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***Abstract*— Interest in integrating distributed energy resources (DERs) into the electric distribution system (EDS) is growing due to the economic and operational benefits that DERs can provide. Consumer-sited photovoltaic (PV) generation is one of those DERs that have been penetrating the EDS over the years; the owner can sell the energy surplus to the EDS, and for the EDS operator it brings the advantage of clean energy from solar irradiation; since the EDS operator doesn't have control of it, the growing of the penetration can leading into technical problems to the EDS. Energy storage systems (ESS) can be used to manage non-dispatchable renewable energy providing ancillary services to the EDS like peak shaving and voltage regulation. However, investors for the ESS planning (allocation and sizing) must consider their cost, EDS constraints, and the future scenarios of PV penetration and uncertainties inherent to the EDS; for this purpose, a stochastic mixed integer linear programming model for the ESS planning is presented integrating a temporal method to model the PV penetration growth over the years. The decision variables are the size and the EDS node where the ESS should be connected. The model is implemented in AMPL and the optimal solution is found with CPLEX for a case study based on the IEEE 33 node test system.**

Keywords—electrical distribution system, energy storage systems, mathematical programming model, photovoltaic generation.

I. Introduction

The use of distributed energy resources (DERs) in the electric distribution system (EDS) can bring several technical and economic benefits to the operator and energy consumers. The interest in photovoltaic (PV) generation has grown in recent years because of technological advancements that have increased efficiency, lifetime, and lowered costs. Therefore, the energy consumer who installs PV generation reduces his energy bill by generating his energy and generating credit with the EDS operator by injecting the energy surplus in the EDS. The EDS operator has the benefits of clean and cheap energy being injected into the system. Despite the benefits, due to the non-dispatchable nature of PV generation the EDS operator can encounter technical problems with the PV penetration; however, investors can install energy storage systems (ESS) in the EDS to provide services to the operator, helping to overcome such situations [1].

The installation of ESS can bring technical and economic benefits to the EDS because by controlling the ESS charging and discharging voltage deviations can be avoided, energy losses can be reduced (also reducing the operational costs) and the EDS's hosting capacity can be increased. On the other hand, installing ESS in the EDS still leads to high investments, thus its allocation and sizing must be carefully planned considering uncertainties associated with energy demand and PV generation. The planning of batteries in EDS is a complex problem because, to extract the maximum benefits from their allocation, factors such as changing PV generation penetration and different operating scenarios must be considered. For this purpose, several methods (exhaustive search, mathematical programming, and metaheuristics) have been proposed, adopting different objectives such as greater DG penetration, minimization of operational violations, improvement of system reliability, and minimization of operating costs [1], [2].

In [3], a multi-objective approach has been proposed to the sizing (modules and converter unit) of ESS in the EDS optimizing the total costs, payback period, the ESS life span, and the grid impact, in a context where the ESS can provide different applications such as frequency regulation and peak shaving. For a profit-oriented optimization, in [4] It proposed a stochastic programming model in which the first stage determines the ESS size and placement under a budget limit, and the second stage maximizes the investor's arbitrage profit over a long-term operation. From the perspective of the EDS operator, in [5] a method is proposed for the availability assessment of different technologies of ESS aiming the transmission and distribution deferral, energy arbitrage, and loss minimization. Adding the goal of minimizing the emission of gases that intensify the greenhouse effect, and reducing problems due to the high penetration of PV generation, [6] proposes a method that considers restrictions on the reverse power flow in the EDS, as well as aspects related to ESS (allocation, sizing, and operation).

The grow of new technologies that have an impact on the EDS has been studied in the literature, in [7] it's proposed the use of spatial-temporal analyses of geographical data to estimate the adoption of the technologies and to estimate where in the EDS the impact will be critical. The authors proposed the use of a logistic growth model (LGM) that

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considers socioeconomic metrics and benefits from energy-efficiency programs. Accounting for the growth of rooftop PV generation, in [8] the authors proposed a heuristic procedure to select the investment with the best cost-benefit ratio; the investments are related to expansion or upgrading the network to keep acceptable limits of congestion and voltage deviations.

