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RESEARCH ARTICLE

Strategic Integration of Battery Energy Storage Systems for Effective EV Charging Demand Management in Transactive Energy Markets

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ABSTRACT The increasing penetration of electric vehicles (EVs) and photovoltaic (PV) systems poses significant challenges to distribution grid performance and reliability. Battery energy storage systems (BESS) offer a promising solution to mitigate these challenges; however, most existing BESS optimization strategies fail to simultaneously enhance grid performance and maximize economic benefits for BESS owners. This research proposes an optimized BESS dispatch strategy that balances both grid performance and BESS bid pricing in the transactive energy (TE) market through a multi-criteria decision-making (MCDM) method. The strategy aims to reduce energy procurement costs and create a more favorable system for EV users by minimizing their charging expenses. Using the DIgSILENT PowerFactory power system software for modeling and simulation, the active and reactive power dispatch of BESS is optimized via a differential evolution (DE) algorithm. The experimental validation of the proposed approach demonstrates significant improvements in grid performance, reduced energy costs, and enhanced flexibility for distribution network operators (DNOs) in prioritizing either grid performance or financial considerations, or both. Overall, this novel approach provides an effective framework for DNOs to enhance grid performance while strategically incorporating the economic aspects of BESS, ultimately lowering EV charging costs compared to existing methods.

INDEX TERMS Distributed generation, differential evolution algorithm, energy storage, electric vehicle, transactive energy, voltage unbalance.

I. INTRODUCTION

The global adoption of electric vehicles (EVs) is accelerating, primarily driven by environmental concerns and government policies that promote clean energy solutions [1]. Despite these positive trends, a significant portion of EVs still rely on conventional fossil-fuel-based energy for charging. This reliance not only increases costs, particularly when accounting for associated emissions, but also conflicts with broader sustainability goals. Renewable energy (RE) systems offer a compelling solution, providing the potential to lower both charging costs and greenhouse gas emissions. However, while RE systems and EVs are key contributors to reducing emissions and improving energy efficiency, their uncoordinated integration can introduce serious operational challenges, jeopardizing grid performance and efficiency. Typically, distribution network operators (DNOs) are responsible for forecasting EV demand and RE-based distributed generation (DG) to maintain the low-voltage (LV) distribution grid. However, the inherent variability of RE-based DGs and the mobility uncertainty of EV users introduce significant demand-generation imbalances, potentially degrading grid performance [2]. Additionally, the uncoordinated distribution of 1-ph EVs among phases causes unbalance in a LV distribution grid [3], [4], [5], [6]. This imbalance is further exacerbated when time-of-use (ToU)

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based charging strategies are employed, potentially leading to unexpected demand peaks. Such peaks increase the risk of overloading, which places additional thermal stress on transformers and other critical infrastructure. Consequently, uncoordinated EV integration can result in increased grid demand, network imbalances, higher power losses, voltage fluctuations, potential overloading of local distribution networks, and reduced hosting capacity [7], [8], [9]. These issues can escalate grid instability and operational costs, presenting significant challenges for DNOs. Moreover, reduced hosting capacity limits the grid's ability to accommodate additional EVs and RE systems, often necessitating costly upgrades to the distribution network [10], [11].

A viable solution to the complex challenges of integrating RE sources and EVs charging into distribution networks is the strategic use of battery energy storage systems (BESS) in transactive energy (TE) market framework. These systems play a crucial role in strengthening grid resilience by stabilizing the intermittent and variable output of RE-based DGs, particularly photovoltaic (PV) systems. Additionally, BESS help manage the fluctuating demand from EVs charging, reduce voltage imbalances, and minimize power losses in the distribution grid [12]. Recent research emphasizes the significance of optimal BESS placement and sizing, demonstrating their potential to improve voltage regulation, decrease power losses, and enhance overall grid performance [13], [14], [15], [16], [17], [18], [19], [20]. For instance, the study in [13] proposes a robust BESS dispatch framework designed to reduce voltage deviations while providing fast frequency response in weak distribution grids. Similarly, authors in [14] examines optimal DG sizing and node selection to improve voltage profiles and reduce emissions. The study in [15] focuses on optimizing BESS dispatch to address DG uncertainty, mitigating voltage deviations and reducing energy losses. According to studies [17], [18], determining the optimal location and capacity of BESS is critical for maximizing operational effectiveness. Furthermore, coordinated strategies that combine optimal BESS placement with managed EVs charging have been shown to significantly reduce voltage unbalance and alleviate network congestion [19]. Additionally, the study in [20] investigates BESS performance under various PV production scenarios—maximum, rated, and minimum—and proposes an optimal dispatch strategy for efficient active power management. While these studies contribute significantly to technical advancements, they often overlook important economic and market considerations.

Several research works are incorporating BESS into power networks involves significant financial considerations that affect the feasibility and sustainability of such projects. For example, in [21] authors optimized BESS capacity by minimizing investment cost to store surplus PV energy. In [22] authors proposed charging the BESS during off-peak hour and discharges it during peak for maximizing net revenue of BESS owner where battery degradation cost is considered as a key parameter. In [23] authors optimized residential BESS scheduling to minimize energy cost (saving in electricity bill) and emission cost. In [24] authors optimized sizing and placement of BESS in the distribution network by minimizing BESS's capital cost and operation cost aiming to minimize active/reactive power import from grid. While some other researchers optimize the on-grid BESS for economic operation to maximize revenue. For example, in [25] authors identify optimal location and optimum dispatch for minimizing annualized cost (BESS investment, operation and maintenance, replacement and power import) considering variable scenario of PV based DGs. In [26] authors gives flexibility to the private owned BESS owners to offer bid for either discharging or charging. The developed method tunes optimum operation strategy for charging/discharging based on price for maximizing individual BESS owner's profit. In [27] authors consider PV and EV's battery as DG of a building for TE market participation to support the grid. The developed method ensures incentives to each DG (dispatchable BESS) owners if the bid price is lower than the TE market clearing price. Similarly, in [28] authors presents a TE market framework for an EV parking lot with PV and battery systems, optimizing cost-effective charging. In [29] authors optimized the BESS installation capacity to maximize the net present value considering capital cost, operational cost, service time, and cash flow under various market types and ownership. This study identified that energy storage sharing operation require least BESS capacity while increase the distribution loss to highest. In [30], the authors proposed a two-level optimization model for BESS aimed at maximizing the net revenue of the BESS owner while minimizing total operational costs. The model accounts for participation in multiple markets, including reserve, energy capacity, and regulation mileage, as well as the costs associated with battery degradation. In [31] authors proposed a BESS bidding strategy that maximizes the revenue from selling (discharging) and minimize the cost of buying (charging) to maximize profit for renewable energy sources producers. Another study [32] introduces a bilateral trading and auction mechanism between EV aggregators and EVs to provide ancillary services and address grid challenges. This approach creates a TE market where aggregators sell aggregated EV energy (similar to BESS) to DNOs for grid support.

In summary, authors [13], [14], [15], [16], [17], [18], [19], [20] develop methods for identifying optimal location for integrating BESS with optimal BESS dispatch for improving grid performances whereas authors in [21], [22], [23], [24], and [25] minimizes levelized cost of electricity production using BESS without accounting grid performance. Additionally, research in [26], [27], [28], [29], [30], [31], and [32] has explored BESS participation in TE market environments, yet without integrating grid performance considerations. To the best of the authors' knowledge, based on our literature review of existing BESS optimization strategies [13], [14],

[15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], no prior research has simultaneously addressed EV charging demand mitigation, grid performance improvement, and BESS owner participation in the TE market through strategic BESS integration into the distribution grid. Hence, there is a need for an enhanced approach that effectively considers these critical factors. This research introduces an advanced system for BESS integration to address these challenges.

The key contributions of this research are summarized as follows:

- Unlike traditional approaches (optimal placement and sizing) that predefine BESS dispatch, the proposed work introduces a dynamic, market-based bidding mechanism, enabling individual BESS owners to participate in energy trading while ensuring cost-effective EV charging.
- A novel multi-criteria decision-making (MCDM) based BESS ranking method is proposed to determine the most suitable BESS dispatch nodes, considering both technical and financial requirements, whereas traditional approaches considers either technical or financial aspects. The proposed approach allows DNOs to trade-off between technical and financial performance based on their requirements.
- A price-based bidding mechanism is introduced, ensuring only cost-efficient BESS units are dispatched which is reducing energy cost for DNOs. The proposed method reduces the energy cost which ultimately reduces the EVs charging cost.
- Unlike commonly used evolutionary algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO), which are widely implemented for power system applications, this study evaluates the differential evolution (DE) algorithm for optimizing BESS dispatch and compares its performance to GA and PSO.
- The proposed approach is validated using a practical LV grid, demonstrating improved grid performance and suggesting the least EV charging cost. In general, it can be applied to any LV distribution grid.

The rest of this paper is organized as follows: Section II introduces the control system architecture. Section III presents the problem formulation, detailing the objectives and constraints of the control model. Section IV describes the DE optimization algorithms, while Section V outlines the proposed methodology. Section VI covers the experimental setup, Section VII provides the results and discussion, and finally, Section VIII offers concluding insights and future work.

