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Rolling Horizon-Based Operation Optimisation of Energy Storage Systems and Electric Vehicles Integrated in Distribution Networks

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***Abstract*— Effective management algorithms have emerged to mitigate the adverse effects of high renewable energy systems and electric vehicle (EV) penetration on distribution networks. This study proposes a rolling horizon optimization-based approach to reduce power loss in distribution networks that incorporate EVs, battery-based energy storage systems (BESS) and photovoltaic (PV) plants. This approach entails an efficient charging algorithm for EVs and BESS, formulated as a mixed-integer linear programming (MILP) model and the power loss equation is linearized using a piecewise approach with the Special Ordered Sets of Type 2 (SOS2) method. The algorithm accounts for uncertainties related to EV charging and PV generation, yielding promising results. Our findings indicate that utilizing BESS and effectively managing EV charging profiles can be leveraged to reduce the power loss on the PV-integrated distribution systems. Also, the effects of the location of BESS and EV parking lot on the network are analysed thoroughly and even a decrease of 7.6% in power loss is evidenced due to the relocation of the EV parking lot between feeders.**

Keywords*— *Battery-based energy storage systems, electric vehicles parking lot, rolling horizon optimization.

NOMENCLATURE

The abbreviations, sets and indices, parameters, and variables used in this study are alphabetically listed in Tables I-IV.

TABLE I
ABBREVIATIONS

BESS	Battery-based energy storage systems.
ESS	Energy storage systems.
EV	Electric vehicle.
PV	Photovoltaic.
SoE	State-of-Energy.

TABLE II
SETS AND INDICES

b	Set of branches.
i	Set of buses.
k	Set of battery-based energy storage systems.
l	Set of loads.
m	Set of electric vehicles.
p	Set of photovoltaic units.
t	Set of time periods.

TABLE III
PARAMETERS

$CR_{i,k/m}^{ESS/EV}$	Charging rate of ESS k / EV m on bus i.
$DR_{i,k/m}^{ESS/EV}$	Discharging rate of ESS k / EV m on bus i.
$N^{Grid/ESS}$	The efficiently large number for grid / BESS.
$P_b^{Line,Cap}$	The active power capacity of line [kW].
$P_{i,l,t}^{Load}$	The power demand l on bus i at time t [kW].
$SoE_{i,m}^{EV,des}$	The desired SoE of EV m on bus [kWh].
$SoE_{i,k/m}^{ESS/EV,i}$	State-of-energy of energy storage system k / electric vehicle m at initial/arrival time [kWh].
$SoE_{i,k/m}^{ESS/EV,r}$	The allowable maximum SoE of ESS k / EV m on bus [kWh].
$SoE_{i,k/m}^{ESS/EV,r}$	The allowable minimum state-of-energy energy storage system k / electric vehicle m on bus [kWh].
$T_{i,m}^{arr}$	Arrival time of electric vehicle m on bus i.
$T_{i,m}^{dep}$	Departure time of electric vehicle m on bus i.
$\eta_{k/m}^{char/dis}$	The charging / discharging efficiency of ESS k / EV m.
ΔT	Time granularity.
$\alpha_{1,2}$	Constant parameters.

TABLE IV
VARIABLES

$cf_{b,t}^{minus/plus}$	The auxiliary variables [kW].
HL_t	The total power loss across the network at time [kW].
$P_{b,t}^{Abs,line}$	The absolute value of the differences between the auxiliary variables [kW].
$P_{i,k/m,t}^{ESS/EV,char}$	The charging power of ESS k / EV m on bus i at time t [kW].
$P_{k,i,t}^{ESS_{dis}}$	The power discharged by energy storage system k on bus i at time t [kW].
$P_{i,t}^{EV,char_{tot}}$	The total charging power of EV on bus i at time t [kW].
$P_{i,t}^{flow}$	The power flow on bus i at time [kW].
$P_{i,t}^{Grid,sell}$	The power transaction from the grid to the bus i at time [kW].
$P_{i,t}^{Grid,buy}$	The power transaction from bus i to the grid at time [kW].
$P_{i,t}^{Grid,load}$	The total power supplied by the grid for power demand on bus i at t [kW].
$P_{i,t}^{Grid,tot}$	The total power supplied by the grid to bus i [kW].
$P_{i,t}^{Loss}$	The active power loss on bus i at time [kW].
$P_{b,t}^{Line}$	The active power flow across branch b at time [kW].
$P_{b,t}^{Line,squ}$	The approximated value of the square of power flow across branch b at time [kW].
$P_{i,p,t}^{PV}$	The power generated by photovoltaic unit p on bus i at time t [kW].
X_p	Corresponding x coordinate of the point p.
Y_p	Corresponding y coordinate of the point p.
$SoE_{i,k/m,t}^{ESS/EV}$	State-of-energy of energy storage systems k / electric vehicles m on bus i at time [kWh].
$u_{i,t}^{ESS}$	Binary variable for energy storage systems on bus i. 1if it is charging mode, otherwise 0.
$u_{i,t}^{Grid}$	Binary variable for the grid interaction. 1 if the power transaction flows from the grid, otherwise 0.

