable energy penetration (REP) on low-voltage (LV) networks [1,7].

A VPP aggregates widely scattered generation and storage units. The core of the VPP is an energy management system (EMS) that coordinates the resources in order to control the energy flow between the units that make up the part of the VPP [8]. The communication between the controller and the units is bi-directional. This allows each unit to not only receive commands from the controller but also send information back to the controller regarding its current state [9]. The communication allows for informed decisions and opens up the possibility of sharing power between units on the same feeder. This can be made possible by the global controller that controls the energy flow between nodes and sends the excess energy where it is most needed. This energy management method allows for optimal energy generation and utilisation and lowers the dependence on the national grid whilst simultaneously increasing the renewable energy to fossil fuel consumption ratio [10]. The VPP can also provide backup support in the event of transmission or distribution-related failures by assisting with energy provision within its resource capacity. Financial incentives can be provided to the participants of the VPP, which could cause exponential growth and ultimately cost-effective power provision [3]. The control effectiveness is influenced by various factors such as the feeder topology, after diversity maximum demand (ADMD) of the independent houses, load-to-generation ratio, aggregated storage capacity, and energy storage system (ESS) efficiency. The goal is to design the controller assuming a worst-case scenario to ensure that the controller can deal with any configuration and maintain the effectiveness of control. A typical control method evident in the literature related to energy management is the rule-based method developed from expert knowledge [11–13].

Majd et al. [14] propose a composite generation and transmission expansion plan (CGTEP) as an approach to the penetration of renewable energy. The CGTEP model takes into account uncertainties, various types of renewable sources and storage, reliability criteria, and energy export. All of the mentioned information is used in formulating a multi-objective optimisation algorithm. Gill et al. [15] developed two techniques to increase renewable penetration in islanded networks. An envelope of stability for wind generation is used in conjunction with a dynamic optimal power flow (DOPF) to schedule flexible technologies. Guerrero et al. [16] introduce a general transactive energy framework to systematically compare and contrast DER integration approaches. VPP is used as the main technology to address renewable energy integration. The proposed DER integration methods are classified into three categories: uncoordinated, coordinated, and peer-to-peer. Five DER integration models were simulated, and their performance was evaluated using a generic LV network as a case study.

This paper contributes by investigating the use of PV plus storage-based VPPs as a method of safely increasing renewable energy penetration and improving energy security, while remaining within the South African LV regulatory limits. Regulatory requirements indicate that the voltage level on the feeder be maintained between 0.85 p.u. and 1.1 p.u. voltage. The primary objective of the VPP in this paper is to maintain the network integrity of the feeder. With the ESS being the primary controllable unit and the PV system being the secondary controllable unit, the effective operation requires that the ESS be controlled as both the load and the generator. The PV generation is only curtailed once the ESS is fully charged or power needs to be drawn from the grid in an emergency [17]. The energy management constraints pertaining to the ESS and the PV generation are set. In addition to local support, the VPP also provides collective support to the medium-voltage (MV) network and assists in additional ancillary service provisions such as peak shaving.

This paper is organised as follows. Section 2 gives an overview of the challenges associated with REP, and Section 3 identifies the LV reticulation network topology that presents the greatest control challenge. Section 4 is devoted to the modelling of a representative LV network in Simulink®. Section 5 presents an energy management algorithm (EMA) based on expert knowledge, and Section 6 evaluates the EMA. The paper is concluded in Section 7.

2. Renewable Energy Penetration

The National Rationalised Specifications (NRS) 097-2-3 document limits the renewable energy penetration (REP) of a household to a percentage of its notified maximum demand (NMD), primarily to mitigate and prevent network instability. Increasing the REP above this level without energy storage or proper control is likely to adversely affect the network. Under worst-case conditions—when the load is at its lowest and generation is at its highest—significant amounts of energy can be fed back into the grid. This reverse power flow causes the voltage to rise above the maximum voltage limit, potentially activating protection equipment to safeguard the feeder transformer by tripping breakers or causing inverters to switch off to protect users on the network.

The increase in REP as a percentage of the after diversity maximum demand (ADMD) leads to a voltage rise exceeding the upper voltage limit, as determined by NRS-097-2-3. This phenomenon is illustrated in Figure 1 [18], which depicts the relationship between REP and feeder voltage levels. Figure 1 [18] illustrates how the feeder voltage level responds to increasing REP expressed as a percentage of ADMD. The horizontal axis represents the REP percentage relative to the ADMD, while the vertical axis shows the feeder voltage level in per unit (p.u.) values, where 1.0 p.u. corresponds to the nominal voltage of the network.

At lower REP levels below 50% of ADMD, the feeder voltage remains relatively stable and within acceptable limits (typically between 0.95 p.u. and 1.05 p.u.). This is depicted by the initial flat portion of the curve in Figure 1 [18]. In this region, the renewable energy generated is largely consumed locally, and minimal excess energy is exported to the grid.

As the REP increases towards a critical threshold (50% to 75% of ADMD), the curve begins to rise more noticeably. This indicates that the network's capacity to absorb additional renewable energy without voltage issues is diminishing, highlighting the need for careful management.

When the REP exceeds the local load demand (above 75% of ADMD), the collective generation surpasses consumption, causing significant energy to be fed back into the medium-voltage (MV) network. This reverse power flow leads to a rapid escalation in feeder voltage, as shown by the steep portion of the curve, exceeding the upper voltage limit (e.g., 1.1 p.u.) in Figure 1 [18].

Exceeding the upper voltage limit has several adverse effects:

- **Activation of protection equipment:** Protective devices such as over-voltage relays, circuit breakers, and inverter protections may activate to prevent equipment damage, leading to power supply disruptions.
- **Network instability:** The sudden loss of generation due to protection activation can destabilise the network, affecting both utility operations and consumer experiences [7].
- **Equipment stress:** Operating near or beyond voltage limits can accelerate the ageing of network components, reducing reliability and increasing maintenance costs.

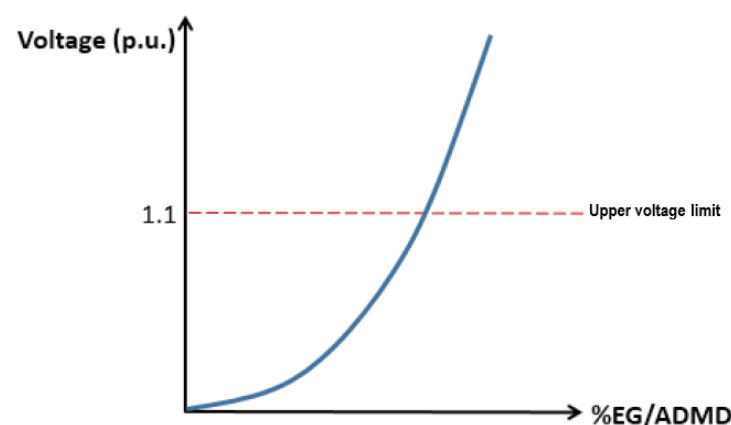


Figure 1. Voltage rise constraints with the increase in renewable energy penetration [18].

Increasing the REP without the use of storage and effective control not only is hazardous to the local feeder network but also has adverse effects on the larger network. The state of California has over the years allowed both residential and commercial consumers to unlimitedly increase their renewable energy generation capacity in an attempt to shift towards greener energy generation. Over the years, the increase in generation capacity has resulted in a phenomenon called the duck curve [19], as can be seen in Figure 2.

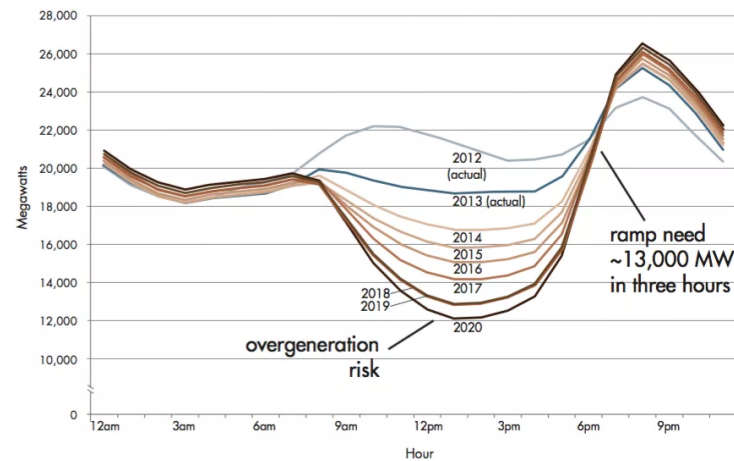


Figure 2. Energy generation yearly comparison in the state of California [19].

The mismatch of generation and consumption causes the duck curve. The increase in REP worsens this mismatch and exacerbates the risk of over-generation. If the possibility of over-generation occurs while frequency and voltage are kept within limits at various levels, the network still runs the risk of tripping the centralised generation structures. The need, therefore, arises for a method of increasing renewable energy generation and utilisation. This can only be safely accomplished by means of implementing an expert knowledge-based algorithm capable of controlling the various ESS and generation systems. In order to effectively control the network under all conditions, a worst-case scenario test is conducted to determine which network topology presents the worst results in the presence of renewable energy.