II. CONTROL SYSTEM ARCHITECTURE

Fig. 1 illustrates the configuration of the proposed control strategy, with arrows clearly depicting the power flow pathways. The system is composed of diverse types of EVs connected to a central AC bus, while both the PV system and the BESS are interfaced via dedicated DC/AC converters. The integration of the BESS with the PV system enables the storage of excess solar energy during off-peak periods, maximizing renewable energy usage and supporting grid stability. A versatile bi-directional converter empowers the BESS to either inject or draw power from the system, depending on dynamic control settings and grid demands. This LV distribution grid, incorporating EVs, PV panels, BESS, and residential loads, connects to the primary utility network through a 0.4/11kV transformer, ensuring a seamless interaction with the main grid. In the simulation study, the EVs adhere to the proposed optimal charging schedule, while the BESS plays a crucial role in providing grid support services and flexibility within a DNO controlled TE market framework. However, EV uncertainty impacts the modeling of PV-powered BESS by introducing variability in charging demand and grid interactions. Incorporating this uncertainty is crucial for optimizing system efficiency and ensuring grid stability.

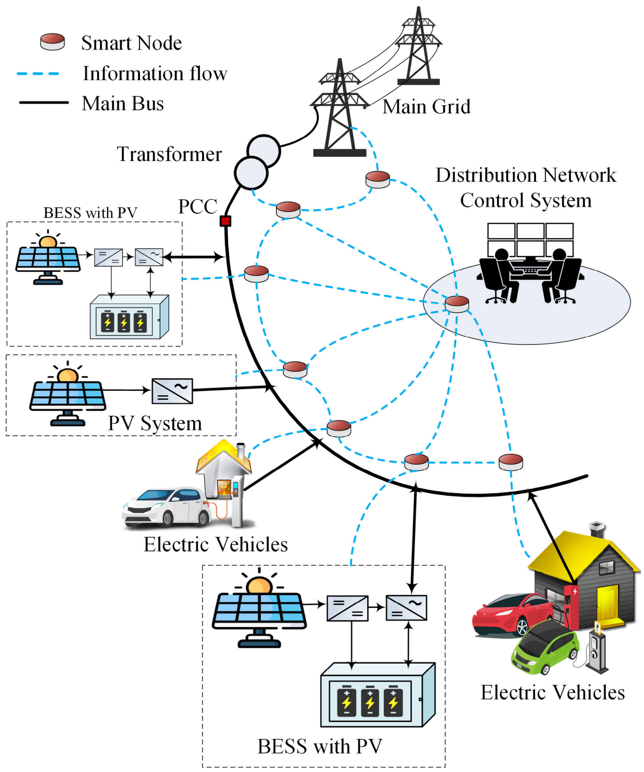

FIGURE 1. Proposed control system structure.

A. MODELING OF EV UNCERTAINTY

EVs play a vital role in reducing emissions generated by traditional vehicles. However, EVs loads introduce several uncertainties that impact key parameters, including peak power demand, load profiles, voltage levels, system reliability, and frequency stability [33]. To account the variability in factors such as the plug-in times (arrival time), state of charge (SoC), energy demand, and plug-in duration of EVs, stochastic modeling of uncertainty can be written as:

Arrival time uncertainty:

$$t_i^{arr} = \bar{t}_i^{arr} + U_t \ where, U_t \sim N(0, \sigma_t^2) \tag{1.1}$$

This represents uncertainty in the actual arrival time of the EV around the expected arrival $\bar{t}_i^{arr}$.

Charging duration uncertainty:

$$T_i = \bar{T}_i + \Delta T_i \ where, \Delta T_i \sim N(0, \sigma_T^2) \tag{1.2}$$

Energy demand uncertainty:

$$E_i^{req} = \bar{E}_i^{req} + U_E \ where, U_E \sim N(0, \sigma_E^2) \tag{1.3}$$

The actual required energy in real-time may vary from the forecasted value $\bar{E}_i^{req}$.

Equation (1.1) to (1.3) subject to the following constraints (2.1) to (2.3):

1. Charging power limit:

$$0 \leq P_{i,t} \leq P_i^{max} \tag{2.1}$$

2. SoC bound:

$$SoC_{min} \leq SoC_{i,t} \leq SoC_i^{max} \tag{2.2}$$

3. Energy required:

$$E_i \geq E_i^{req} \tag{2.3}$$

where,

E_i^{req} : Required energy by EV i for a complete charge (in kWh).

t_i^{arr} :Arrival time of EV i.

$U_E \sim N(\mu, \sigma_E^2)$:Arrival time of EV i.

P_i^{max} :Maximum charging power limit for EV i (in kW).

E_i :Total available energy for EV i.

μ :Represents average(mean) or expected value of the random variable.

σ :Represents standard deviation used to measure the uncertainty around the mean value.

Therefore, it is clear that the forecasting of EVs charging demand is crucial due to human behavior. The amount of error will increase with the growing number of EV. To mitigate such error, this study has proposed strategic management of BESS and the modeling of BESS is described in the later subsection.

B. MODELING OF BESS

The BESS model is composed of a battery bank and a bi-directional DC/AC converter, which enables two-way energy exchange. The available active power for grid support services is constrained by the battery's storage capacity and the rating of the PWM-controlled converter. In this approach, BESS units operate in grid-following mode, synchronizing with the grid's voltage and frequency rather than establishing an independent reference. This mode ensures that BESS units respond dynamically to grid conditions and TE market signals rather than acting as standalone power sources. The grid-following inverters adjust power injection or absorption based on real-time grid requirements while maintaining synchronization with the primary grid. Unlike grid-forming BESS, which are used in isolated microgrids or black-start scenarios, grid-following BESS do not dictate system frequency or voltage. Instead, they contribute to grid stability by modulating active and reactive power, following the dispatch instructions provided by DNO within the TE market framework.

In this study, the BESS configuration, depicted in Fig. 2, incorporates a PQ controller, a charge controller, and a power reference generator (P_{ref}). The (P_{ref}) generator plays a critical role by generating a reference signal that adjusts the BESS's active power output based on the real-time power levels measured at the grid connection point. This ensures that the BESS output power, denoted as (P_{in}), is effectively managed, as shown in Fig. 2(a). Each component of the control system is discussed in detail in the following subsection, offering a deeper understanding of their specific functions and contributions to the overall operation of the BESS.

1) ACTIVE/REACTIVE (PQ) CONTROLLER

As highlighted in green in Fig. 2(a), the PQ controller features two PI controllers (PI-1 and PI-2) that are responsible for regulating the active and reactive power of the BESS, ensuring precise control over the power exchange with the grid.

a: ACTIVE POWER DISPATCH CONTROL

This study addresses the uncertainties in EV travel patterns, which can potentially disrupt grid stability by invalidating scheduled charging times and leading to the need for rapid charging. In such scenarios, the BESS acts as an essential support mechanism by supplying the necessary active power. The BESS's reference active power signal, P_{ref}, is determined using P-f droop characteristics, which respond to deviations between the grid frequency and the target reference frequency. This P_{ref} signal guides the magnitude and direction of active power adjustment, aligning it with the BESS output AC power signal, P_{in}, as illustrated in Fig. 2(a).

Within the active power control section, the P_{ref} signal is compared to the BESS output, generating a direct-axis current reference, $i_{d-ref-in}$, which passes through a filter and a PI controller. The output of this process is fed into the charge controller to manage the charging and discharging states of the battery. The BESS discharges to supply active power if the frequency deviation is positive, indicating a need for additional grid support, and charges the battery if the deviation is negative. To ensure accurate power regulation, the system calculates the difference between the generated current reference, $i_{d-ref-in}$, and the actual direct-axis current, $i_{dref-out}$, producing a correction signal, Δi_d. This signal is then fed back to PI-1, which generates an error signal to fine-tune the active power output of the BESS, adjusting it according to real-time grid conditions. This feedback loop

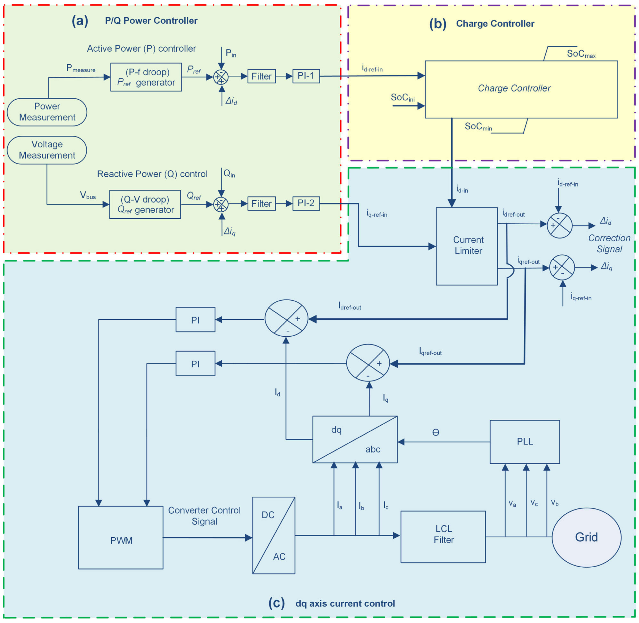

FIGURE 2. BESS model and controllers.