I. INTRODUCTION

A. Motivation and Background

The rising demand for electricity in various areas has led to a corresponding increase in energy production and consumption-related greenhouse gas emissions. To address these energy production-related issues, there has been a significant surge in the adoption of renewable energy sources. While effective in reducing emissions, these renewable systems introduce notable challenges to the electricity grid due to their intermittent nature and dependence on specific locations [1]. Additionally, to mitigate energy consumption-

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related emissions, electric vehicles (EVs) are being increasingly employed. However, the rapid integration of EVs into networks poses additional challenges by introducing uncertainty and increasing peak power demand, particularly during limited time charging scenarios. Nevertheless, these challenges also present opportunities for mitigating adverse effects by utilizing the storage capacity of EVs while they are parked.

In addition to harnessing the storage capacity of EVs, Energy Storage Systems (ESSs) play a pivotal role in addressing the challenges posed by renewable energy sources and the integration of EVs in modern power systems. ESSs offer a multifaceted solution by storing excess generated energy, thereby acting as a buffer during periods of low generation or high demand. This storing capability of ESSs and EVs not only helps balance the supply-demand dynamics but also significantly contributes to grid stability and reliability. Through strategic deployment of ESSs and EVs within distribution networks, operators can effectively manage energy flow variations, reduce peak power demand during hours of high demand, and enhance overall grid resilience.

B. Literature Summary

The significance of ESSs and their diverse applications in power systems is extensively explored in the literature. The study in [3] offers a comprehensive review of ESSs, encompassing their types, models, and roles in power systems, notably in enhancing grid resiliency and reliability. One of the widely explored applications ESSs involves their integration into the grid to enhance the reliability and power quality of the network. A study by [4] provides an insightful review of grid-connected ESSs along with real-time industrial case studies to illustrate their practical implementation and benefits.

In recent studies, ESSs have been increasingly deployed to support the grid by storing excessive energy and supplying it when required, serving various objectives. For instance, in [2], ESSs is strategically placed within the power network, and its capacity is optimized to minimize power flow fluctuations. Another approach is detailed in [5], where a multi-objective optimal power flow algorithm is implemented to minimize grid power purchase costs, active power losses in the network, and voltage deviations, all achieved through second-order conic programming. Similarly, [6] employs mixed-integer linear programming (MILP) to reduce costs associated with power transactions between transmission and distribution networks, along with managing voltage deviations. However, these methods, as presented in [5,6], assume a scenario where Photovoltaics (PV) and ESSs are located on different buses, overlooking uncertainties related to PV generation. To address this limitation, [7] proposes a three-level stochastic model designed to minimize ESSs installation costs and maximize PV penetration. The network, and EVs are not considered in any of the aforementioned studies [2,5,6,7].

Effective charging management of EVs provides improving the reliability and resiliency of distribution networks by counteracting various problems in the network. It is well explained in [8] that in addition to their voltage and frequency regulation, their storage can be used to help the grid by supplying flexibility to the grid. The study in [9] reviews the challenges of the integration of EVs into distribution networks and emphases the significance of the proactive role of when especially the reliable operation of future distribution systems operation is considered. Therefore, in the literature many studies provide flexibility solutions to the grid by utilizing the storage and ancillary service capacity of EVs. The introduction of a distributed-based energy management algorithm is detailed in [12], targeting a distribution network that incorporates EVs to minimize power generation costs. Another study, [13], presents a linear management algorithm for an EV aggregator aiming to leverage the storage capacity of EVs and utilize their ancillary services to enhance the unbalanced distribution network. While these studies propose effective solutions to mitigate the challenges posed by integrating EVs into distribution networks, they overlook power loss in the network and the integration of ESSs.