3. Identifying a Representative Network

To test and simulate the performance of the VPP, a network model that accurately represents real-world characteristics is required. The performance of the stability controller can then be verified before implementation in a real-world application.

Hardware-in-the-loop testing of the controller commonly follows simulation verification. However, in this case it is not possible. Alternative methods of validating the simulation model and control architecture are thus considered.

The network shown in Figure 3 is developed in accordance with the NRS 034-1 specification as representative of a residential reticulation network. The network is an LV three-phase single-line feeder network that operates on a line-to-line voltage of 400 V. The network has a full load capacity of 315 kVA, with a range of 20 to 40 residential units. Each unit has an ADMD of 4.5 kW. The load profile of each unit is representative of a real-world residential load profile over 24 h. The reticulation line lengths between each node within the network are calculated to be 40 m, which is represented by the resistance and inductance values that characterise the transmission lines. Each node within the network is limited to three units. A set of nine randomised networks have been designed based on the predetermined network parameters. The next section describes the simulation environment and the results obtained from simulating each of the nine networks. For each of the nine networks, a range of parameter changes are introduced, namely, varying levels of renewable energy penetration, balanced to imbalanced generation, and worst-case load scenarios.

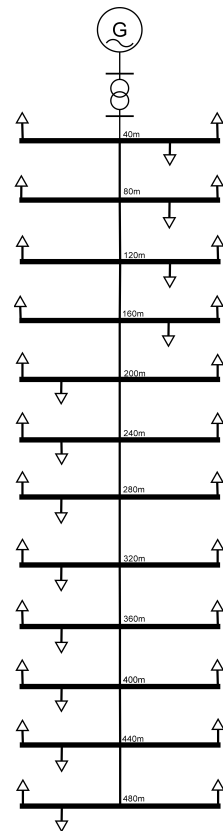


Figure 3. Single-line reticulation feeder network.

4. Modelling a Representative Network

The modelling of the LV network in this study is conducted by means of a MATLAB Simulink® Release 2021b model, as shown in Figure 4. The model facilitates the implementation of expert knowledge-based control algorithms capable of increasing the renewable energy penetration of a residential LV feeder and ultimately the national grid. The model is based on the representative single-line feeder identified in the previous section. The Simulink® model, network architecture, and characteristics are validated before any simulation experiments on the effects of expert knowledge-based control can be conducted. A complete description and derivation of the Simulink® model is given in [20]. The Simulink® code and generated datasets can be found in the DaYta repository [21].

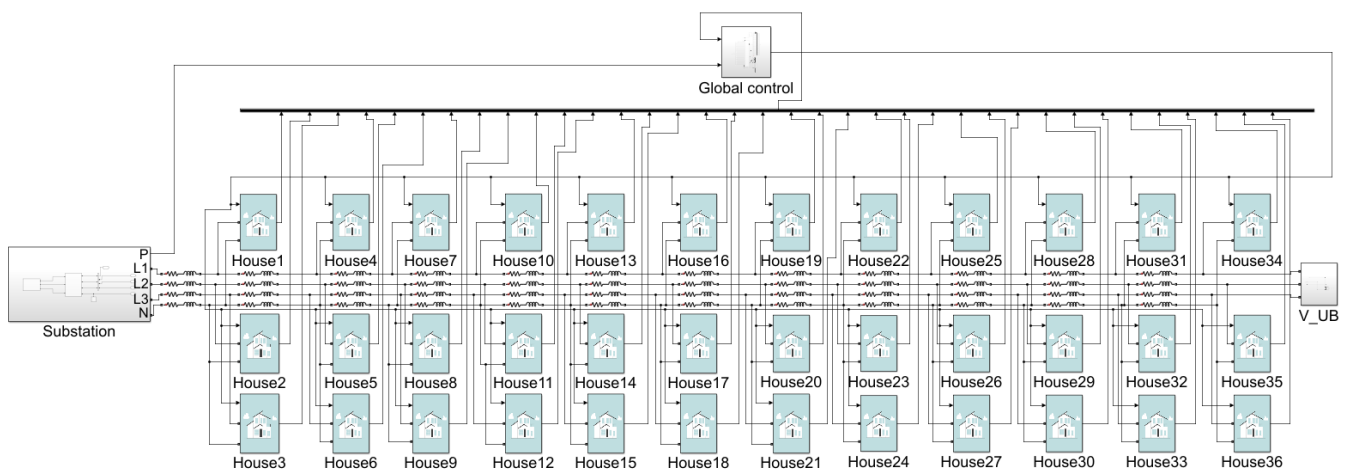


Figure 4. Single-line feeder network Simulink® model [20].

The standard approach for the design of a South African residential LV network based on worst-case conditions is with the Herman Beta (HB) method. The HB method is a probabilistic method used to calculate the voltage drop beta distribution within a feeder from the beta-distributed current values of said feeder. The HB method is efficient since these transformations are based on analytical statistics, which automatically include the effects of load dispersion. The HB method is recommended and nationally accepted by the SANS 507 regulations and the NRS 034 LV feeder design guidelines [22–24]. For the Simulink® model to be validated, the HB characterisation of the results from the Simulink® model need to resemble the HB characterisation of the base-case calibration network example provided in the NRS 034-1, as shown in Figure 5.

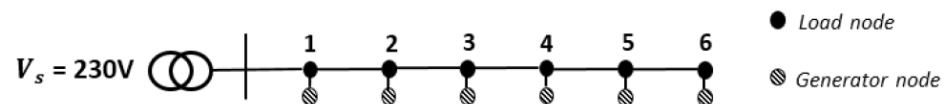


Figure 5. Base-case calibration network [18].

The foundational assumptions that underpin both the Simulink® model and the modified HB characterization approach utilized for designing active LV feeders, as detailed in [25], are as follows:

- The peak voltage drop happens when there is the greatest asymmetry between phases during the interval with the highest demand among the chosen consumers.
- Present sources are indicative of loads operating at a unity power factor, aligning with voltages, as loads typically achieve a unity power factor during peak demand.
- At any given moment, the total loads can be represented statistically as a beta probability density function (PDF).
- At a particular moment, the load currents are considered to be independently distributed. This assumption holds true when the statistic is examined over a single time interval.
- At a given temperature, the impedance of LV feeders is generally considered to be mostly resistive. The feeders under consideration usually possess minimal reactance, with phase spacings approximately 200 mm for bare conductors and under 20 mm for both aerial bundled and underground conductors.
- Distributed generation (DG) is modeled within the network as negative loads, as it absorbs power negatively.

These assumptions, along with the base-case LV feeder parameters in Table 1, provide the necessary data to recreate the network in Simulink® and obtain the characteristic HB load distribution.

Table 1. Base-case LV feeder parameters [18].

Feeder Parameters		Value	
Winter load ADMD beta parameters	$\alpha = 0.8625$	$\beta = 0.8625$	$c = 50.01270$
Summer load beta parameters	$\alpha = 0.4366$	$\beta = 1.2877$	$c = 24.8680$
1 kW, 1-phase PV unit beta parameters	$\alpha = 255.50$	$\beta = 255.50$	$c = 6.8696$
Maximum number of PV units (per customer)	7		

In this paper, the HB method was utilised to characterise the voltage drop on an active LV feeder with a renewable energy presence, whereas the Simulink® model was used to evaluate the effects of renewable energy on the feeder voltage levels by means of actively simulating the LV network. This test procedure aims to conduct worst-case scenario tests regarding PV penetration and its effects on the network voltage drop.

The Simulink® model is represented as an LV three-phase, four-wire distribution feeder, which is used as a network building block in this experiment. The measured voltage imbalance present on the LV feeder is caused by the PV-based generation uncertainty. This uncertainty, in turn, is caused by the random allocation of the generators on:

- Identical phase—Various nodes along the feeder;
- Various nodes along the feeder—Distinct phases;
- Nodes on the feeder corresponding to distinct phases.