In the context of the presented literature review, this paper proposes a method for investors interested in generating profit with energy arbitrage with possibility of participating in other electricity markets. The method is based on stochastic mixed integer linear programming for the planning (placement and sizing) of ESS in the EDS, accounting with an LGM to estimate the future PV penetration. The energy prices are estimated based on historical day-ahead energy prices.

The remaining of this paper is organized as follows: Section II presents the mathematical model for the battery planning; Section III presents a test case and results; finally, conclusions are presented in Section IV.

II. Mathematical Model

This section introduces the stochastic mixed integer linear mathematical programming model for the ESS planning. The model represents the EDS as a single-phase equivalent, the objective function is designed to minimize the cost of the investment in ESS and maximize the profit expectation with energy arbitrage. The index m and n represents the EDS nodes and mn the circuit between m and n; the decision variables represent the ESS allocation node (binary variable Ψ_m), the number of storage modules and the number of inverters (integer variables ψ_m and ϕ_m). The model accounts for daily variations in PV generation and power demand linked with the index t, that represents periods as a fraction of a day, and the index s represent the scenarios of solar irradiance. The incorporation of a LGM enables to project the increase of the PV penetration, in which is linked with the index y, that represents the years of planning; the estimation of PV penetration is based on the relation of the energy price and how much energy the PV system can produce.

A. Power Flow

The EDS operation is based on Farivar and Low [9], with the modification to represent the ESS operation, the presence of PV generation, and also to represent t, y and s. The active and reactive power balance, defined in (1) and (2), establishes the relation between the power injected into the EDS by the substation ($P^{se}_{m,t,y,s}$), the power injected by consumers' PV systems ($P^{pv}_{m,t,y,s}$), the power absorbed or injected by the ESS ($P^{ess+}_{m,t,y,s}$ and $P^{ess-}_{m,t,y,s}$), the flows of active and reactive power ($P_{mn,t,y,s}$ and $Q_{mn,t,y,s}$), the power losses (in the product of the square current $I^{sqr}_{mn,t,y,s}$ with R_{mn} and X_{mn}) and the power demand ($P^{d}_{m,t}$). The variables and parameters from (1) and (2) are illustrated in the Fig. 1.

$$\sum_{km} P_{km,t,y,s} - \sum_{mn}\left(P_{mn,t,y,s} + R_{mn}\cdot I^{sqr}_{mn,t,y,s}\right) + P^{se}_{m,t,y,s} + P^{pv}_{m,t,y,s} + P^{ess+}_{m,t,y,s} - P^{ess-}_{m,t,y,s} = P^{d}_{m,t};\ \forall\, m,t,y,s \quad (1)$$

$$\sum_{km} Q_{km,t,y,s} - \sum_{mn}\left(Q_{mn,t,y,s} + X_{mn}\cdot I^{sqr}_{mn,t,y,s}\right) + Q^{se}_{m,t,y,s} = Q^{d}_{m,t};\ \forall\, m,t,y,s \quad (2)$$

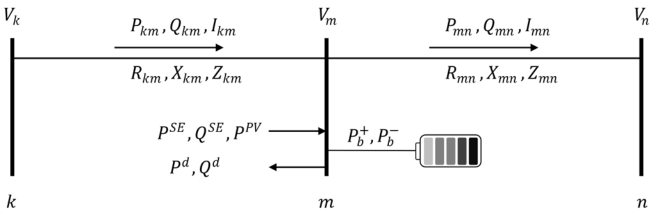

Fig. 1 Relationship between power flow variables and parameters

Equation (3) imposes the voltage drop that occurs in circuit mn, relating the difference between the voltages at node m and n to the energy losses in circuit mn, where $V^{sqr}_{n,t,y,s}$ represent the square voltage in the node n and Z^2_{mn} the impedance of the circuit mn. The current in circuit mn is related to the voltage at node n and the active and reactive power flow in (4). Additionally the EDS operational limits are defined in (5) and (6), the node voltages are constrained by the parameters for the voltage limit $\underline{V}$ and $\overline{V}$ including the slack variables and the currents in each EDS circuit mn are constrained by the maximum current $\overline{I}$.