Integrating ESSs alongside EVs in distribution networks not only enhances network flexibility but also mitigates challenges associated with EV integration. In [10], a real-time optimal energy management algorithm is introduced to integrate EVs and stationary ESS in a PV-integrated distribution network. The study demonstrates that employing stationary ESS enables the network to operate even during network faults, showcasing the benefits of this combined approach. Similarly, [11] presents a multi-objective mixed-integer nonlinear programming model for mobile ESS and EVs in distribution networks. This model focuses on minimizing operational costs and voltage limit violations, and maximizing PV generation output. However, these studies overlook power loss considerations in distribution networks. Another study introduces an efficient cost-minimization oriented distributed algorithm for distribution networks with shared ESS and EV charging stations. While this model includes comprehensive elements like ESS and EV charging stations, it fails to integrate renewable energy sources and does not address uncertainties. A study explores the use of battery-based ESS (BESS) and fast EV charging stations with PVs in the energy market to reduce peak power caused by fast EV charger integration [15]. While ESS implementation successfully reduces peak power and associated grid connection tariffs, power loss and uncertainty remain unaddressed in this study.

C. Content and Contributions

This study introduces an efficient energy management algorithm that incorporates BESSs and manages EVs charging to minimize active power loss on PV-penetrated distribution networks. The proposed algorithm is formulated as a MILP problem through the linearization of power losses using the Special Ordered Sets of Type 2 (SOS2) approach. Uncertainties regarding the arrival/departure times of EVs and PV-based power generation are addressed through rolling horizon optimization. The contributions of this proposed concept are twofold:

- Although the aforementioned studies provided seminal contributions to the existing knowledge on the use of grid connected distributed generation, EV and ESS technologies, none of them have provided a comprehensive analysis combining all these technologies together with a multiple uncertainty aware decision-making approach.
- Active management of demand-side flexibility through EVs, coupled with the fluctuating production profile of PV, and augmented flexibility from BESSs, is implemented in a loss minimization-oriented approach for distribution networks. This approach takes into account various types of loads to ensure efficient operation and management.

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D. Paper Organization

The paper is structured into four main sections. Section II outlines the methodology employed for this study, while Section III provides a detailed analysis of the test data and results. Subsequently, in Section IV, the key findings and conclusions of the study are presented and summarized.

II. Methodology

The proposed study is implemented on a modified IEEE 33-Bus test system, as depicted in Fig. 1. This system is enriched with the integration of BESS alongside PV units, battery-based EVs, and various consumer types such as residential, commercial, and industrial consumers.

A. Objective Function

The objective of this study is to minimize the total power loss in the distribution network while considering energy transactions involving BESSs and PV systems with the grid, as outlined in equation (1).

$$min(TL) = \sum_t HL_t, \qquad \forall t \tag{1}$$

B. Power Balance and BESS Model

The power source and demand balance equation is represented by equation (2). The load power demand and charging demand of the ESS can be met by power generated by the PV system, discharged energy from the ESSs, or sourced from the grid when demand exceeds the capacity of distributed generation sources.

$$\sum_p P^{PV}_{i,p,t} + \sum_k P^{ESS_{dis}}_{i,k,t} + P^{Flow}_{i,t} + P^{Grid,load}_{i,t} = \sum_l P^{Load}_{i,l,t} + \sum_{ess} P^{ESS,char}_{i,k,t}, \qquad \forall\, i,k,l,p,t \tag{2}$$

The simultaneous charging and discharging of BESSs are regulated by equations (3) and (4), respectively. The maximum charging and discharging rates of BESS are stipulated in equations (5) and (6), respectively. The initial state-of-energy (SoE) of BESS is denoted by equation (7), while the maximum and minimum SoE levels are defined in equations (8) and (9), respectively. The minimum required energy for storage systems is set at 25% of their maximum capacity [17]. Equation (10) signifies that the SoE of BESSs increases during charging and decreases during discharging.