The literature data exhibited in Figure 6 are obtained from the research conducted in [18], whereas the experimental data presented are obtained from the Simulink® model by conducting the test in the following order:

- The *betarnd* function is used to configure the active LV feeder according to the summer beta parameters. Randomised load data are generated and implemented across the phases on the feeder in a balanced way.
- Taking into account the maximum generation capacity that a consumer can install, the embedded generation (EG) is incremented in increments of 7 kW per phase. The PV is allocated in such a way that it will enable the identification of the envelope that shows the extrema of most balanced allocations to most imbalanced allocations.
- Most imbalanced allocations:
 - Seven units are placed on the last node (node 6) of the first phase, and the maximum voltage on the feeder profile is recorded. The first phase is filled progressively with 7 kW each time from node 6 to node 1. The maximum voltage on the feeder profile is recorded in Table 2 for every 7 kW fill in the phase.
 - Once the first phase is fully loaded with PV units, PV units are progressively added to the second and third phases, starting from node 1 and working towards node 6. With each iteration, EG allocation is alternated between the two phases.
 - The feeder is considered full when every unit of every node on the feeder is assigned 7 kW of generation. The maximum voltage recordings are plotted on the graph in Figure 6 to form the upper limit of the deterministic envelope. This allocation is considered the most imbalanced. Each allocation of 7 kW generation ensures the most significant deviation between the loaded and unloaded phases in terms of voltage imbalance along the feeder. The allocation also ensures the most significant deviation in the amount of PV-based generation among the phases.
- Most balanced PV allocations:
 - In each phase, 7 kW of EG are placed at node 1 (start of the feeder). The total generation added to each node per iteration equals 21 kW, and the maximum voltage on the feeder profile is recorded. The nodes are progressively loaded from node 1 to node 6.
 - When 7 kW of generation is assigned to each node in every phase on the feeder, the feeder is then considered full, and the maximum recorded voltage is plotted on the graph, which forms the lower limit of the deterministic envelope. This allocation method is the most balanced allocation, as each 7 kW of generation allocation maintain the balance between the phases, with the implementation direction as indicated in Table 3.

After carefully analysing the graph data in Figure 6, it becomes evident that the feeder imbalance causes the phase voltage to exceed the 1.1 p.u. limit when compared to the balanced feeder. The voltage rise is caused by the high neutral currents induced by the imbalance, which increases the voltage difference between the phases.

The increase in REP causes the two plots to converge due to the re-balancing effect of the PV added to the other phases. The form similarities between the graph obtained from the literature and the graph generated from the simulation results indicate that the network characteristics are the same and effectively serve as validation for the Simulink® model. The results in Table 3 indicate the correlation between the literature values and experimental values of the balanced PV allocation test, whereas the results in Table 2

indicate the correlation between the literature values and experimental values of the imbalanced PV allocation test. The results demonstrate the validation of the Simulink[®] model via the HB characterisation method. The Simulink[®] model is therefore deemed reliable for simulating an array of different network topologies if the network parameters are correctly defined.

With the 12-node extended feeder network being the chosen network to evaluate the VPP control on, the next step is to develop and implement the REP control in order to mitigate extreme voltage deviations under worst-case conditions. The control development and implementation step tests the effectiveness of control on the feeder. This test is carried out over 24 h with real-world load profiles.

Table 2. Imbalanced PV allocation result comparison.

PV Generation on Feeder [kW]	Penetration Level [%EG/ADMD]	Reference Maximum Voltage on Feeder Profile [p.u.]	Maximum Voltage on Feeder Profile [p.u.]
0	0.00	1.01	1.01
7	10.78	1.05	1.03
14	21.57	1.08	1.07
21	32.35	1.11	1.11
28	43.14	1.13	1.13
35	53.92	1.15	1.15
42	64.71	1.15	1.15
49	75.49	1.15	1.15
56	86.28	1.15	1.15
63	97.06	1.15	1.15
70	107.85	1.14	1.14
77	118.63	1.14	1.14
84	129.42	1.13	1.13
91	140.20	1.13	1.12
98	150.99	1.12	1.12
105	161.77	1.11	1.11
112	172.56	1.10	1.10
119	183.34	1.09	1.09
126	194.13	1.08	1.07

Table 3. Balanced PV allocation result comparison.

PV Generation on Feeder [kW]	Penetration Level [%EG/ADMD]	Reference Maximum Voltage on Feeder Profile [p.u.]	Maximum Voltage on Feeder Profile [p.u.]
0	0.00	1.0057	1.0044
21	32.36	1.0092	1.0111
42	64.71	1.0163	1.0177
63	97.06	1.0269	1.0241
84	129.42	1.0410	1.0327
105	161.77	1.0587	1.0494
126	194.13	1.0799	1.0735

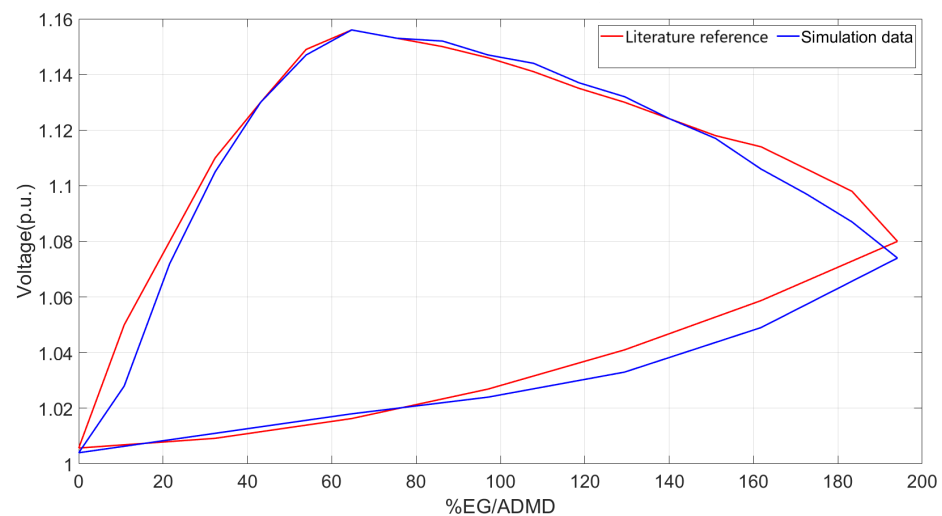


Figure 6. Worst-case voltage envelope comparison (literature vs. simulated data).

5. REP Control Strategy

Control is critical to increasing the REP level on LV feeder networks. Before control can be implemented, a thorough analysis must first be conducted to determine the best method for controlling the individual nodes on the feeder and ultimately the collective power on the feeder. The generalised consumption profile of the average South African household can be obtained from the data generated by the NRS load research project [26].

Thirty-six household consumption profiles have been implemented in the Simulink® model that are representative of the generalised consumption profile. When measured at the transformer supplying the feeder, the simulation model produced the load profile shown in Figure 7. From these data, the high demand in the early evening stands out. This leads to thermal overload on the transmission lines, indicated by the dashed red line.

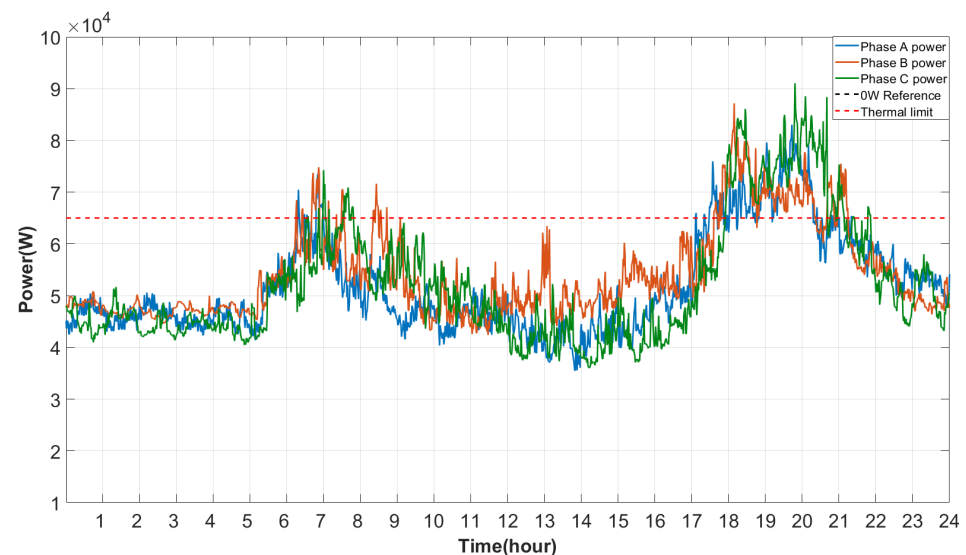


Figure 7. The 24-h reference load profile as measured at the transformer supplying the feeder.

Figure 8 shows the corresponding voltage profile at the various stages of the power consumption profile. The voltage level is affected by the level of power drawn and the balance of power across the three phases. The voltage level of each phase is also affected by the position of the load. If the load is situated near the transformer, then a high load has minimal effect on the voltage level. If the high load is situated at the end of the feeder, it significantly affects the voltage level. The NRS 097-2-1 dictates that the inverter must

remain operational while the voltage limit is between 1.1 p.u. and 0.85 p.u. However, the South African grid code stipulates that the voltage needs to remain between 1.1 p.u. and 0.9 p.u. The reason for this is for the inverters to be able to conduct fault ride-through.