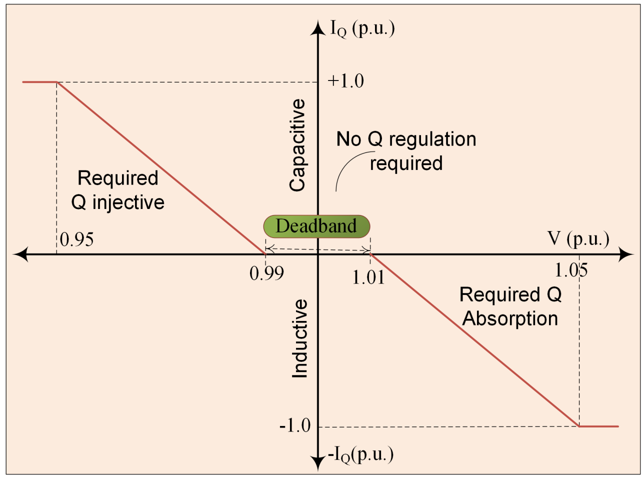

FIGURE 3. Reactive current-voltage Q(V) characteristics.

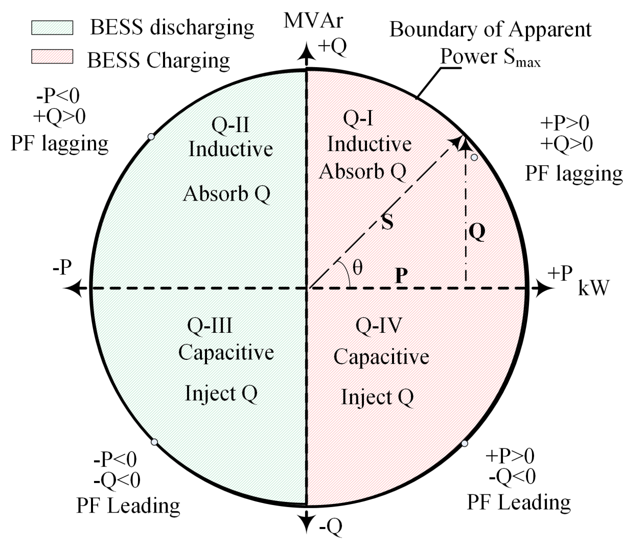

FIGURE 4. Four-quadrant PQ control capability of a BESS converter model [35].

is crucial for maintaining stable and reliable power delivery, adapting the BESS response dynamically to fluctuations in grid demand.

b: REACTIVE POWER DISPATCH CONTROL

For efficient and reliable operation of power systems, voltages of all the nodes must be maintained within desired limits for power system stability enhancement. Reactive power dispatch control significantly influences voltage regulation, enhancing the stability of the power system. The reactive power voltage regulation Q(V) droop characteristics illustrated in Fig. 3. If node voltage is below deadband voltage then Q injection increase the voltage level and BESS converter is operated in capacitive mode and while node voltage above the deadband voltage it is required to absorb Q and BESS converter operate in inductive mode. Reactive power can be injected into or absorbed from the grid solely through electronic BESS converters without negatively affecting battery lifespan [34].

In this study, BESS units are connected to the distribution network via single-phase converters. These converters can manage the injection or absorption of reactive power based on their nominal apparent power rating and the BESS's active power output. The capability to handle reactive power is guided by a four-quadrant operation model, as shown in Fig. 4. This model allows the BESS to function as a flexible source of reactive power support within distribution networks, enhancing voltage stability.

The BESS inverter can operate in either capacitive or inductive modes, depending on the quadrant in which it is functioning. For reactive power injection, it operates in quadrants III and IV, while reactive power absorption occurs in quadrants I and II. This operational flexibility enables the inverter to seamlessly transition across all power factor modes, ranging from +1 to −1, where negative values indicate reactive power injection (capacitive mode) and positive values signify reactive power consumption (inductive mode). Such adaptability is crucial for maintaining grid voltage within desired limits, particularly in systems with high levels of distributed energy resources (DER). It should be noted that this paper does not delve into the specific topologies of power converters used for BESS integration. Various converter designs can be applied in practice, as noted in [36]. The key requirement for addressing the optimal reactive power dispatch problem is that the converters must have a rated power capacity equal to or exceeding the battery's rated power and must support effective reactive power control. This ensures that the BESS can reliably contribute to voltage regulation and system stability, regardless of the specific converter technology employed.

2) BESS CHARGE CONTROLLER

Fig. 2(b) illustrates the charge controller, which manages SoC within the specified range. The charge controller output passes through a current limiter to ensure compliance with Eq.(3):

$$S = \sqrt{P^2 + Q^2} \tag{3}$$

where S is the converter's apparent power.

The charge controller mainly manages the active current (d-axis). The regulation of the d-axis current reference value based on the battery's SoC level can be represented as follows [36]:

$$i_{\text{dref-out}} = \begin{cases} i_{\text{d-ref-in}} & \text{if SoC} \geq \text{SoC}_{\min}, \\ -i_{\text{d-ref-in}} & \text{if SoC} \leq \text{SoC}_{\max}, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

BESS can be set to discharge if battery $SoC \geq 0.3p.u.$ (SoC minimum) and charge (consume) if battery $SoC \leq 0.90p.u$ (SoC Maximum) is below maximum SOC and no active power deficit in the system. The d-axis and q-axis current controllers manage the active and reactive power output of the BESS. The reference values for active and reactive power on the d-axis and q-axis are constrained by a maximum absolute value of 1 p.u., which represents the total capacity of the BESS converter. The q-axis current is set to 0 to regulate only active power dispatch in response of error (Δi_d) between the input reference ($i_{d-ref-in}$) and generated current reference ($i_{dref-out}$).

The controller prioritizes reactive power support to address voltage deviations only when the node voltages fall outside the deadband voltage range, as illustrated in Fig. 3.

3) THE D AND Q AXIS CURRENT CONTROLLER

Fig. 2(c) illustrates the d-q axis current controller, which plays a critical role in regulating the active and reactive power (PQ) output of the BESS by minimizing the error between the grid current reference and the generated current reference. This controller receives input from the converter's AC current in the d-q reference frame, acquired via a phase-locked loop (PLL). Its output is a pulse-width modulation (PWM) index on the d-q axis, which sets the reference phase angle for controlling the DC/AC converter.

III. PROBLEM FORMULATION

To address the additional EVs energy demand arising from forecasting uncertainty, this study proposes a novel method for integrating BESS to improve key network indicators at minimal cost. This study considers energy loss and network imbalance as the key network indicators.

A. OBJECTIVES

1) MINIMIZATION OF VOLTAGE UNBALANCE FACTOR

The voltage unbalance factor (VUF) is a crucial metric used to quantify imbalance in a power system. It is expressed as the percentage ratio of the negative sequence voltage to the positive sequence voltage, as defined in Eq.(5). Minimizing the VUF helps ensure power quality and stability within the network.

$$f_1^{\text{obj}} = \min \sum_{k \in K_{\text{node}}} \text{VUF}^k(t) \tag{5}$$

where t represents each time step, covering a 24-hour period, with t = 1, 2, ..., 24. The VUF at a specific node k and time step t is calculated using the following expression:

$$\text{VUF}_v^k(t) = \frac{|V^k(t)_-|}{|V^k(t)_+|}$$

Here, $V^k(t)_-$ and $V^k(t)_+$ denote the magnitudes of the negative and positive sequence voltages, respectively, at node k and time step t. The index k refers to a measurement node within the set of all measuring nodes, K_{node}. According to IEEE Standard 141-1993 [37], the acceptable limit for VUF in distribution networks should not exceed 2%. Keeping the VUF below this threshold is essential to maintain power quality and reduce the risk of equipment malfunction or inefficiency due to voltage imbalances.

2) MINIMIZATION OF ENERGY LOSS

In this study, energy loss in terms of active power losses is a key indicator of the efficiency of distribution network management, as they directly translate to costs for distribution companies. Consequently, minimizing active power losses is one of the most frequent and essential objectives in optimal power flow (OPF) studies conducted by distribution system operators. Incorporating EVs uncertainties and BESS into the formulation of power loss minimization introduces complexities. These uncertainties stem from the unpredictable behavior of EVs in terms of their charging/discharging schedules, SoC, and energy demand. BESS, on the other hand, can reduce losses and improve grid performance through optimal dispatch.

The total power loss for all branches can be formulated as:

$$P_{\text{loss, total}} = \sum_{i,j \in B} r_{i,j} \frac{P_{i,j}^2 + Q_{i,j}^2}{V_i^2} \tag{6}$$

where $P_{i,j}$ and $Q_{i,j}$ are active and reactive power flow from bus i to j.

The goal is to minimize the anticipated power loss, and it can be expressed as:

$$f_2^{\text{obj}} = \min \sum_{(i,j) \in B} r_{i,j} \frac{P_{i,j}^2 + Q_{i,j}^2}{V_i^2} \tag{7}$$

3) MINIMIZATION OF VOLTAGE DEVIATION

Voltage deviation refers to the difference between the actual voltage at a bus (node) in a power system and its nominal or target voltage. It quantifies how far the voltage deviates from its desired value, often set around 1 p.u. Maintaining voltage within acceptable limits is crucial for the stability, reliability, and efficiency of the power system. Excessive deviation can lead to equipment malfunctions, increased power losses, and network instability.