$$P^{ESS,char}_{i,k,t} \leq N^{ESS}.\, u^{ESS}_{i,t}, \qquad \forall\, i,k,t \tag{3}$$

$$P^{ESS,dis}_{i,k,t} \leq N^{ESS}.\left(1 - u^{ESS}_{i,t}\right), \qquad \forall\, i,k,t \tag{4}$$

$$P^{ESS,char}_{i,k,t} \leq CR^{ESS}_{i,k}, \qquad \forall\, i,k,t \tag{5}$$

$$P^{ESS,dis}_{i,k,t} \leq DR^{ESS}_{i,k}, \qquad \forall\, i,k,t \tag{6}$$

$$SoE^{ESS}_{i,k,t} = SoE^{ESS,init}_{i,k}, \qquad if\ \ t = 1,\ \forall\, i,k \tag{7}$$

$$SoE^{ESS}_{i,k,t} \geq SoE^{ESS,min}_{i,k}, \qquad \forall\, i,k,t \tag{8}$$

$$SoE^{ESS}_{i,k,t} \leq SoE^{ESS,max}_{i,k}, \qquad \forall\, i,k,t \tag{9}$$

$$SoE^{ESS}_{i,k,t} = SoE^{ESS}_{i,k,t-1} + \left(P^{ESS,char}_{i,k,t}.\,\eta^{char}_k.\,\Delta T - \frac{P^{ESS,dis}_{i,k,t}.\Delta T}{\eta^{dis}_k}\right), \qquad if\ \ t > 1,\ \forall\, i,k \tag{10}$$

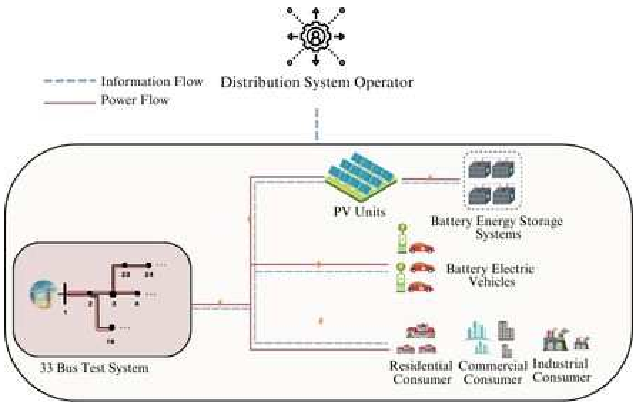

Fig. 1 Proposed modified IEEE 33-bus test system.

C. DSO Model

When there is excess power from distributed generation covering load power demand and network power loss, it is sold to the grid. Conversely, if the generated power falls short, the deficit is supplied by the grid. This balance is depicted in (11). Equations (12) and (13) prevent simultaneous selling and buying operations. The complexity is reduced by linearizing the quadratic power loss equation using SOS2, resulting in an optimization model as a MILP. The total power loss is calculated as shown in (14), while (15) describes the line power capacity. The positive auxiliary variables in (16) and (17) represent absolute value functions within the model. These equations define the net power flow on the lines at time t [16].

$$P^{Grid,sell}_{i,t} = \sum_l P^{Load}_{i,l,t} + P^{Loss}_{i,t} + P^{Grid,buy}_{i,t}, \qquad \forall\, i,t \tag{11}$$

$$P^{Grid,sell}_{i,t} = N^{Grid}.\, u^{Grid}_{i,t}, \qquad \forall\, i,t \tag{12}$$

$$P^{Grid,buy}_{i,t} = N^{Grid}.\left(1 - u^{Grid}_{i,t}\right), \qquad \forall\, i,t \tag{13}$$

$$P^{Loss}_{i,t} = \sum_i HL_{i,t}, \qquad \forall\, i,t \tag{14}$$

$$-P^{Line,Cap}_b \leq P^{Line}_{b,t} \leq P^{Line,Cap}_b, \qquad \forall\, b,t \tag{15}$$

$$P^{Line}_{b,t} = cf^{\ plus}_{b,t} - cf^{\ minus}_{b,t}, \qquad \forall\, b,t \tag{16}$$

$$P^{Abs,line}_{b,t} = cf^{\ plus}_{b,t} + cf^{\ minus}_{b,t}, \qquad \forall\, b,t \tag{17}$$

The power loss equation is linearized using the SOS2 approach. This method transforms a nonlinear function into a piecewise linear function by creating independent variables known as weighting functions, which are used to compute the approximate value of the nonlinear function [16]. In (18), the set of independent variables is shown, where zAP represents the associated parameter to calculate the approximated value of power flow. Multiplying the system parameters and SOS2 variables, as shown in (19) and (20) respectively, calculates the power flowing through the lines and its square. The power loss on the lines is then computed in (21) using the calculated power flow variables and parameters determined through linearization.