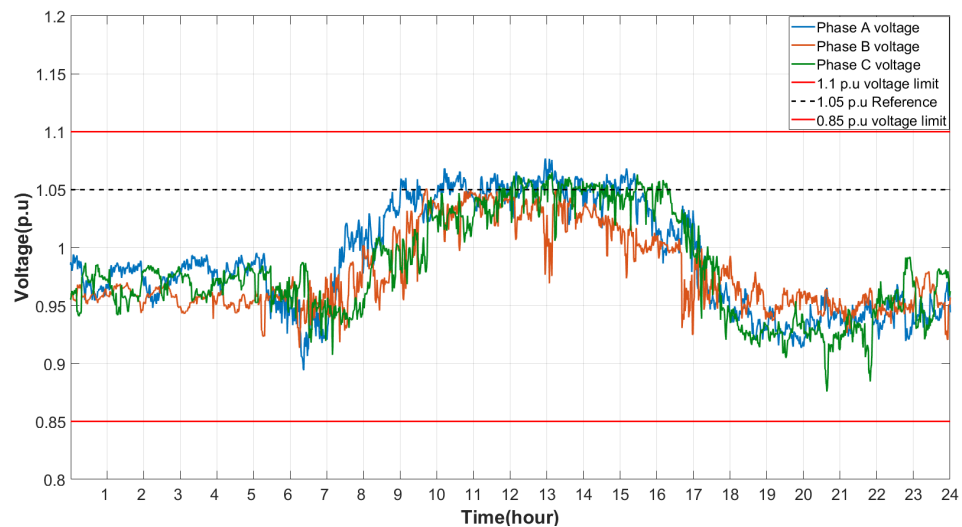


Figure 8. The 24-h reference voltage profile measured at the most volatile node on the feeder.

The data indicate that the voltage violation during midday is caused by imbalance in the system, and the violations at 8 p.m. are caused by excessive load. The implementation of PV-based generation will affect the effective load profile as well as the feeder voltage level over the 24 h period. The renewable energy limit stipulated by NRS 097-2-3 is equal to 25% of the household NMD when situated on a shared feeder. This should not exceed 75% of the transformer's NMD, which could result in damage to the transformer. The following test conducted without the implementation of regulatory control at a REP level of 50% indicates the effect of uncontrolled power generation. All units on the feeder have the same amount of PV generation at their disposal. The data in Figure 9 indicate that, during maximum generation and minimum load, the generation exceeds the load and feeds energy back into the network. When the generation subsides and the load increases, the effective feeder load exceeds the thermal line limits, damaging the network when exceeded for a prolonged period.

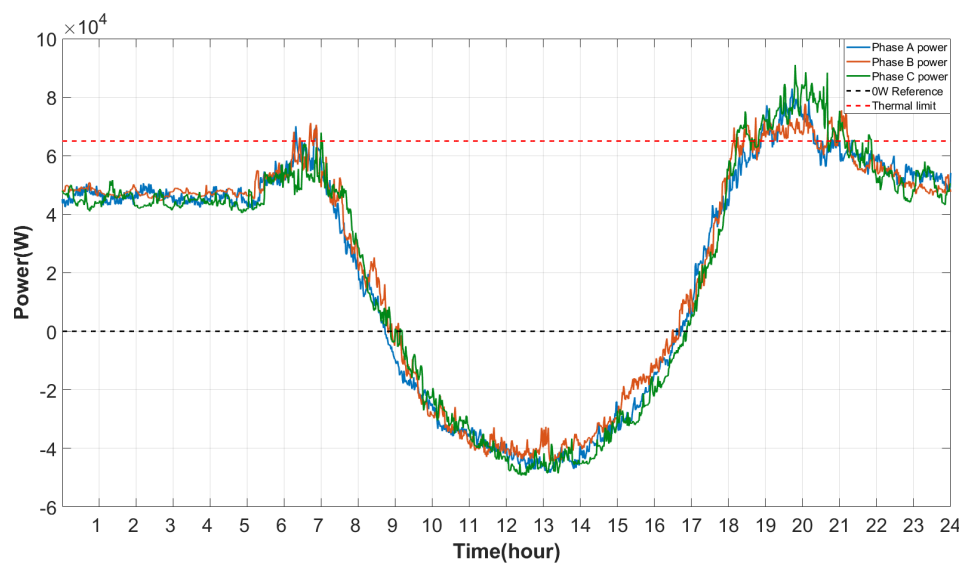


Figure 9. The 24-h transformer load profile with unregulated PV generation for 50% REP.

The corresponding voltage profile in Figure 10 indicates that the voltage exceeds the upper voltage limit under worst-case conditions. This violation would cause the inverters to trip in the presence of the NRS 097-2-3 control structure, possibly causing an energy oscillation on the feeder. After the generation has subsided, the voltage drops within range before the high power requirements force the voltage to violate the minimum voltage limit.

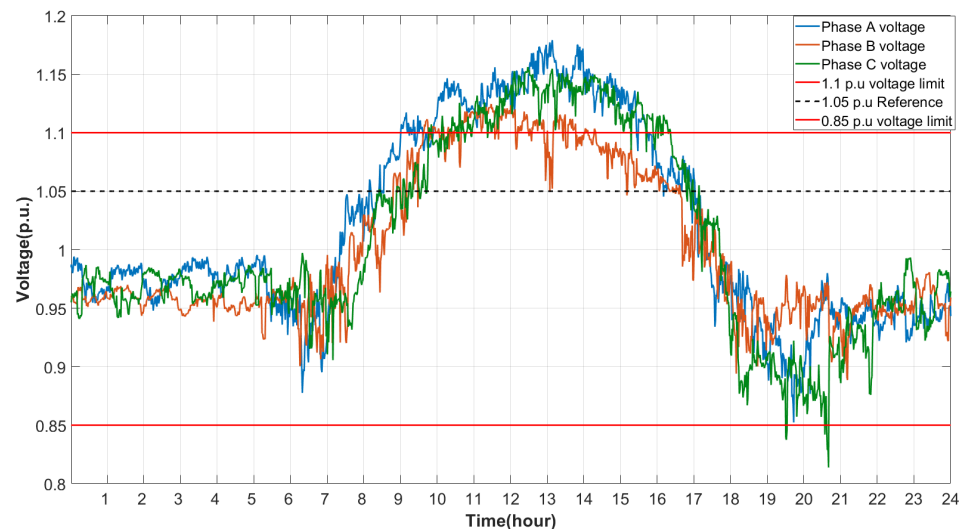


Figure 10. The 24-h worst-case voltage profile with unregulated PV generation for 50% REP.

The acquired data emphasise the need for a control structure capable of controlling the energy flow and energy storage in the system to efficiently distribute the generated energy to where it is needed most and store the excess energy for reallocation at a later stage while minimising the generation curtailment. In order to achieve efficient aggregation, a two-level expert knowledge-based control approach is adopted with a local level controller and a global level controller.

5.1. Local Controller

The local controller controls vital functions of the DER, such as charging and discharging the ESS and curtailing the PV if need be, all while fully servicing the local load. The local controller receives setpoint values for the power to be drawn from the grid from the global controller. Based on this setpoint, the local controller then schedules the resources accordingly in order to match the requirements. The ESS is modelled based on the following assumptions:

- The battery chemistry to be mimicked is lithium-ion phosphate (LiFePO_4), which has a high current rating and a high depth of discharge.
- Batteries made from LiFePO_4 allow for a 90% depth of discharge and offer a lifespan of 6000 cycles.
- The battery system is represented as an AC battery, meaning that the conversion between DC and AC is not taken into account within the Simulink® model.
- According to the manufacturer's data sheet, the batteries exhibit an energy conversion efficiency of 85% in total.
- The battery capacity is indicated in kWh.
- At the beginning of the simulation, every battery in the feeder has a state of charge (SOC) of 20%. This level is considered the minimum SOC threshold and signifies that the battery is depleted.
- The battery's maximum SOC is capped at 99% because all energy storage system (ESS) owners strive to optimise the levelised cost of energy for the hybrid system, and overcharging an ESS significantly reduces its lifespan.
- The battery is assumed to be thermally ideal, meaning its efficiency remains unaffected by changes in temperature.

- The batteries are limited to 0.5 C, i.e., they have a maximum demand of half its capacity.

The ESS size is selected to be three times the capacity of the installed generation capacity. This ensures that the system design is not fully independent from the grid to ensure that there is always a reliance on the grid. This sizing method allows the ESS to charge at maximum capacity at maximum generation and curtail the power once the ESS is fully charged. When required, the system will also feed the excess energy back into the grid. An expert knowledge-based control approach is implemented to improve energy flow management on the feeder when aggregating resources.

The local controller parameters include the load, ESS SOC, active power flow at the PCC, local PV generation, positive sequence node voltage, total local ESS capacity, and the grid setpoint. The local controller manages the energy flow behind the meter between the load, generation, and storage mechanisms based on the input received from an external controller or user. The controller processes the incoming data to produce the required outputs to be read by the PV inverter and the ESS inverter. The value to the PV inverter will be 0 to 100%, and the value to the ESS inverter will be positive or negative 0 to 100% to indicate whether the ESS will deliver or draw power. The ESS operates in an SOC range of 20% to 97% in order to make provision for unforeseen condition changes. The local controller indicates the amount of energy to be generated by the PV array while remaining within limits. The local controller will instruct the inverter to curtail its generation to match the power demand once the ESS is fully charged. The ESS reacts to the instantaneous change in power requirements. The ability to shift loads with the ESS allows for energy stability during times of uncertainty.