The voltage deviation for a system with N buses for minimization of voltage deviation can be formulated as shown in Eq.(8).

$$f_3^{\text{obj}} = \min \sum_{i=1}^{N} |V_i - V_i^{\text{nom}}| \tag{8}$$

where, V_i and V_i^{nom} are actual and nominal (1p.u.) voltage at bus i.

In the multi-objective function shown in Eq.(9), we consider the VUF as the key grid performance indicator, which helps mitigate grid imbalances, increase hosting capacity, and reduce overall power demand [38]. Additionally, voltage deviations and energy loss are included in Eq.(9).

$$F_{\text{obj}} = \min \left(\omega_1 f_1^{\text{obj}} + \omega_2 f_2^{\text{obj}} + \omega_3 f_3^{\text{obj}}\right) \tag{9}$$

where ω_1, ω_2 and ω_3 are weights factor for different objectives and treated equally in this paper.

B. CONSTRAINTS

Evaluating the optimization requires consideration of particular constraints. The power limits for BESS charging and discharging must stay within the defined maximum and minimum active/reactive power thresholds, as specified in Eq.(10.1), Eq.(10.2), and Eq.(10.3). Furthermore, BESS operation should adhere to grid security constraints (voltage, branch current) outlined in Eq.(10.4) and Eq.(10.5).

$$P_{\text{BESS},i}^{\min} \le P_{\text{BESS},i}^{(\text{ch},t)} \le P_{\text{BESS},i}^{\max}, \quad \forall i, \forall t \tag{10.1}$$

$$-P_{\text{BESS},i}^{\max} \le P_{\text{BESS},i}^{(\text{dch},t)} \le 0, \quad \forall i, \forall t \tag{10.2}$$

$$-Q_{\text{BESS},i}^{\max} \le Q_{\text{BESS},i}^{t} \le Q_{\text{BESS},i}^{\max}, \quad \forall i, \forall t \tag{10.3}$$

$$V_{\min} \le V_i \le V_{\max}, \quad \forall i \in \{1, 2, \ldots, N\} \tag{10.4}$$

$$I_{\text{br},t} \le I_{\text{br}}^{\max}, \quad \forall t \tag{10.5}$$

where, $P_{\text{BESS},i}^{\text{min/max}}$ denotes the minimum and maximum active power dispatch limits of the BESS, respectively. $P_{\text{BESS},i}^{(\text{ch/dch},t)}$ represents the active power charged or discharged by the BESS at time step t at node i. $Q_{\text{BESS},i}^{\max}$ indicates the maximum reactive power capacity of the BESS. $V_{\text{min/max}}$ corresponds to the minimum and maximum voltage levels at the nodes, while $I_{\text{br}}^{\max}$ denotes the maximum allowable current limit of the branch.

The DE algorithm is employed to solve the control objective in Eq.(9) under the constraints specified in Eq.(10.1) through Eq.(10.5). The implementation of the proposed method within smart grids will be detailed in section VI.

IV. OPTIMIZATION ALGORITHM

This study employs the DE technique to address the optimal BESS deployment challenge. DE is preferred over GA and PSO due to its robustness in handling multi-objective constraints and its higher solution accuracy. As a stochastic, population-based evolutionary algorithm, DE is widely used for solving complex optimization problems in power systems due to its simplicity, robustness, and efficiency [39]. The algorithm operates on a population of candidate solutions that evolve over several generations. Each solution represents a potential BESS dispatch configuration, which is improved using three key operators: mutation, crossover (recombination), and selection. The flowchart of the basic DE algorithm is illustrated in Fig. 5.

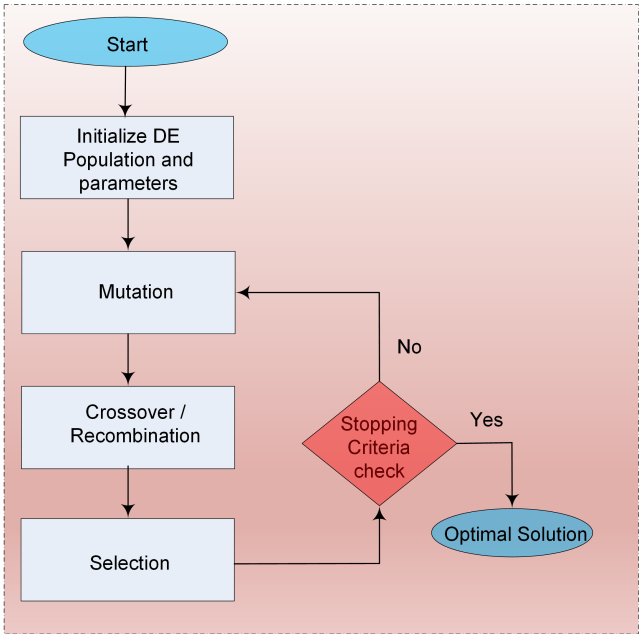

FIGURE 5. Basic flowchart of the DE algorithm.

- **Initialization:** The algorithm initializes a population of candidate solutions, representing potential BESS dispatch configurations. Each solution is randomly assigned within predefined constraints to ensure diversity and prevent premature convergence.
- **Mutation Operator:** During mutation, a mutant vector is generated by adding a scaled difference between two or more randomly chosen population vectors to a base vector. Various mutation strategies exist to govern how this process is implemented.
- **Crossover Operator:** The crossover operator generates a trial vector by mixing elements from the mutant vector and the original target vector, typically using a binomial crossover. Each element of the trial vector is selected from either the mutant or the target vector based on a crossover probability (CR). When CR is high, the trial vector closely resembles the mutant vector, supporting exploration. In contrast, a low CR makes the trial vector more similar to the target vector, encouraging exploitation of the existing population.
- **Selection Operator:** The trial vector is evaluated against the target vector, retaining the more optimal solution for the next iteration.

The process continues until convergence criteria, such as minimized VUF, energy losses and Voltage Deviation, are met.

V. PROPOSED METHODOLOGY

The proposed methodology integrates BESS dispatch within a TE market framework, ensuring optimal grid performance while enabling BESS owners to participate in energy trading. The core objective is to optimize BESS dispatch by considering both grid performance (e.g., voltage profile and loss reduction) and economic efficiency (e.g., energy procurement cost minimization) through a price-based bidding mechanism. The proposed framework consists of the following key steps:

A. OVERVIEW OF THE TE MARKET FRAMEWORK

In this study, the TE market operates on a price-based bidding mechanism, where independent BESS owners submit bids to supply energy in response to real-time grid demand. The DNO evaluates these bids based on both economic and grid performance criteria, ensuring cost-efficient energy procurement while maintaining grid performance.

The market participation process follows these key steps:

1) DEMAND FORECASTING AND REAL-TIME ASSESSMENT

- The DNO forecasts the total demand, including EVs charging demand, and schedules generation on a day-ahead basis. To maintain grid performance, the DNO monitors demand and generation in real time. If the distribution grid requires additional generation due to higher-than-forecasted EVs charging demand, BESS units will provide support to maintain grid performance.
- In real time, if EVs actual demand (P_{rt}) exceeds the scheduled demand (P_{sch}), the DNO issues a demand request for additional energy supply from BESS owner at each time step. Thus, the real-time additional demand bids for the DNO at each time step t are calculated by subtracting the scheduled power demand from the real-time power demand using Eq.(11).

$$P_{\mathrm{AD}}(t) = \begin{cases} P_{\mathrm{rt}} - P_{\mathrm{sch}} & \text{if } P_{\mathrm{rt}}(t) > P_{\mathrm{sch}} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

2) BESS MARKET PARTICIPATION AND BIDDING PROCESS

- To address the additional demand arising from the DNO's demand bids, BESS owners submit bids specifying the amount of energy they can supply and the corresponding price (\$/kWh). In this study, we assumed that BESS owners operate independently, covering all investment, maintenance, and life cycle costs and profits in their bids to the DNO.
- To ensure cost-effectiveness, each bid price must be below or equal to the grid locational marginal price (LMP) as shown in Eq.(12).

$$BESS_{\mathrm{Price}}^{bid} \leq \mathrm{LMP} \tag{12}$$

This constraint restricts BESS owners from exploiting excessively high supply bid prices.

3) OPTIMAL NODE SELECTION AND MARKET CLEARING

To select the most suitable BESS units for dispatch, the MCDM method evaluates each node based on VUF and Bid Price. VUF and Bid price are normalized for each node i using Eq.(13) and Eq.(14). A higher normalized VUF indicates greater node imbalance, boosting the likelihood of selection for BESS dispatch, while a higher normalized bid price reflects lower cost, increasing the chances of selection.

$$VUF_i^{\mathrm{Norm}} = \frac{\text{Actual VUF}_i}{\text{Most worst node VUF}} \tag{13}$$

$$\mathrm{BidPrice}_i^{\mathrm{Norm}} = \frac{\text{Best BidPrice}}{\text{Actual BidPrice}_i} \tag{14}$$

The weighted score for each node i is calculated by multiplying the normalized VUF and bid price values by their respective weights and summing them, as shown in Eq.(15). The nodes are then ranked in descending order based on these weighted scores, with the highest score indicating the optimal node.

$$\text{Weighted Score}_i = \left(w_{\mathrm{gp}} \cdot VUF_i^{\mathrm{Norm}} + w_{\mathrm{fp}} \cdot \mathrm{BidPrice}_i^{\mathrm{Norm}} \right) \tag{15}$$

where, $w_{\mathrm{gp}} + w_{\mathrm{fp}} = 1$

Here, w_{gp} and w_{fp} are the weight factors for grid performance and financial performance, respectively, reflecting their relative importance.