$$\sum_{points} zAP_{t,b,points} = 1, \qquad \forall\, b, points, t \tag{18}$$

$$P^{Line}_{b,t} = \sum_{points}\left(X_p.\, zAP_{t,b,points}\right), \quad \forall\, b, points, t \tag{19}$$

$$P^{Line,squ}_{b,t} = \sum_{points}\left(Y_p.\, zAP_{t,b,points}\right), \qquad \forall\, b, points, t \tag{20}$$

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$$HL_t = \sum_b (\alpha_1 \ . P_{b,t}^{Abs,line} . \Delta T + \alpha_2 . P_{b,t}^{Line,squ} . \Delta T), \quad \forall\, b, t \tag{21}$$

D. EV Model

The charging rate of each EV is limited by its capacity, as shown in (22), and the total charging power used for EVs is described in (23). The initial SoE for each EV upon arrival at the parking area is set equal to their initial values, as indicated in (24). Equation (25) ensures that SoE for each EV equals their desired level upon departure. When EVs are not in the parking area, their SoE and charging power demand are assumed to be zero, as described in (26) and (27). Equation (28) outlines the minimum and maximum SoE values for each EV during their time at the parking area. Charging during EV's are located in the parking area operations of EVs while they are located in the parking area are detailed in (29).

$$P_{i,m,t}^{EV,char} \leq CR_{i,m}^{EV}, \qquad \forall\, i, m, t \tag{22}$$

$$P_{i,t}^{EV,char_{tot}} = \sum_m P_{i,m,t}^{EV,char}, \qquad \forall\, i, m, t \tag{23}$$

$$SoE_{i,m,t}^{EV} = SoE_{i,m}^{EV,init}, \quad \text{if } t = 1, \qquad \forall\, i, k, t \tag{24}$$

$$SoE_{i,m,t}^{EV} = SoE_{i,m}^{EV,des}, \quad if\ t = T_{i,d}^{dep}, \qquad \forall\, i, m \tag{25}$$

$$SoE_{i,m,t}^{EV} = 0, \quad T_{i,m}^{dep} < t < T_{i,m}^{arr}, \qquad \forall\, i, m \tag{26}$$

$$P_{i,m,t}^{EV,char} = 0, \quad T_{i,m}^{dep} < t < T_{i,m}^{arr}, \qquad \forall\, i, m \tag{27}$$

$$SoE_{i,m}^{EV,min} \leq SoE_{i,m,t}^{EV} \leq SoE_{i,m}^{EV,max}, \quad T_{i,m}^{arr} \leq t \leq T_{i,m}^{dep}, \ \forall\, i, m \tag{28}$$

$$SoE_{i,m,t}^{EV} = SoE_{i,m,t-1}^{EV} + \left(P_{i,m,t}^{EV,char} . \eta_m^{char} . \Delta T\right) \quad T_{i,m}^{arr} < t \leq T_{i,m}^{dep}, \ \forall\, i, m \tag{29}$$

III. Test and Results

An optimal energy management strategy is introduced for a distribution network equipped with distributed generation systems, incorporating multiple BESSs and EVs. This strategy aims to minimize total energy loss within the network, and a real-time energy management algorithm is provided to consider uncertainties in PV generation and the arrival/departure times of EVs. The optimization problem employed in this study is modeled using MILP. The effectiveness of the proposed algorithm is evaluated using the General Algebraic Modelling System (GAMS) programming language, version 24.1.3, with an optimization horizon set at a time granularity of 15 minutes on the IEEE 33-bus system.

A. Input Data

In this study, a modified IEEE 33-bus test system is utilized, featuring domestic loads at each bus, an EV parking lot and different PV units along with BESSs. The location of BESSs, the EV parking lot, and PV units are changed to analyse the impact of distributed generation sources on the network, creating worst and best-case scenarios by placing the EV parking lot, BESS, and PV units at both the beginning and end of the feeder. The total power demands of loads on the network for a day is illustrated in Fig. 2, while Fig. 3 illustrates the comparison between actual and expected power generation at 07:00 and 14:00, highlighting significant

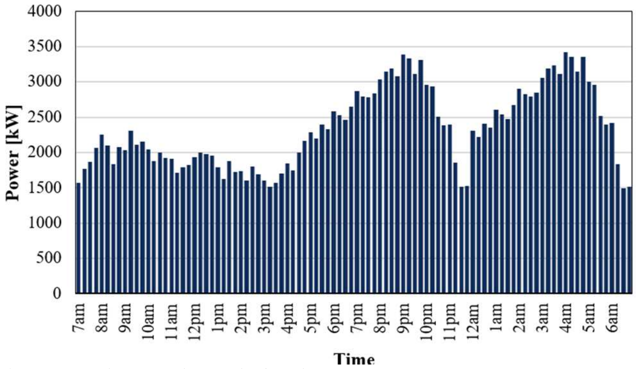

Fig. 2. Total power demand of 33-bus system.