$$V^{sqr}_{m,t,y,s} - V^{sqr}_{n,t,y,s} = 2\cdot\left(R_{mn}\cdot P_{mn,t,y,s} + X_{mn}\cdot Q_{mn,t,y,s}\right) + Z^2_{mn}\cdot I^{sqr}_{mn,t,y,s} \forall\, mn,t,y,s \quad (3)$$

$$V^{sqr}_{n,t,y,s}\cdot I^{sqr}_{mn,t,y,s} = P^2_{mn,t,y,s} + Q^2_{mn,t,y,s};\ \forall\, mn,t,y,s \quad (4)$$

$$\underline{V}^2 - V^{\underline{f}}_{n,t,y,s} \le V^{sqr}_{n,t,y,s} \le \overline{V}^2 + V^{\overline{f}}_{n,t,y,s};\ \forall\, n,t,y,s \quad (5)$$

$$0 \le I^{sqr}_{mn,t,y,s} \le \overline{I}^2;\ \forall\, mn,t,y,s \quad (6)$$

Eq. (4) calculates the current in the mn circuits based on the power flows and node voltages; because of its nonlinearity, the search for an optimal solution is a challenge to linear solvers, besides the uncertainty of finding a global optimal solution; Therefore, a set of linear equations will replace (4) guaranteeing that global optimal solution can be found assuming an error [10].

The linearization, presented in (7)–(15), involves discretizing the variable $V^{sqr}_{n,t,y,s}$ into W blocks (where a high number increases precision) and replacing $V^{sqr}_{n,t,y,s}$ with the parameter $\tilde{V}^{sqr}_{n,t,y,s}$, representing the estimated value of the squared voltage. As established in (7), the product of $\tilde{V}^{sqr}_{n,t,y,s}$ with the current in circuit mn ($I^{sqr}_{mn,t,y,s}$) must be equal to the sum of the product of auxiliary variables $\Lambda^{P}_{mn,w,t,y,s}$ and $\Lambda^{Q}_{mn,w,t,y,s}$ by the parameter $m^{s}_{mn,w,t,y,s}$; each of these products consecutively represents the variables $P_{mn,t,y,s}$ and $Q_{mn,t,y,s}$. Additionally, the parameter $m^{s}_{mn,w,t,y,s}$, calculated according to (8) and (9), represents a line segment of the w-th block, of the maximum limit of apparent power flow in circuit mn.

$$\tilde{V}^{sqr}_{n,t,y,s}\cdot I^{sqr}_{mn,t,y,s} = \sum_{w=1}^{W} m^{s}_{mn,w,t,y,s}\cdot \Lambda^{P}_{mn,w,t,y,s} + \sum_{w=1}^{W} m^{s}_{mn,w,t,y,s}\cdot \Lambda^{Q}_{mn,w,t,y,s};\ \forall\, mn,w,t,y,s \quad (7)$$

$$m^{s}_{mn,w,t,y,s} = (2\cdot w - 1)\cdot \overline{\Lambda}^{S}_{mn};\ \forall\, mn,w,t,y,s \quad (8)$$

$$\overline{\Lambda}^{S}_{mn} = \overline{V}\cdot \overline{I}_{mn} \Big/ W;\ \forall\, mn \quad (9)$$

To relate the product of $\Lambda^{P}_{mn,w,t,y,s}$ and $\Lambda^{Q}_{mn,w,t,y,s}$ to $m^{s}_{mn,w,t,y,s}$ and the variables of active and reactive power flow in the circuits, the sums of $\Lambda_{mn,w,t,y,s}^{P}$ and $\Lambda_{mn,w,t,y,s}^{Q}$ are related in (10) and (11) to the auxiliary variables $P_{mn,t,y,s}^{+}$, $P_{mn,t,y,s}^{-}$, $Q_{mn,t,y,s}^{+}$, and $Q_{mn,t,y,s}^{-}$. On the other hand, those auxiliary variables are related with the absolute value of $P_{mn,t,y,s}$ and $Q_{mn,t,y,s}$ in (12) and (13). Finally, the variables $\Lambda_{mn,w,t,y,s}^{P}$ and $\Lambda_{mn,w,t,y,s}^{Q}$ are constrained by the parameter $\overline{\Lambda}_{mn}^{S}$, as shown in (14).