Once the optimal BESS units are selected, their active and reactive power dispatch is optimized using the DE algorithm to solve Eq.(9). The aggregated BESS dispatch must satisfy the additional demand as shown in Eq.(16):

$$\sum_{i=1}^{N} P_{\mathrm{BESS}} \geq P_{\mathrm{AD}} \tag{16}$$

This constraint ensures that the sum of power injections from selected BESS units must match the DNO's additional demand request. The TE market clearing price is set by the last accepted bid price, provided it remains below or equal to grid LMP.

B. IMPLEMENTATION OF THE CONTROL STRATEGY

A central controller collects network data at each time step to assess additional demand requirements and subsequently sends power demand signals to all BESS owners in real time. Each BESS owner has a local controller installed to manage operations. The proposed strategy is implemented within the central controller, which determines the optimal dispatch and transmits dispatch signals to the respective BESS local controllers for execution. Ultimately, BESS participation dynamically adjusts based on real-time pricing signals and grid conditions. The complete steps of the proposed methodology for strategic BESS integration and dispatch within the TE framework are illustrated in Fig. 6.

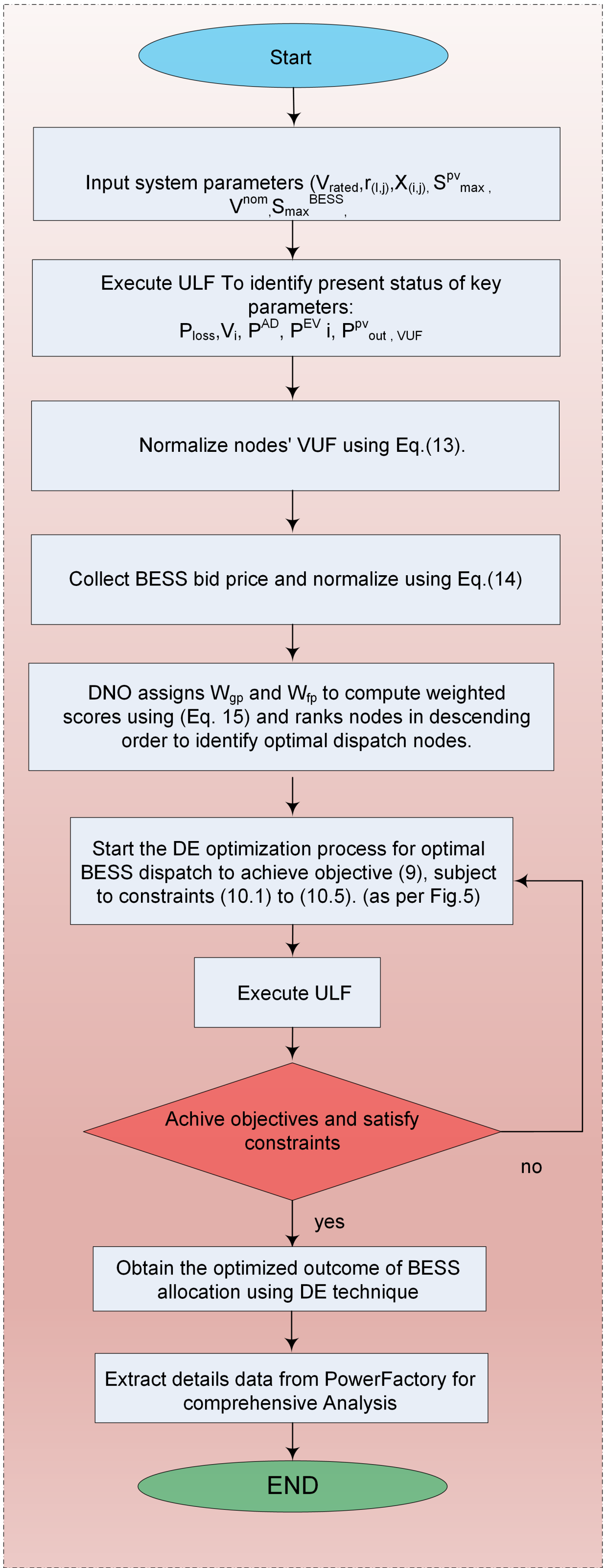

FIGURE 6. **Proposed TE market based BESS's optimal allocation strategy using DE algorithm.**

The proposed method only considers bids that satisfy the condition in Eq.(12). BESS units are then allocated to the optimal nodes based on this selection strategy. The DE optimization algorithm is applied to determine the optimal dispatch of BESS units, ensuring that the aggregated supply bid power meets the demand specified in Eq.(16). This strategy ensures an efficient, cost-effective, and reliable approach to meeting additional demand while maintaining grid performance and minimizing energy procurement costs.

VI. EXPERIMENTAL SETUP

To validate the proposed price-based bidding mechanism within a TE market framework for the strategic integration and dispatch control of BESS, using a practical Australian LV grid serving 1,020 residential consumers is used as the test grid, as depicted in Fig. 7. The grid includes 12 single-phase BESS units of varying capacities, 36 single-phase PV sources with a total capacity of 2,880 kW, and 12 synchronous machine-based DER units with a combined capacity of 1,665 kW. The modeling and simulation were conducted using DigSILENT PowerFactory.

In the test grid, all residential consumers are assumed to own EVs equipped with single-phase chargers of varying capacities: Level 2 HCS-80 (15.4 kW), HCS-60 (11.5 kW), HCS-50 (9.6 kW), and HCS-40 (7.7 kW). The base residential load is modeled as a constant active power demand with a 0.96 lagging power factor. During charging, EV batteries are represented as constant power loads operating at unity power factor to facilitate grid management. The test grid remains interconnected with the main grid, enabling the DNOs to dynamically import or export energy based on real-time conditions. In general, the proposed approach is applicable to any LV distribution grid.

VII. RESULTS AND DISCUSSION

This section presents the results of the proposed method for the optimal coordination of BESS. The method effectively addresses the EV charging demand, provides ancillary services through a novel TE market-clearing approach, and improves grid performance. The system without BESS serves as the base case. This study examines the effect of different additional power requirements (P_{AD}) under the base case and evaluates the impact of the proposed method considering the following scenarios:

- **Case I:** Network without BESS (base case)
- **Case II:** Optimal allocation of BESS using the strategy discussed in section V (proposed method)

Three different hours during the peak period are considered to investigate the impact of the base case and the proposed method while the DNOs face additional EV charging demand.

A. IMPACT OF THE PROPOSED METHOD ON GRID PERFORMANCE

This section examines the impact of the base case and the proposed BESS integration strategy by comparing Case I and Case II. In the base case (Case I), grid performance was

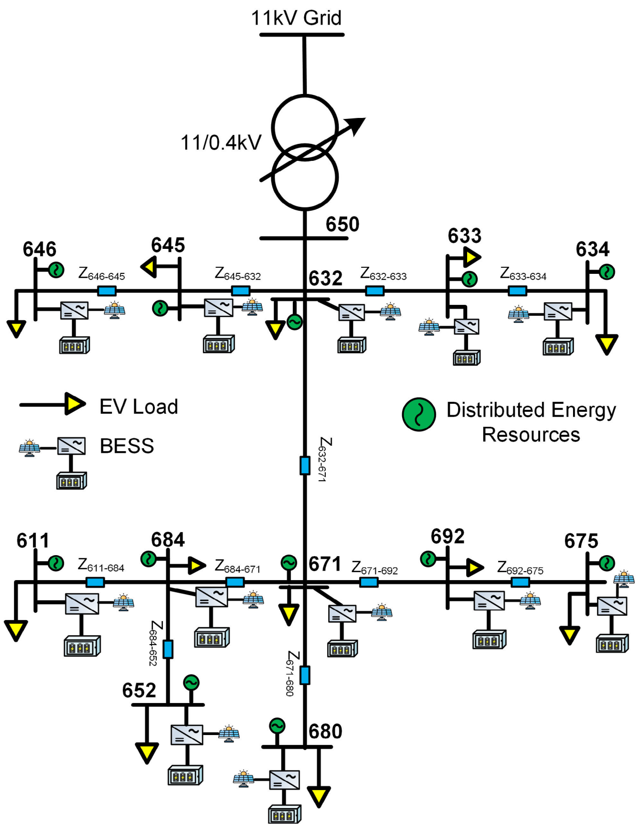

FIGURE 7. Modeled test grid for case study.

TABLE 1. Selection of BESS dispatch nodes using the proposed method (Hour 18).

Node Name	Normalize VUF	Normalize Bid Price	Weighted Score
N611	1.00	0.90	0.95
N632	0.42	0.98	0.70
N633	0.94	1.00	0.97
N634	0.87	> LMP	> LMP
N645	0.60	> LMP	> LMP
N646	0.64	> LMP	> LMP
N652	0.47	> LMP	> LMP
N671	0.71	0.96	0.83
N675	0.92	1.00	0.96
N680	0.75	> LMP	> LMP
N684	0.97	> LMP	> LMP
N692	0.85	0.92	0.88

TABLE 2. Selection of BESS dispatch nodes using the proposed method (Hour 19).