The local control algorithm represented by the flow diagram in Figure 11 indicates the decision-making process of the local controller to manage the flow of energy within the small-scale embedded generation (SSEG) system. The power reference value received from the global controller indicates the power exchange between the unit and grid (positive or negative). The default value is zero with the global controller disconnected. This is due to the lack of competitive feed-in tariffs in South Africa. The algorithm determines whether the difference between the load and reference is smaller than the energy generation. If the difference is smaller than the generation, the algorithm allocates the excess energy to the ESS while the SOC is within bounds. Otherwise, the generation will be curtailed to match the difference.

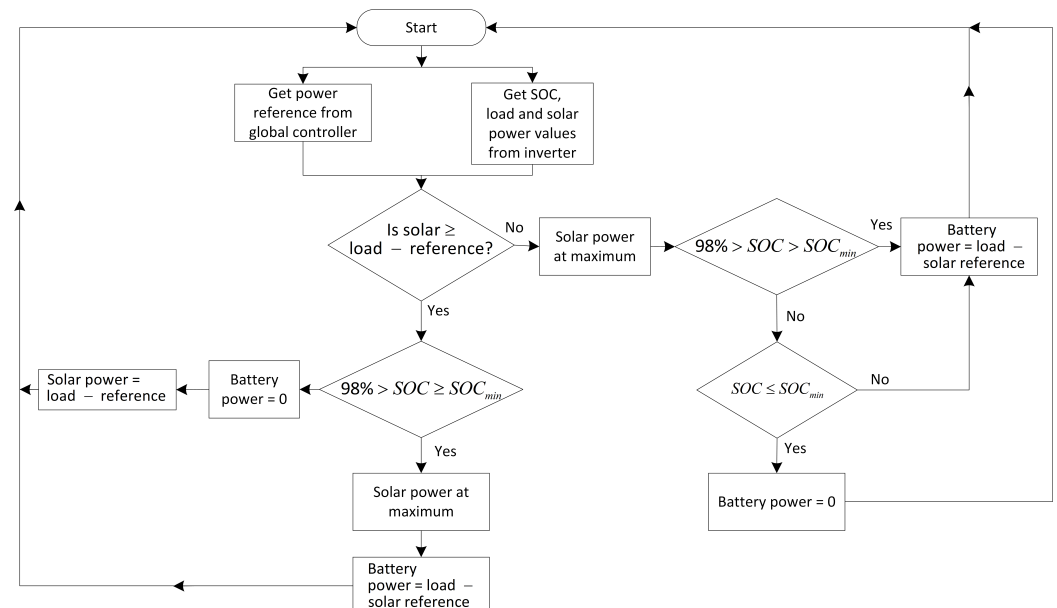


Figure 11. Flow diagram of the local control algorithm.

The difference provides the additional functionality of allowing a predetermined amount of power to be exchanged if required. If the energy generation falls below the difference, the ESS supplies the shortfall between the difference and PV generation until the latter ceases. Once the PV generation ceases, the ESS supplies the full difference while the ESS SOC is within limits. The local controller will automatically draw energy from the grid when the ESS is depleted.

The voltage regulation protocol functions in the background, monitoring for voltage violations and curtailing the energy fed into the grid to maintain network stability. The role of the ESS is to indicate if the renewable energy penetration can be increased while simultaneously mitigating power curtailment. The effect of the local controller is illustrated in Figures 12 and 13 for a 50% REP case. The power curve in Figure 12 indicates that, with the implementation of the ESS control algorithm, the feeder loading only violates the thermal limit in the morning, after which the PV generation causes a decrease in power drawn from the transformer. The excess generated power is stored in the ESS, indicated by the flat line at the 0 W mark. The ESS discharges later in the day, resulting in the night peak remaining below the thermal line limit.



Figure 12. Local control power curve for 50% REP.

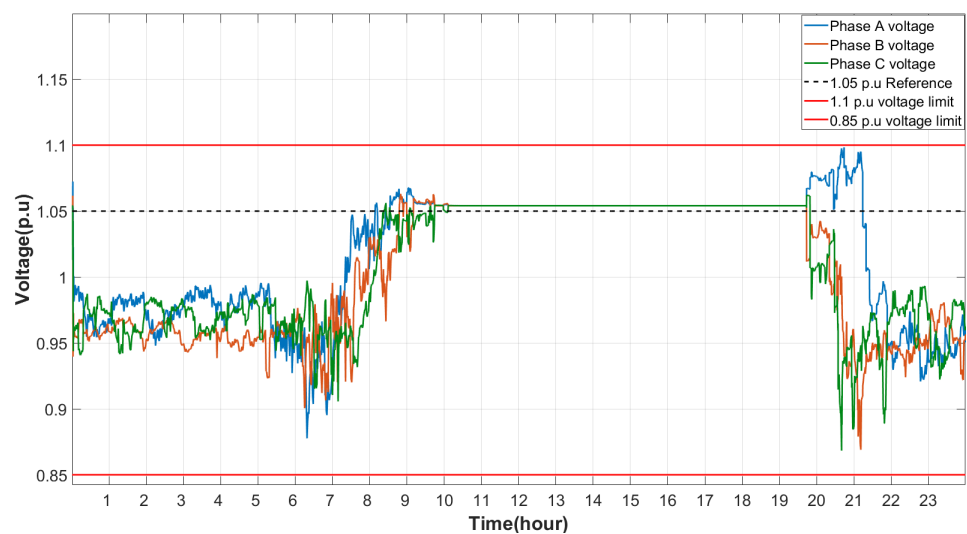


Figure 13. Local control worst-case voltage profile for 50% REP.

The corresponding voltage profile in Figure 13 indicates that the voltage remains within the required voltage limit at all times and that imbalance is minimised during excess generation due to optimal self-consumption. The local control on its own is not optimal due to the unknowns on the rest of the feeder. The system thus requires a global control structure.

5.2. Global Controller

The global controller manages and aggregates all the resources within the network to optimally distribute the renewable energy for increasing the REP while regulating the voltage to remain within specification limits. The global controller controls all local controllers in the network while measuring the energy exchange between the LV and MV networks. The global controller considers seven parameters from each residential unit as follows:

- Variable used to classify the presence and combination of generation and ESS;
- ESS capacity;
- PV power;
- Load;
- Phase node voltage;
- SOC;
- ESS energy flow.

The algorithm processes each variable and, through mathematical calculations, determines the reference power value for each unit. The reference power value indicates to the local controller what the power requirement is at the specific node based on the energy flow on the rest of the feeder. The polarity of the reference indicates the direction of flow. The algorithm sorts the incoming data and assigns a local controller to a specific phase based on its classification variable. The global controller is tasked with two main functions: keeping the voltage within the limits as specified by the grid code for renewable power producers and optimising energy distribution. Voltage regulation is the algorithm's main priority. The algorithm compares the voltages at each node on a respective phase and identifies both the highest and lowest voltages. The values will then be compared to the upper and lower limits to determine if the voltage level is acceptable. If not, the algorithm will allocate a positive reference value to the applicable controller if the voltage is high and a negative reference value if the voltage is low to firstly balance out the network. If the issue persists, the controller will lower the feed-in energy to the MV network.

The attempt to increase renewable energy will be made by implementing a technical virtual power plant (TVPP) capable of controlling the energy flow between the MV network and residential LV network in unison with the energy control between the nodes on the feeder. The TVPP is defined as a VPP aggregator that consists of DERs in the same geographical region. The TVPP utilises detailed knowledge of the local network to ensure the satisfactory operation of the DER energy flow management and energy reserve management for balancing the network and providing ancillary services. Two proportional controllers collectively regulate the upper and lower voltage extremes. The first controller evaluates the upper voltage, and the second controller alters the reference of the first controller based on the lower voltage. In addition to the voltage regulation, the TVPP attempts to optimise the energy flow by forecasting the stored energy availability in the system in the near future. The stored energy is forecasted based on the average power, $ESS_{av}(t)$, flowing into the ESS. The average power is obtained through a moving average filter. From this, the time-based prediction of when the ESS will be charged to a desired state of charge, SOC_{des} , is given by:

$$t_{SOC_{des}}(t) = \frac{SOC_{des} - SOC(t)}{0.85 \times ESS_{av}(t)} \times ESS_{cap} + t, \quad (1)$$

where ESS_{cap} is the ESS capacity in kWh. The charging efficiency of the ESS is taken to be 85%. The prediction allows the algorithm to determine when the ESS will reach the preset SOC and decide whether the specific node needs to be a load or a generator. The global controller decision-making process is illustrated in Figure 14. The global controller receives as input the detailed characteristics of the residential units on the feeder. This includes information on whether each unit is equipped with ESSs, PV systems, or a combination of both. For each unit, it collects data on the installed capacities of these resources as well as the usable capacities, which represent the current available storage in the ESS and the real-time generation output from the PV panels. By aggregating this information, the global controller can accurately assess the collective generation and storage capabilities of the network. This enables it to optimise energy distribution, manage voltage levels, and implement effective peak shaving strategies by coordinating the operation of ESS and PV systems across all residential units. Once a unit is identified as a load, a calculation is done to determine how much power can be drawn to reach an equilibrium on the feeder. The same applies to generation. The power limit for loading or generation is set to 6 kW. The network load generation balance occurs early on in the self-consumption cycle, during which the algorithm determines the amount of energy to be exported to the MV network. The maximum export is limited to the phase with the least amount of excess energy. As the excess generation increases, so does the energy export. The energy export is limited to the thermal limit or 75% on the MV-LV transformer. The controller will set the limit to the one that is reached first.