$$P_{mn,t,y,s}^{+} + P_{mn,t,y,s}^{-} = \sum_{w=1}^{W} \Lambda_{mn,w,t,y,s}^{P} \; ; \; \forall\, mn, w, t, y, s \quad (10)$$

$$Q_{mn,t,y,s}^{+} + Q_{mn,t,y,s}^{-} = \sum_{w=1}^{W} \Lambda_{mn,w,t,y,s}^{Q} \; ; \; \forall\, mn, w, t, y, s \quad (11)$$

$$P_{mn,t,y,s} = P_{mn,t,y,s}^{+} + P_{mn,t,y,s}^{-}; \; \forall\, mn, t, y, s \quad (12)$$

$$Q_{mn,t,y,s} = Q_{mn,t,y,s}^{+} + Q_{mn,t,y,s}^{-}; \; \forall\, mn, t, y, s \quad (13)$$

$$0 \le \Lambda_{mn,w,t,y,s}^{P}, \Lambda_{mn,w,t,y,s}^{Q} \le \overline{\Lambda}_{mn}^{S}; \; \forall\, mn, w, t, y, s \quad (14)$$

$$P_{mn,t,y,s}^{+}, P_{mn,t,y,s}^{-}, Q_{mn,t,y,s}^{+}, Q_{mn,t,y,s}^{-} \ge 0; \; \forall\, mn, t, y, s \quad (15)$$

B. Energy Storage System

The integration of ESS in the EDS allows operators to control aspects such as power demand peaks, voltage profiles, and the power flow, additionally, the direct control of power flow reduces energy losses and contributes to cost savings by utilizing locally generated energy. The representation of the ESS is presented in (16)–(20) based on [2].

The ESS power absorption and injection at node m of the EDS ($P_{m,t,y,s}^{ess+}$ and $P_{m,t,y,s}^{ess-}$) are constrained by its maximum operational power ($\overline{P}^{inv}$) with the decision variable ϕ_m, as determined in (16) and (17). Constraints (18) and (19) controls the update of the state of charge ($SoC_{m,t,y,s}^{ess}$) during the periods $t = 1$ and $t > 1$, respectively, according to the previous state of charge, the injected or absorbed power with the related efficiencies of charging and discharging (η^{ess-} and η^{ess+}), and the self-discharge of the batteries modules (product of the state of charge and the parameter β^{ess}). The state of charge is limited in (20) by the product of the parameters of maximum and minimum state of charge that a module can reach ($\overline{SoC}^{ess}$ and $\underline{SoC}^{ess}$), with the decision variable ψ_m.

$$0 \le P_{m,t,y,s}^{ess+} \le \overline{P}^{inv} \cdot \phi_m; \; \forall\, m, t, y, s \quad (16)$$

$$0 \le P_{m,t,y,s}^{ess-} \le \overline{P}^{inv} \cdot \phi_m; \; \forall\, m, t, y, s \quad (17)$$

$$SoC_{m,t,y,s}^{ess} = \underline{SoC}^{ess} \cdot \psi_m + \Delta t \left(P_{m,t,y,s}^{ess-} \cdot \eta^{ess-} - \frac{P_{m,t,y,s}^{ess+}}{\eta^{ess+}} \right) - SoC_{m,t,y,s}^{ess} \cdot \beta^{ess}; \; \forall\, m, t = 1, y, s \quad (18)$$

$$SoC_{m,t,y,s}^{ess} = SoC_{m,t-1,y,s}^{ess} + \Delta t \left(P_{m,t,y,s}^{ess-} \cdot \eta^{ess-} - \frac{P_{m,t,y,s}^{ess+}}{\eta^{ess+}} \right) - SoC_{m,t,y,s}^{ess} \cdot \beta^{ess}; \; \forall\, m, t > 1, y, s \quad (19)$$

$$\underline{SoC}^{ess} \cdot \psi_m \le SoC_{m,t,y,s}^{ess} \le \overline{SoC}^{ess} \cdot \psi_m; \; \forall\, m, t, y, s \quad (20)$$