Node Name	Normalize VUF	Normalize Bid Price	Weighted Score
N611	0.68	0.81	0.74
N632	0.12	1.00	0.56
N633	0.40	0.98	0.69
N634	1.00	> LMP	> LMP
N645	0.04	0.95	0.50
N646	0.09	0.91	0.50
N652	0.59	> LMP	> LMP
N671	0.52	0.88	0.70
N675	0.88	0.89	0.89
N680	0.73	> LMP	> LMP
N684	0.71	> LMP	> LMP
N692	0.67	0.93	0.80

TABLE 3. Selection of BESS dispatch nodes using the proposed method (Hour 20).

Node Name	Normalize VUF	Normalize Bid Price	Weighted Score
N611	0.15	> LMP	> LMP
N632	0.48	0.96	0.72
N633	0.69	0.96	0.82
N634	0.89	0.98	0.94
N645	0.85	1.00	0.92
N646	1.0	0.98	0.99
N652	0.40	> LMP	> LMP
N671	0.37	> LMP	> LMP
N675	0.36	0.94	0.65
N680	0.15	> LMP	> LMP
N684	0.33	0.96	0.64
N692	0.36	0.90	0.63

evaluated without BESS. In Case II, the proposed approach was implemented to select optimal nodes for dispatching the active and reactive power of the BESS, improving VUF regulation, reducing node voltage deviation, and minimizing energy costs.

To ensure a balanced trade-off between grid performance and energy procurement costs, equal importance was assigned to VUF and bid price ($w_{gp} = 0.5$, $w_{fp} = 0.5$) in Eq.(15). While this subsection analyzes key grid performance metrics (VUF, node voltage, and energy losses), the next subsection will examine the impact of weighting factor selection in Eq.(15) and its effect on energy procurement costs compared to existing optimization methods.

To evaluate the impact of the proposed method, we analyzed three peak hours (18, 19, and 20). For each hour, normalized weighted scores were calculated using Eq.(15), ranked in descending order, and filtered to exclude bids exceeding the LMP based on the constraints in Eq.(12). The most suitable nodes for BESS dispatch were then selected sequentially, starting from the highest-ranked node, followed by the next highest, and so on, until the constraints in Eq.(16) were satisfied. Tables 1, 2, and 3 present the normalized weighted scores for Hours 18, 19, and 20, respectively.

At Hour 18, the optimal nodes identified based on weighted score rankings—N632, N671, N633, N611, N692, and N675—dispatch a total of 684 kW to meet an additional EV charging demand of 544 kW, as shown in Table 1. At Hour 19, the selected nodes—N645, N646, N632, N633, N671, N692, N611, and N675—dispatch 775 kW, fully covering the additional EV charging demand of 767 kW and eliminating the need for grid energy imports, as presented in Table 2. Similarly, at Hour 20, the identified nodes—N684, N675, N692, N632, N645, N633, N634, and N646—dispatch 710 kW against an additional EV charging demand of 894 kW, necessitating the import of 184 kW from the external grid, as detailed in Table 3.

Notably, nodes N632, N633, N675, and N692 are consistently selected across all studied hours due to their worst VUF, low BESS bid price, or a combination of both.

Fig. 8 illustrates the grid performance (VUF and node voltages) for Cases I and II during the three peak hours (18, 19, and 20). The case-wise observations from this figure are as follows:

- **Case I:** During peak demand, for an example at Hour 19, VUF at nodes N634, N675, N680, N684 and N692 exceeds 2% standard, and voltage levels at most nodes drop below the standard threshold (0.99 p.u.).
- **Case II:** The proposed method significantly improves VUF and node voltage across all nodes compared to the Case I during all observed peak hours.

Based on the observations in Fig. 8(a)-(f), it can be concluded that the proposed method effectively enhances grid performance by maintaining VUF and node voltage levels within acceptable standards.

Additionally, Fig. 9 shows a substantial reduction in total energy losses using the proposed method compared to Case I. This reduction - 47%, 32%, and 41% for Hours 18, 19, and 20, respectively aligns with the study's objectives and highlights significant advantages in improving distribution network efficiency. Moreover, the optimal injection of reactive power leads to further reductions in system energy loss and improvements in the node voltage profile.

B. VALIDATION OF THE PROPOSED METHOD

This section presents a comparative analysis to validate the proposed strategic integration and dispatch method against the developed optimal placement of DGs and optimal dispatch methods cited in [16], [18], [40], and [41]. The validation is carried out by comparing key performance metrics such as VUF, node voltage, and energy procurement cost. Additionally, a sensitivity analysis is conducted to evaluate the impact of weighting factor selection on BESS dispatch strategy.

1) THE WEIGHTING FACTOR SENSITIVITY ANALYSIS

In our proposed strategy, the weighting factor plays a crucial role in the selection of BESS from the submitted supply bids as shown in Eq.(15). Also, allows DNOs to trade-off between technical and financial performance as per their requirement by selecting the value of w_{gp} and w_{fp}. To validate the applicability of the proposed method in BESS selection, a sensitivity analysis is carried out.

In the proposed method, BESS units that submit bids higher than the LMP are first excluded from the ranking. The remaining BESS units are ranked based on their weighted scores, and power dispatch begins from the highest-ranked BESS. The process continues until the additional demand is met for the given time step t.

We have evaluated three different scenarios for BESS selection strategy:

Scenario 1: In this scenario, we place less emphasis on grid performance and focus more on cost minimization ($w_{gp} = 0.1$, $w_{fp} = 0.9$). Based on the weighted score, the proposed strategy ranks the BESS units in descending order while excluding those with bid prices higher than the LMP. As a result, the strategy ranks 6 out of 12 BESS units. However, it ultimately recommends dispatching only 4 BESS units (BESS 611, BESS 633, BESS 671, and BESS 675), as they offer the lowest cost, while excluding the other 2 ranked BESS units due to emphasize on bid price.

Fig. 10 shows that nodes N611, N634, N652, N671, N675, N680, N684, and N692 have VUF values exceeding 2%, which is beyond the standard limit. This occurs because prioritizing cost minimization prevents the system from selecting other 2 potential nodes that could improve grid performance. The proposed method demonstrates that for this scenario the total cost for meeting an additional EV charging demand of 684 kW is $267.75. This weighting factor reduces energy procurement costs by 26% compared to the existing full BESS dispatch method.

Scenario 2: In this scenario, we place greater emphasis on grid performance and less on cost minimization ($w_{gp} = 0.9$, $w_{fp} = 0.1$). Based on the weighted score, the proposed strategy ranks the BESS units in descending order while excluding those with bid prices higher than the LMP. As a result, the strategy ranks 6 out of 12 BESS units. However, it ultimately recommends dispatching 5 BESS units (BESS 611, BESS 633, BESS 671, BESS 675, and BESS 692) to improve grid performance, ensuring that VUF remains below 2% at all nodes as shown in Fig. 10, while meeting the required additional EV charging demand. Notably, although BESS 632 was ranked, it was not dispatched to achieve the desired goal, which is influenced by the selected weighting factor. The proposed method demonstrates that the total cost for meeting an additional demand of 684 kW is $267.75 in Scenario 1, compared to $282.43 in Scenario 2. This weighting factor reduces energy procurement costs by 23% compared to the existing all BESS dispatch method. This highlights the impact of weighting factor selection of BESS energy procurement costs.

Scenario 3: In Scenario 1, cost is given higher priority, whereas in Scenario 2, grid performance is prioritized. As a result, in Scenario 1, grid performance deteriorates while achieving minimal cost, whereas in Scenario 2, grid performance improves significantly compared to Scenario 1 but at a higher cost. In this scenario, equal importance ($w_{gp} = 0.5$, $w_{fp} = 0.5$) is given to both grid performance and financial benefit. The proposed method demonstrates that the total cost for meeting an additional EV charging demand of 684 kW is $277. This weighting factor reduces energy procurement costs by 22% compared to the existing all BESS dispatch method.

Therefore, to ensure a balanced evaluation, this study examines the impact of assigning equal importance to both grid performance and cost minimization ($w_{gp} = 0.5$, $w_{fp} = 0.5$).