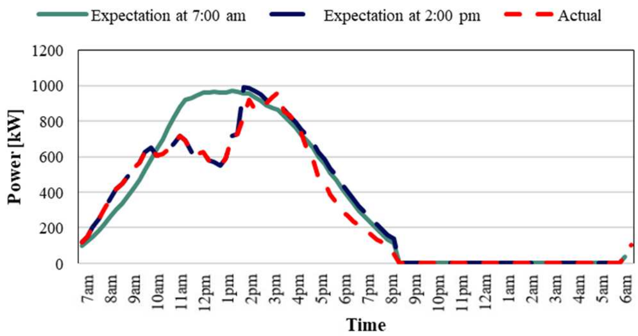

Fig. 3. Power generation of the PV systems in different executions.

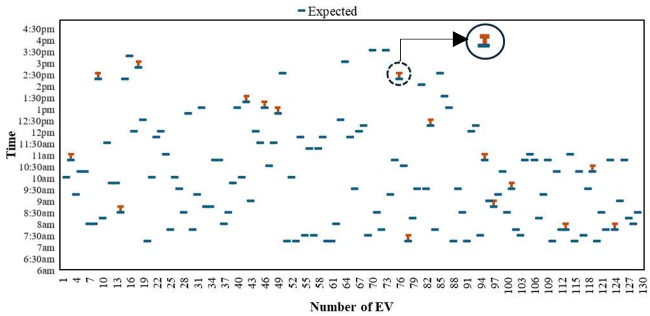

Fig. 4. The expected and actual of arrival times of EVs by illustrating their level of uncertainty. (Red bars indicate the extent of delays at arrival times.)

deviations in estimated energy production based on real-time data compared to actual production throughout the day. Real-time data is used for optimization within the current horizon, with estimated power generation employed for subsequent periods. Fig. 4 provides a visual analysis contrasting the expected versus the actual timings concerning the arrival and departure time of EVs within the designated parking zone. This figure incorporates scenarios involving EVs that either failed to arrive as anticipated or did so at unexpected times. The discrepancy between the actual and forecasted arrival times is depicted through error bars, which quantify the uncertainty inherent in the expectation. Instances where these error bars project above the expected timeline indicate that the EVs arrived later than initially predicted, with the length of each bar representing the magnitude of this delay. Upon closer examination, it was found that roughly 13% of the 130 evaluated EVs experienced delays.

B. Simulation and Results

The proposed model was analyzed under three distinct operating scenarios to evaluate the influence of EVs, PVs, and BESSs locations on the distribution network. The scenarios considered are detailed as follows:

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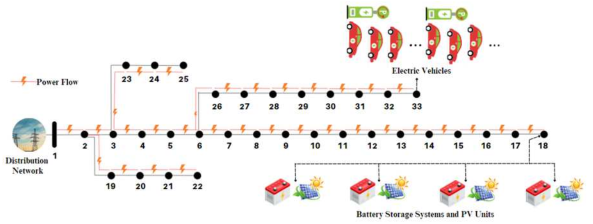

Fig. 5. Modified IEEE 33-Bus test feeder system for the Base-Case.

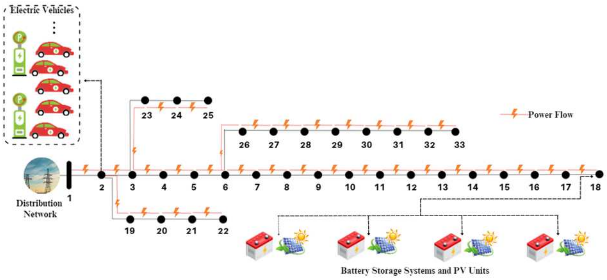

Fig. 6. Modified IEEE 33-Bus test feeder system for the Case-1.