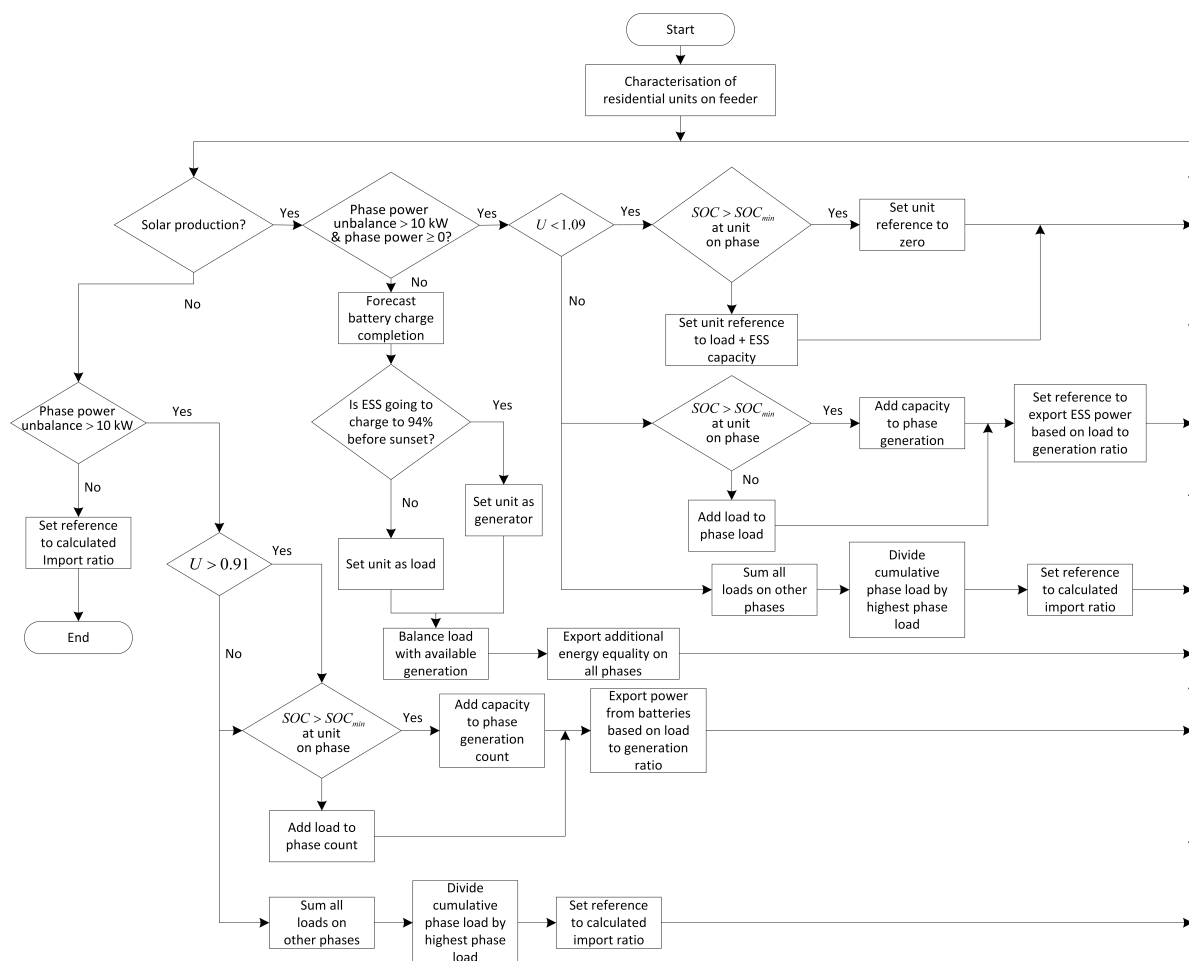


Figure 14. Flow diagram of the global control algorithm.

Lastly, the balancing and peak shaving algorithms are also implemented. The balancing algorithm is needed when the load is higher than the generation. This is evident in the

discharge cycle when certain ESSs discharge faster than others. The algorithm forces ESSs with sufficient capacity to increase their discharge power to fill the void left by the depleted ESSs while the network maintains optimal self-consumption. The peak shaving algorithm utilises the reserves on the ESSs when peak shaving is necessary. When the power flow through the transformer equates to 90% of the thermal limit, the algorithm discharges the batteries a further 10% if required to ensure that the peak does not rise any further. Once the spike has subsided and the SOC is below 20%, the system slowly charges the ESS of each unit up to 20% over 6 h.

6. Results

The performance of the TVPP controller is evaluated for both a 50% REP and a 75% REP test case. The 50% REP case provides for sufficient energy generation to exceed the ADMD. The results will demonstrate whether the control has maintained acceptable voltage regulation with increased renewable energy penetration. At the start of each test, the ESS starts at the minimum SOC to represent worst-case conditions.

The load profile as measured at the transformer for the 50% REP test case is shown in Figure 15. The result indicates that, in the early morning hours, the effects of energy aggregation are not yet evident, as the network is still dormant. At dawn, the demand increases, but the thermal limit is not exceeded. This is due to the peak shaving command sent to specific high-load units to partially discharge their ESSs and utilise the generation to cover the load.

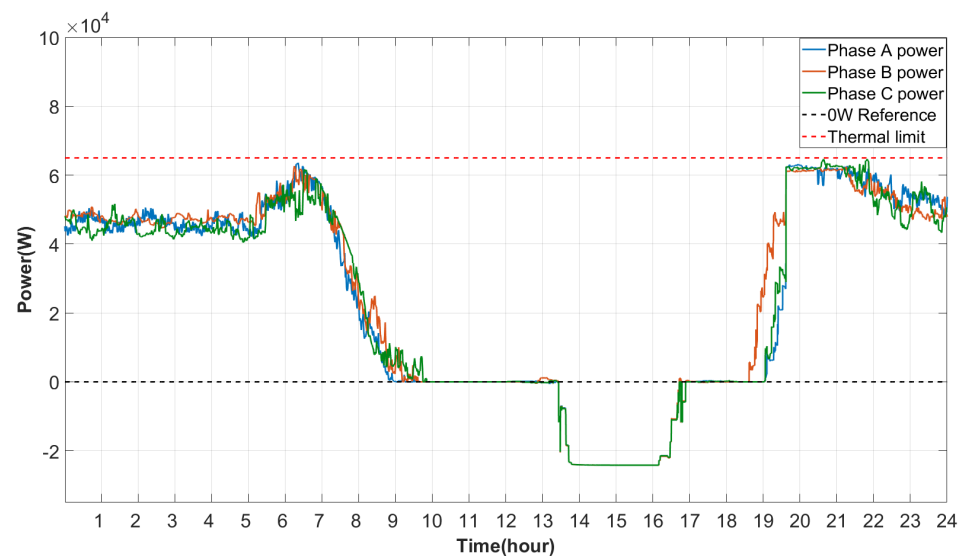


Figure 15. Load profile for the 50% REP test case with TVPP control.

The increase in generation decreases the effective transformer load and alleviates the need for peak shaving. Once the generation has exceeded the consumption on the feeder, the units start to charge their ESSs, absorbing the excess energy on the feeder. The prediction algorithm then determines when the ESS will reach the setpoint at which the systems are allowed to start exporting energy to other units on the feeder. The moment all three phases have the same minimum amount of excess energy available, the units start to export energy to the MV network in a balanced manner. As more power becomes readily available, the exported power increases until either the thermal limit or voltage limit is reached. This is evident from Figure 15 at the -21 kW level, where the exported power remains constant. The corresponding voltage profile in Figure 16 indicates that this is the 1.1 p.u. voltage limit. The export power limit is set by the controller based on the voltage limit.

The decrease in generation allows units return to self-consumption mode once the ESS SOC falls below 60%. This causes the energy being fed into the MV network to be curtailed

to optimally utilise the ESS for consumption during the night. The energy drawn from the grid increases as the ESS of the units reaches the minimum SOC. The imbalanced load causes stochastic ESS depletion leading to voltage variation, as seen in Figure 16.