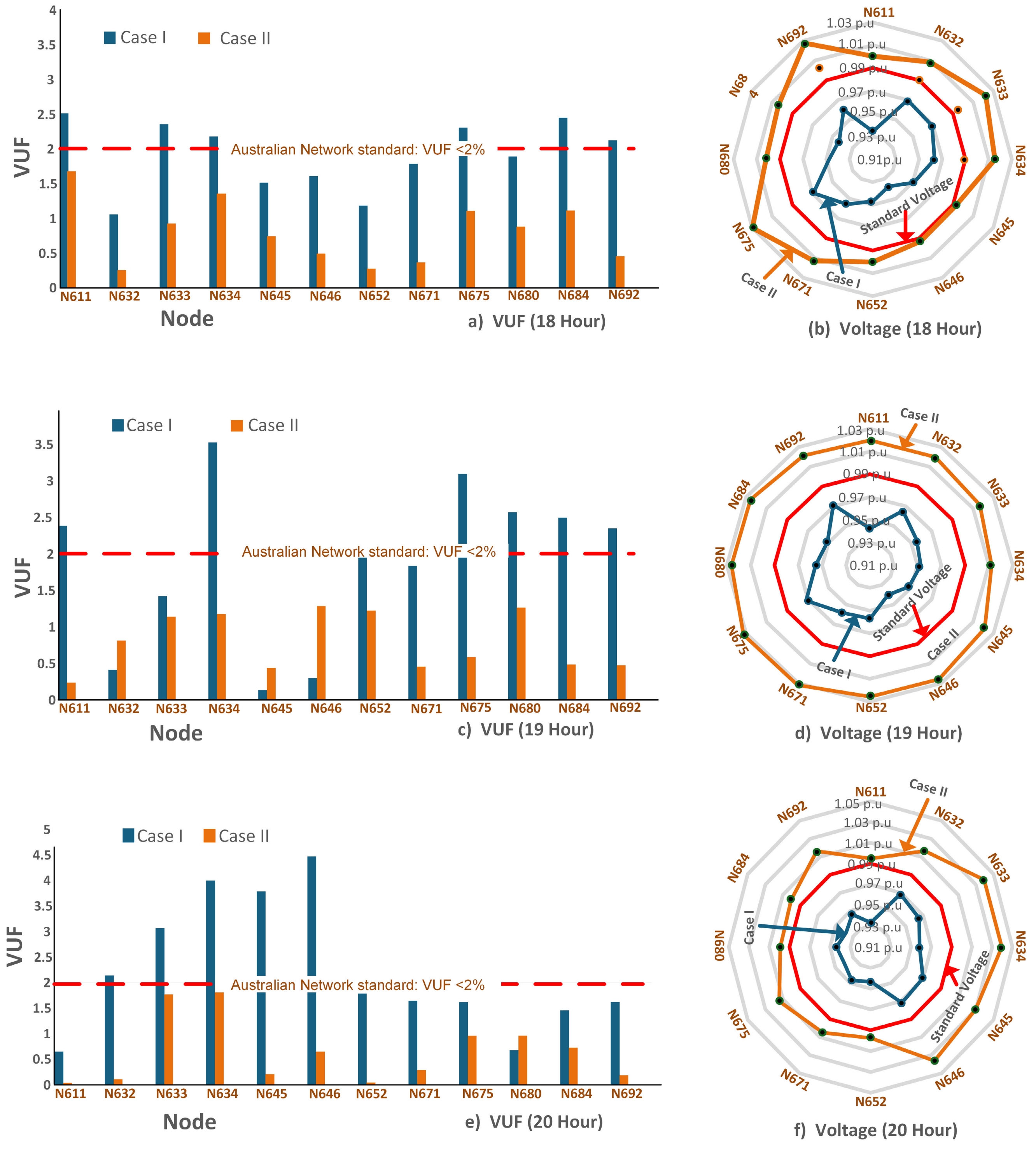

FIGURE 8. **Comparison of VUF and node voltage of the proposed method.**

2) COMPARATIVE ANALYSIS WITH EXISTING METHODS

Currently, existing methods [16], [18], [40], [41] recommend dispatching an optimal amount of energy from every BESS at all nodes using optimization algorithms to solve the problem in Eq.(9). This study evaluates the proposed method against the existing approaches [16], [18], [40], [41], considering grid performance as key optimization criteria.

The proposed method recommends dispatches BESS units based on bid prices, prioritizing higher power allocation from the least expensive bidders, utilizing only 50% of available

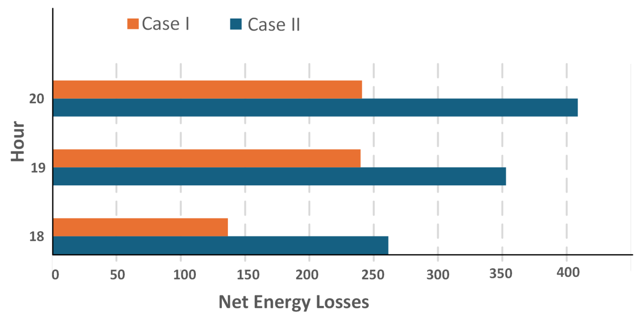

FIGURE 9. Comparison of losses between Case I and Case II.

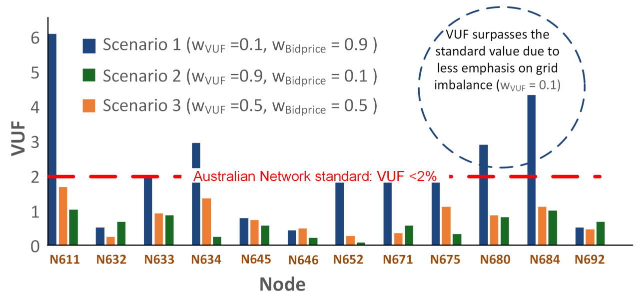

FIGURE 10. Impact of different weighting factors on BESS selection and grid performance.

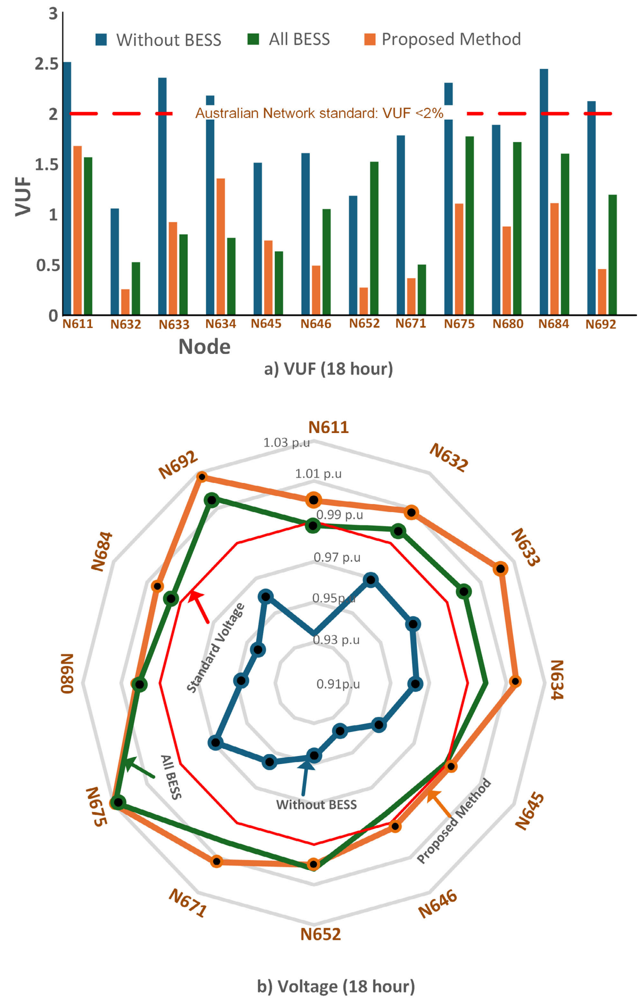

FIGURE 11. Comparison of VUF and node voltage with existing DG integration method [16], [18], [40], [41].

BESS units, whereas existing methods [16], [18], [40], [41] recommends dispatch all BESS units without considering energy procurement costs as shown in Table 4. Specifically, the proposed method dispatches power from 6 BESS units—BESS611, BESS632, BESS633, BESS671, BESS675, and BESS692—out of 12, enhancing grid performance. Notably, the existing dispatch method [16], [18], [40], [41] dispatches a substantial amount of power from BESS646, which has the highest bid price, whereas the proposed method excludes this unit. The proposed method meets an additional energy demand of 684 kWh at a cost of \$256, compared to \$354 with the existing method [16], [18], [40], [41], resulting in energy procurement costs savings of \$98 at Hour 18. Additionally, the superiority of the proposed method over the without BESS and existing method (All BESS) is demonstrated in Fig. 11. Fig. 11(a) clearly indicate that the proposed method significantly reduces the VUF compared to the without BESS and the existing method [16], [18], [40], [41]. Also, Fig. 11(b) shows that the proposed method is able to maintain all node voltages above 0.99 p.u., whereas the existing method fail to maintain the standard voltage for all nodes. For example, at node N646, the existing method [16], [18], [40], [41] fails to maintain the voltage at 0.99 p.u. This is because the proposed method provides coordinated reactive power support, which enhances node voltage stability.

From the above discussion it is evident that the proposed method outperforms the commonly recommended optimal dispatch methods [16], [18], [26], [40], [41], not only by improving grid performance but also by reducing energy import costs for DNOs, thereby lowering overall energy procurement costs as well provide operational flexibility to DNOs.

TABLE 4. Existing method [16], [18], [40], [41] vs proposed method (BESS dispatch).