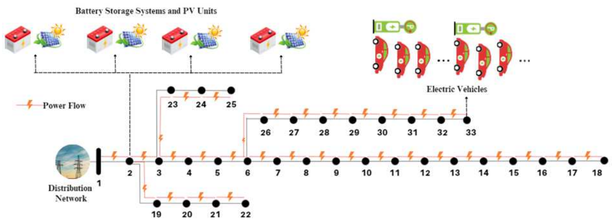

Fig. 7. Modified IEEE 33-Bus Test Feeder System for the Case-2.

- *Base-Case:* The operational periods for BESS, EVs, and PV units are set, with the BESSs and PV units positioned at Bus-18 and the EV parking lot is positioned at Bus-33. This configuration is depicted in Fig. 5.
- *Case-1:* The EV parking lot location is shifted from Bus-33 to Bus-2, while the rest of the system remains unchanged as illustrated in Fig. 6.
- *Case-2:* The BESS and PV systems location is shifted from Bus-18 to Bus-2, while the rest of the system remains unchanged as shown in Fig. 7.

The total charging and discharging power, and SoE of BESSs located at Bus-18 in the base case are displayed in Fig. 8. It can be seen that the storage system is charged during the peak PV production hours and discharged during the evening when consumption is higher. Fig. 9 shows the energy transactions of BESSs for Case 1 where the charge and discharge times and quantities vary with the intensity of consumption. The PV systems supply energy to meet nearby demand, with excess energy stored in BESSs. Meanwhile, EVs are charged from the grid, all with the goal of minimizing power loss as defined by the objective function. In Case 2, with PV units and BESS positioned at Bus-2, a comparison of BESS SoE to the Base-Case reveals increased discharge between 6 pm and 10 pm due to higher load demand near its new location, depicted in Fig. 10. Since moving BESS from Bus-18 to Bus-2, BESS can serve more buses' power demand when power loss is considered. Compared to the base case, it is noted that there is 7.76% an increase in the amount of charging around afternoon and a total 12.48% increase in the amount of discharging in the evening hours in Case 2.

Fig. 11 details the charging cycle and SoE of an EV throughout a day within the utilized model, showing that the

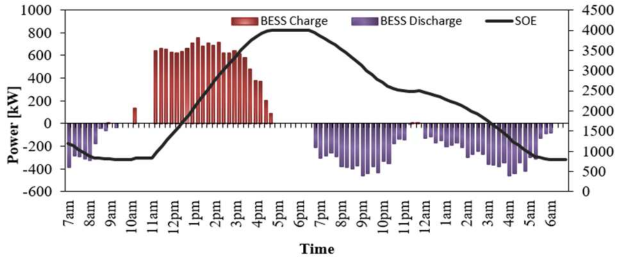

Fig. 8. Total charging/discharging power and State-of-Energy level of BESS for Base-Case.

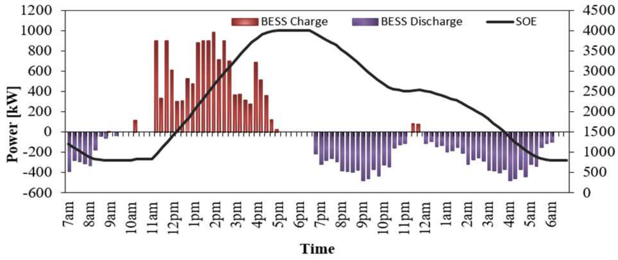

Fig. 9. Total charging/discharging power and State-of-Energy level of BESS for Case-1.

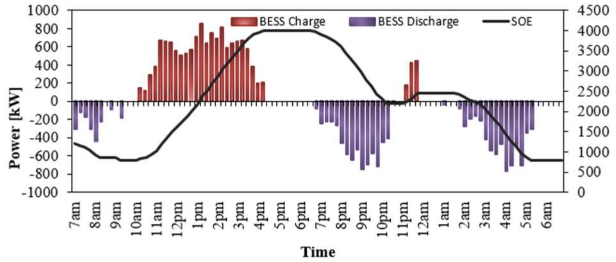

Fig. 10. Total charging/discharging power and State-of-Energy level of BESS for Case-2.