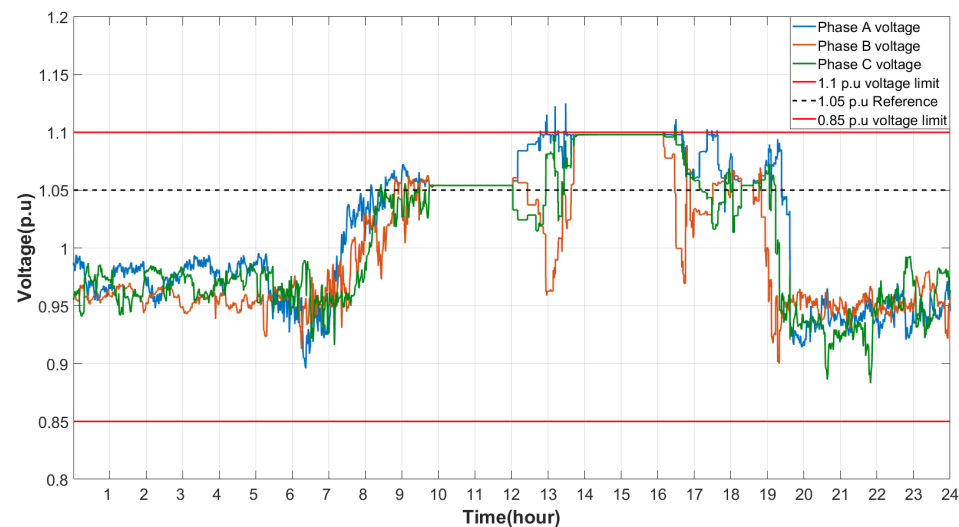


Figure 16. Voltage profile for the 50% REP test case with TVPP control.

The voltage graph further indicates that the stable load in the early morning and late afternoons has little to no effect on the voltage levels. The peak shaving function with support from the ESS further assists in mitigating LV violations. The increase in generation leads to a voltage rise due to the position and intensity of the generation. The voltage settles when the effective power at all phases reaches the 0 W equilibrium. The MV feeder export limitation also affects the voltage, which is notable during the voltage decrease from 1.1 p.u. to 1.05 p.u.

When the ESS discharges, the voltage decreases below the original source voltage of 1.05 p.u., nearing the lower voltage threshold with rising demand. At times of maximum demand, with the voltage approaching the 0.85 p.u. lower limit, the controller evaluates the imbalance and re-balances the network accordingly by influencing the power drawn on the other two phases. Additionally, the controller discharges the ESS to below the minimum SOC for a short period of time and, after the peak has passed, slowly recharges the ESS to the minimum SOC value.

The results generated for the 50% REP test case of the TVPP algorithm indicate that the voltage remains within the limits while optimally utilising all the generated power within the network. The aggregated power on the feeder equates to 84% of the transformer capacity, exceeding the 75% REP limit. This indicates that a larger renewable energy presence is possible when correctly managed. The next test case carried out is for 75% REP, equating to an aggregated capacity of 130% of the transformer's capacity.

The initial test parameters of the 50% REP and 75% REP test cases are identical. The load profile as measured at the transformer for the 75% REP test case is shown in Figure 17. The results are also quite similar despite the REP increase. The only difference is that the generation exceeds the loads on the feeder faster than in the 50% REP test case due to the increased slope of the power curve. This means that the energy required from the ESS to peak shave is less than before. The increased generation levels lead to the ESS reaching the maximum SOC faster than in the 50% REP test case. The ratio of PV to ESS remains the same, although the ratio of PV to load increases, leading to a higher portion of the generated power absorbed by the ESS. Once the ESS reaches an SOC of 65%, the controller exports the additional power on the condition that the voltage level does not exceed the voltage limit. Once the ESS reaches maximum SOC, the local controller automatically curtails the generation to maintain the reference power set by the TVPP controller. This is also part of the reason that both the voltage and power curves look similar.

The TVPP controller ensures that all system variables remain within limits irrespective of the REP level.

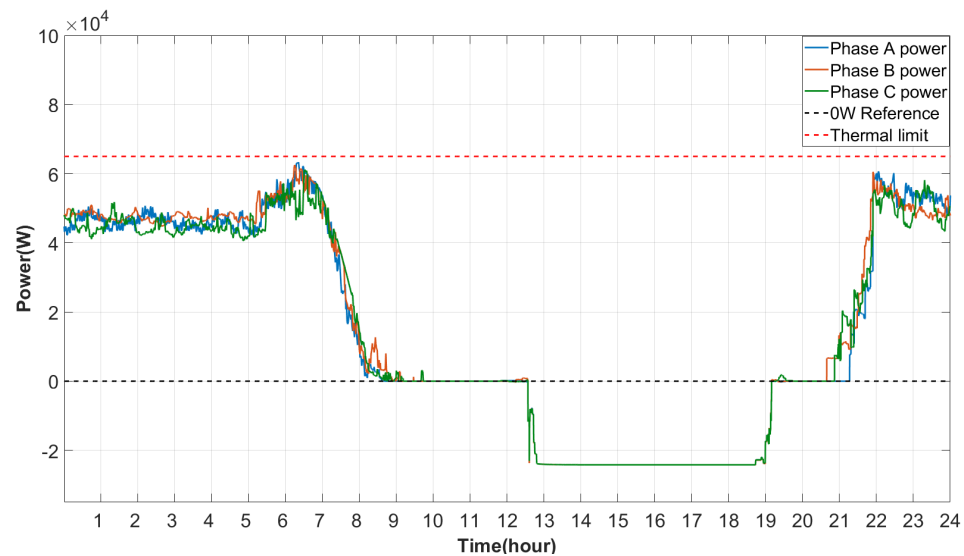


Figure 17. Load profile for the 75% REP test case with TVPP control.

The data indicate that the ESS discharges slower than before during the discharge cycle due to the increased capacity. The ESS therefore provides power until 23:00, leading to the peak shaving algorithm not being required during the nightly peak.

The corresponding voltage profile in Figure 18 indicates a slight imbalance at times of zero generation, with the voltages level just above 0.96 p.u. Once the generation exceeds the load, the voltage settles at 1.05 p.u. due to the self-consumption of each unit. The voltages of each phase deviate as the power is being shared among units. The 1.1 p.u. voltage level is reached earlier in comparison to the 50% REP test case. The voltage spikes on the graph are due to the system's control delay. The spikes still fall within the regulatory limit of not exceeding 40 s. The improved voltage regulation leads to increased green energy utilisation and renewable energy penetration.

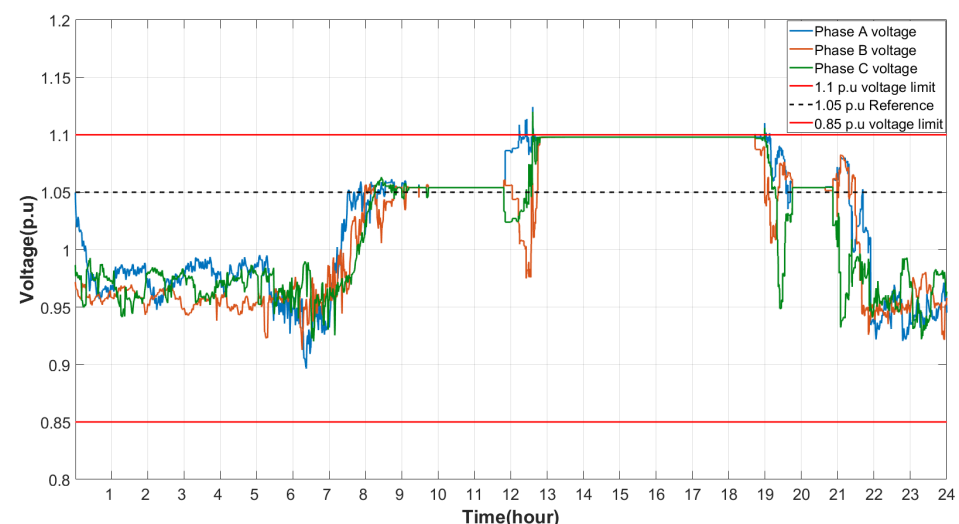


Figure 18. Voltage profile for the 75% REP test case with TVPP control.

The results illustrate the effectiveness of control at increased REP levels. The next step is to evaluate the effectiveness of control when the feeder topology changes. The topology is changed to a radial network with no more than nine units per feeder on a network with 36 units. The load profile displayed in Figure 19 exhibits the load profile of the multi-feeder

network used to validate that the VPP algorithm can be used as a general solution for LV feeder networks. The profile resembles that of the load profile of the original feeder, with minor differences. The load saturation before dusk serves as an indicator of the peak shaving algorithm fulfilling its purpose of not exceeding the thermal limits. The increase in irradiation leads to the effective power approaching zero. Once the ESS has reached 65% SOC, the controller feeds energy back into the grid. The maximum power fed into the grid is 46 kW per phase. This is due to the feeder reaching the thermal limit before reaching the voltage limit. The architecture of a multi-feeder network allows for more energy to be fed into the MV network as opposed to the single-feeder. This is due to the line impedance being lower on a multi-feeder network when compared to a single-feeder network. The only time that a voltage violation can occur on a multi-feeder network with short feeders is when a maximum imbalance exists between the phases. This could likely be caused by either a generation or a load imbalance.