BESS Name	Existing Optimum Dispatch Method (All BESS)	Proposed Method (Case II)		
	P (kW)	P (kW)	Q (kVAR)	Weighted Score
BESS 611	25.182	62.526	34.439	0.95
BESS 632	40.552	126.384	37.027	0.70
BESS 633	42.322	130.808	77.205	0.97
BESS 634	62.354	0	0	> LMP
BESS 645	67.537	0	0	> LMP
BESS 646	104.047	0	0	> LMP
BESS 652	85.067	0	0	> LMP
BESS 671	41.391	122.51	1.052	0.83
BESS 675	44.685	161.617	77.996	0.96
BESS 680	81.936	0	0	> LMP
BESS 684	56.906	0	0	> LMP
BESS 692	32.452	80.552	30.522	0.88

C. EFFECT OF REACTIVE POWER SUPPORT FOR UNBALANCE MITIGATION

It is well known that reactive power support improves the voltage profile of the network. However, the impact of reactive power on mitigating unbalance has not been thoroughly investigated to date. This subsection explores the effect of reactive power support under the following scenarios:

- **Scenario I (Without reactive power support):** We assume Q = 0, so P is tuned from zero to the converter's full capacity (S).
- **Scenario II(Uncoordinated reactive power support):** P is tuned, and the remaining available converter capacity is allocated to Q as calculated by equation below. Therefore, uncoordinated Q is dispatched into the network.

$$Q = \sqrt{S^2 - P^2} \tag{17}$$

- **Scenario III(Coordinated reactive power):** Both P and Q are simultaneously optimized while ensuring that their combined magnitude does not exceed the converter's rated capacity S as shown in equation below.

$$S = \sqrt{P^2 + Q^2} \tag{18}$$

This approach ensures that the converter operates within its limits while optimizing both active and reactive power dispatch to enhance system performance.

In Scenario II, active power (P) is optimized to achieve its optimal value, while the reactive power (Q) is determined according to Eq.(17). In Scenario III, both active power (P) and reactive power (Q) are optimized simultaneously to ensure grid constraints are maintained and overall system efficiency is enhanced.

These scenarios are evaluated during peak periods (Hour 18, Hour 19, and Hour 20), and the results are presented in Fig. 12.

From Fig. 12(a), it is observed that at Hour 18, the VUF exceeds the standard limit at nodes N611, N675, and N684 in Scenario I, and at node N611 in scenario II. In Fig. 12(b), at Hour 19, the VUF surpasses the standard limit at nodes N611, N675, and N692 during Scenario II, and at node N680 in the dispatch scenario I. Similarly, in Fig. 12(c) at Hour 20, the VUF exceeds the standard limit at nodes N675, N684, and N692 in both dispatch Scenarios I and II.

Therefore, Fig. 12, clearly demonstrates that the proposed coordinated reactive power dispatch method (Scenario III) significantly regulates the VUF, keeping it below the standard limit (2%) and outperforming both Scenario I and Scenario II.

The proposed method was implemented on a system running a 64-bit Windows 11 OS, equipped with a Ryzen 9 processor (4.5 GHz) and 16 GB of RAM. Unlike many previous studies that primarily employed GA [24], [40], [43], [44], [45] for solving the optimal BESS integration problem, this study utilizes the DE optimization algorithm due to its robustness in handling multi-objective constraints and higher solution accuracy. Additionally, the study investigates the convergence performance, computational time, and accuracy of DE in comparison to GA and PSO.

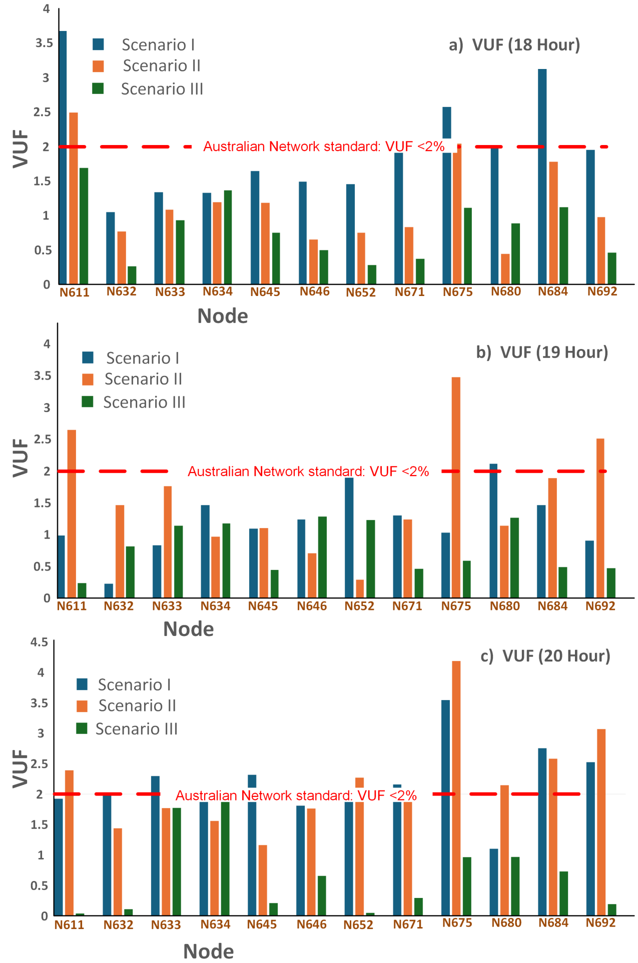

FIGURE 12. Effect of reactive power support.

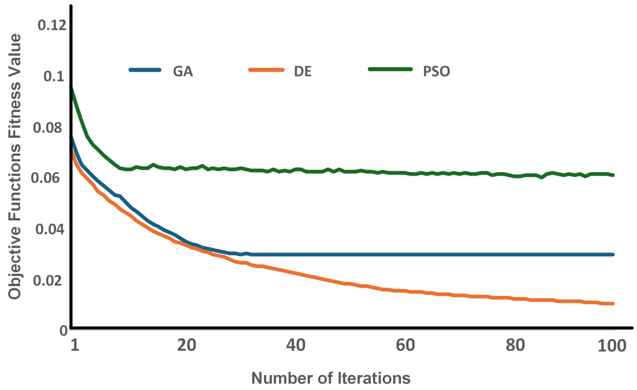

FIGURE 13. Performance comparison of DE, GA, and PSO.

Fig. 13 illustrates the convergence characteristics of the DE, GA, and PSO methods. The key observations are as follows:

TABLE 5. Comparison of computational time and accuracy for DE, GA, and PSO.

Optimization approach	Performance Criteria	
	Computational time (s)	Solution Accuracy
DE	504	Very good
GA	551	Medium
PSO	489	Low

- PSO converges the fastest but results in the worst optimal solution among the three methods.
- GA converges more slowly than PSO but faster than DE, achieving a better optimal solution than PSO while having a higher fitness value than DE.
- In contrast, DE provides the best optimal solution among all three methods, demonstrating its superior performance in terms of accuracy and robustness.

These findings demonstrate that DE outperforms GA and PSO in terms of solution quality, making it more suitable for high-dimensional optimization problems.

Table 5 summarizes the computational times, and accuracy for DE, GA, and PSO for 100 iterations. In terms of real-time computation, DE, GA, and PSO required approximately 504 seconds, 551 seconds, and 489 seconds, respectively. While DE outperforms GA in terms of solution accuracy, its computation time (504 seconds) may present challenges for real-time large-scale applications. To address this, our investigation suggests a hybrid DE-PSO approach as a potential solution. Future work could explore this hybrid method to balance accuracy and computational efficiency by leveraging next-generation computing technologies, including parallel computing, multi-core processing, adaptive control for faster decision-making, and AI-assisted optimization.

A summary of the results obtained using the proposed method is as follows:

I. **Node Voltage and VUF Improvement:** The proposed method improves both node voltage and VUF, outperforming existing methods [16], [18], [40], [41], as shown in Fig. 8 and Fig. 11.

II. **Loss Reduction:** The innovative method reduces system losses and further minimizes them through the coordinated dispatch of BESS reactive power. The average loss reduction during the considered peak hours is approximately 40% (Fig. 9).

III. **Energy Procurement cost Reduction:** The method reduces the BESS's energy procurement cost by approximately 28% compared to existing methods [16], [18], [40], [41], making it possible to charge EVs at a lower cost (Table 4).

IV. **TE Market Participation:** The proposed TE clearing approach enables both the DNO and BESS users to participate in the market, creating a win-win situation for both parties.

V. **Impact of Reactive Power on VUF**: The proposed method analyzes the impact of reactive power on VUF and demonstrates significant reductions in VUF.

VIII. CONCLUSION

This research presents a novel approach to optimizing BESS to address the growing challenges associated with increased EV and PV integration in distribution networks. By considering both grid performance and TE market prices, the proposed optimization model ensures mutual benefits for both BESS owners and DNOs. The proposed approach allows DNOs to trade-off between technical and financial performance as per their requirement. However, by assigning equal importance to both grid performance and cost minimization, the simulation results reveal that the optimized BESS strategy reduces the DNO's energy procurement cost by 28%, enabling the delivery of lower-cost energy to meet the increased demand driven by EVs. Additionally, the impact of optimal reactive power dispatch from BESS further addresses rising demand by reducing overall system losses, providing effective reactive power support during peak periods. On average, this approach reduced system losses by approximately 40% during peak hours compared to scenarios without BESS reactive power support. This dual-focused optimization not only offers an effective framework for DNOs to improve grid reliability but also establishes a pathway for sustainable, economically viable energy trading in decentralized power systems. Future work will focus on incorporating forecasting error modeling to improve the adaptability and robustness of the proposed framework under uncertain conditions. Additionally, implementing real-time adaptive optimization for dynamic BESS dispatch could further enhance grid resilience, efficiency, and responsiveness to fluctuating energy
demands.

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