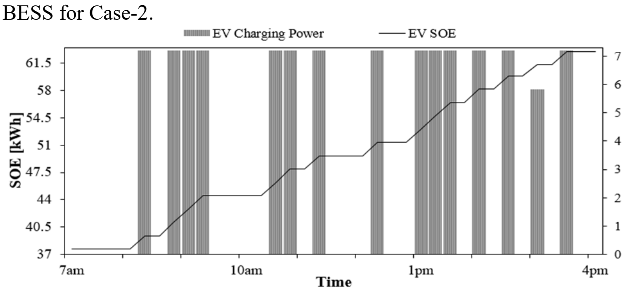

Fig. 11. Charging and State-of-Energy profile of an EV.

EV reaches its desired SoE before departure. Fig. 12 provides a comparative analysis of power flow on Bus-2 between the Base-Case and Case-2, where the BESS is relocated to the beginning of the feeder. When all available power sources, including the grid and BESS, are situated at the beginning of the feeder and BESS charging/discharging dynamics are considered, relocating the BESS from the end of the feeder to its beginning leads to increased power flow on Bus-2 compared to the Base-Case. Specifically, the BESS undergoes charging from 11.00 am to 4.00 pm to coincide with peak PV generation and discharging from 7.00 pm to 5.00 am, aligning with network peak demand hours. This strategic BESS operation leads to a significant 10.31% reduction in grid power supply at 4.00 am, a period experiencing one of the peak demands at around 3500 kW, with BESS covering 24.30% of the total demand during this critical timeframe.

The variation in total power loss across case studies is evaluated, with the base case serving as the reference point. In Case-1, total power loss decreased by 7.61% compared to the

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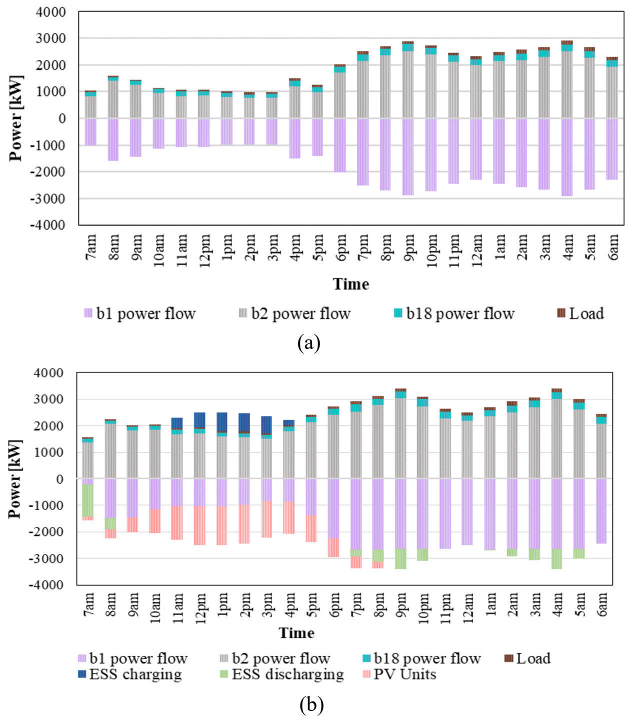

Fig. 12. (a) Power balance for Base-Case at Bus 2, (b) Power balance for Case-2 at Bus 2.

base case due to the location of EV parking lot at the beginning of the feeder, resulting in decreased power loss as it is closer to the power source. When comparing Case-2 to the base case, there is a 22.61% increase in power loss. This is due to the positioning of BESSs and PVs near the grid, which concentrates all power sources at the beginning of the feeder, resulting in higher power losses.

IV. Conclusion

The rising energy demand has led to increased adoption of green energy solutions in both energy generation and consumption. However, this trend has also heightened the complexity of distribution networks, necessitating effective energy management algorithms. This study introduces a rolling horizon optimization-based energy management algorithm aimed at minimizing power loss in distribution networks that incorporate EVs, BESSs and PV plants. The algorithm considers uncertainties and the impact of EVs and BESSs penetration in the network, analysing different scenarios to understand their effects.

This study analyses the impact of the EV parking lot and BESSs' location along the feeder, revealing that relocating the EV parking lot from the end of the feeder to its beginning reduces power loss by 7.61%. Similarly, relocating BESSs along with PVs from the end of the feeder to its beginning results in a 22.61% increase in power loss. Thus, as seen from the mentioned comparative analyses, a comprehensive overlook combining grid connected distributed generation, EV and ESS technologies together with a multiple uncertainty aware decision-making approach was provided. These findings underscore the critical impact of effectively managing BESS charging/discharging and the demand of EVs response on network power loss, highlighting the necessity of considering these factors in network optimization strategies.

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