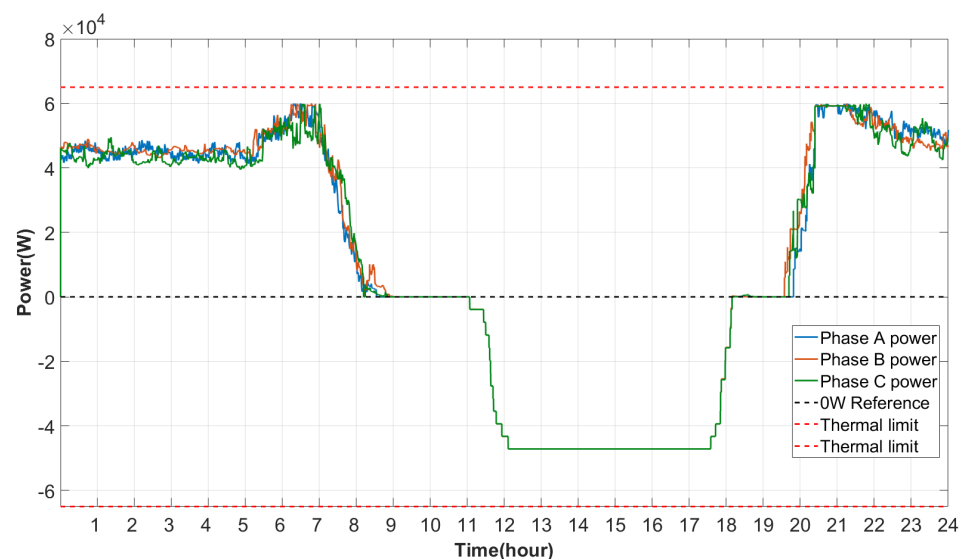


Figure 19. Load profile for multi-feeder network.

The corresponding feeder voltage profile displayed in Figure 20 indicates that the change in network architecture has resulted in an adjustment in voltage sensitivity. The voltage graphs of both the short multi-feeder network and long single-feeder network indicate that, when there is no load on the transformer, the voltage across the feeder equates to the source voltage of the feeder. The lower maximum voltage indicates that more SSEG can be comfortably added and managed. The only limitation would be the thermal limits of the reticulation network.

The resemblance in the power curve between the extended single-feeder network and the multi-feeder network demonstrates the controller's capability to efficiently manage the energy distribution and voltage levels across various feeder topologies, thereby enhancing the level of renewable energy integration.

The implementation of the TVPP showcases a transformative approach to energy management, providing accurate voltage regulation while optimising energy efficiency. The study demonstrates that the TVPP effectively balances energy feed into the MV network during periods of excess generation, maintaining a stable voltage level of 1.1 p.u. This capability is crucial for integrating higher levels of REP without compromising grid stability.

During times of zero generation or when facing generation uncertainty, the TVPP leverages reserve power stored in ESSs to mitigate peak demand. This strategic utilisation of stored energy reduces reliance on expensive peaking power plants, offering a cost-effective and sustainable solution for peak shaving. The ability of the TVPP to respond dynamically to fluctuating demand underscores its potential as a vital component in future energy systems.

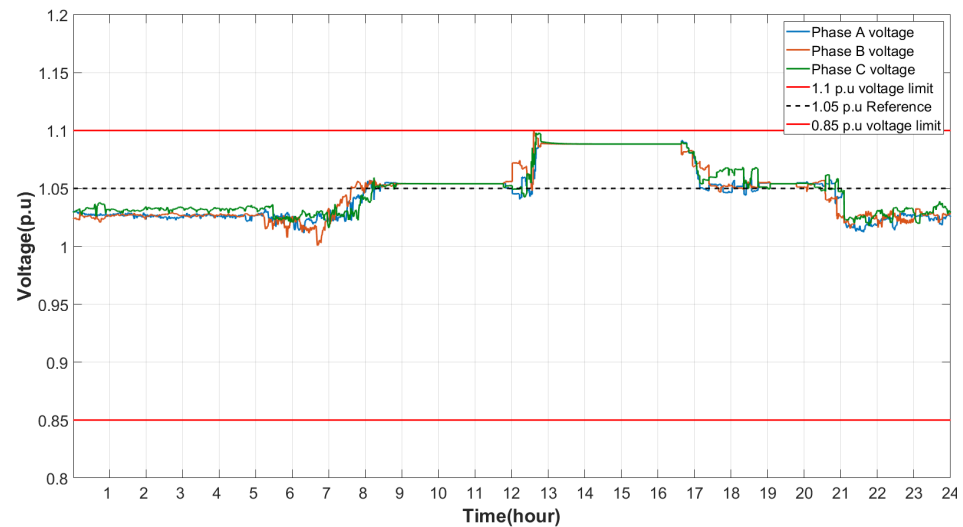


Figure 20. Multi-feeder network voltage profile.

6.1. Policy Implications and Recommendations

The findings suggest that the widespread adoption of TVPPs could significantly alter the landscape of energy generation and distribution. However, this transition assumes that users are adequately incentivised to invest in their systems without relying on government intervention. This highlights the necessity for regulatory policies to evolve, incorporating energy storage considerations into existing frameworks.

It is recommended that policymakers:

- **Integrate energy storage into regulatory policies:** Amend regulations like NRS-097-2-3 to account for the role of ESS in supporting higher levels of REP, ensuring that storage solutions are recognised and incentivised within the grid infrastructure.
- **Provide financial incentives:** Introduce subsidies or tax incentives for consumers and businesses that invest in ESSs and participate in TVPP schemes, lowering the barriers to entry and encouraging widespread adoption.
- **Promote decentralised energy systems:** Support the shift from centralised to decentralised energy structures by facilitating the aggregation of SSEGs, enhancing grid resilience and flexibility.

6.2. Future Challenges and Response Strategies

With the anticipated surge in electricity demand driven by emerging technologies such as AI-driven data centres and electric vehicles, the need for effective peak shaving strategies becomes more pressing. The COVID-19 pandemic has also highlighted vulnerabilities in centralised systems, emphasising the importance of resilient and adaptable energy infrastructures.

To address these challenges, the research suggests:

- **Adopting advanced grid technologies:** Implement intelligent grid solutions like TVPPs that can respond in real time to changing demand and supply conditions.
- **Enhancing energy storage deployment:** Encourage the integration of ESSs at both the utility and consumer levels to provide buffer capacities that can absorb fluctuations and maintain supply during disruptions.
- **Encouraging consumer participation:** Foster a culture where consumers also become producers ('prosumers'), actively contributing to energy generation and participating in demand response programs.

7. Conclusions

The key finding of this paper is that TVPP is a viable method to increase REP in South African LV networks while meeting regulatory limits. The proposed TVPP architecture

ensures network integrity by controlling the ESSs of household units as the primary control method and the PV generation of units as the secondary control method.

The proposed TVPP controller architecture proved to maintain network integrity for test cases of 50% REP and 75% REP on a single-feeder network with a representative load profile. The adaptability of the TVPP controller architecture was also confirmed for a changed feeder topology; in this case, it was a multi-feeder topology.

The current research was limited to PV as the renewable energy generation source since it is the most common source in households on the LV networks. Future work is therefore warranted in terms of scaling the TVPP algorithm to include more renewable energy sources. Future work is also warranted to inform policy (NRS-097-2-3) on the allowed levels of REP to be based not only on demand but also on the level of energy storage present on a network. Future work is also warranted in integrating the TVPP in a global energy market of demand and supply. Dynamic pricing mechanisms that encourage the use of stored energy during peak demand periods would enhance grid flexibility and reduce stress during peak loads.

Author Contributions: L.A.J.—Writing of paper and simulation work. M.G.B.—Supervisor and editing. G.v.S.—Supervisor and editing. K.R.U.—Supervisor and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This project was funded partly by the Erasmus+ DCT-REES project, contract no. 2017-3106/001-001.

Data Availability Statement: Data sets and the simulation models can be accessed at https://dayta.nwu.ac.za/authors/LOHAN_JANSEN/11698642 (accessed on 28 July 2024).

Conflicts of Interest: The authors declare no potential conflicts of interest.

Abbreviations

ADMD	after diversity maximum demand
CGTEP	composite generation and transmission expansion plan
DER	distributed energy resource
DOPF	dynamic optimal power flow
EMA	energy management algorithm
EMS	energy management system
ESS	energy storage system
HB	Herman Beta
LV	low-voltage
MV	medium-voltage
NMD	notified maximum demand
PV	photovoltaic
REP	renewable energy penetration
SSEG	small-scale embedded generation
TVPP	technical virtual power plant
VPP	virtual power plant

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