C. PV Penetration

As previously mentioned, the penetration grow of PV generation is estimated using a LGM. The LGM is a type of model used to describe variables that exhibit an initial exponential growth that slowly decrease when it approaches to the maximum limit, resulting in "S"-shaped curves. This model is applicable in various fields such as population dynamics, resource consumption, and technology adoption, where growth is initially rapid but stabilizes as it reaches carrying capacity [11], [12]. The LGM used in this paper, based on [7], considers the maximum PV possible, the initial state of the penetration and the relation between the energy generated, the investment and the lifespan of the PV system.

The generation and cost rate are represented by the variable κ, defined in (21) that considers the energy price (ς_t^{en}), the solar incidence coefficient $\delta_{t,s}$, period duration Δ_t, scenario probability ξ_s, the number of days in a year (α) and the parameters representing the PV installation cost (ς_{PV} in \$/kWp).

$$\kappa = \frac{\sum_{t,s} \delta_{t,s} \cdot \varsigma_t^{en} \cdot \Delta_t \cdot \xi_s \cdot \alpha - \varsigma_{PV}}{\varsigma_{PV}} \quad (21)$$

The penetration of PV generation ($PV_{m,y}^{pen}$) for each node m of the system in the annual period y is defined in equation (22). The variable $PV_{m,y}^{PV}$ represents the power penetration of PV generation in kWp, modelled by the LGM, characterized by producing an "S" shaped curve; the parameters used $\overline{PV}_m^{pen}$ and $PV_{m,0}^{PV}$ represent the maximum PV generation penetration and the currently installed power, respectively.

$$PV_{m,y}^{pen} = \frac{\overline{PV}_m^{pen}}{1 + \left(\frac{\overline{PV}_m^{pen}}{PV_m^{0}} - 1 \right) \cdot e^{(-y \cdot \kappa)}}; \; \forall\, m, y \quad (22)$$

$$P_{m,t,y,s}^{PV} = PV_m^{0} + PV_{m,y}^{pen} \cdot \delta_{t,s}; \; \forall m, t, y, s \quad (23)$$

D. Energy Trader

To make it possible to control the energy arbitrage, it is necessary constraints to control the power that the trader can purchase from the EDS operator and from the prosumers. Since there is two available power sources, (24) and (25) are defined to limit the power purchased from each one ($P_{m,t,y,s}^{tse}$ coming from the EDS and $P_{m,t,y,s}^{tpv}$ from prosumers). In (26), the ESS charging power is related to the purchased power previously defined.

$$P_{m,t,y,s}^{tse} \le P_{m,t,y,s}^{se}; \; \forall\, m, t, y, s \quad (24)$$

$$P_{m,t,y,s}^{tpv} \le \sum_{m} P_{m,t,y,s}^{pv} \; ; \; \forall\, m, t, y, s \quad (25)$$

$$P_{m,t,y,s}^{ess-} = P_{m,t,y,s}^{tse} + P_{m,t,y,s}^{tpv}; \; \forall\, m, t, y, s \quad (26)$$

E. Objective Function

The cost related with the investment in ESS considers the cost for installation per node ς^{inst}, the cost per module ς^{mod} and the cost per inverter ς^{inv}; then the cost with ESSs (C^{ess}) is defined in (27). The decision variables are defined in (28)–(31), where (28) define the decision variable Ψ_m as binary, ψ_m and ϕ_m are defined as nonnegative integer variables in (29) and those are related to Ψ_m in (30) and (31). Additionally, the investment is constrained by an assumed budget $\overline{B}$, as defined in (6).

$$C^{ess} = \varsigma^{inst} \cdot \sum_{m} \Psi_m + \varsigma^{mod} \cdot \sum_{m} \psi_m + \varsigma^{inv} \cdot \sum_{m} \phi_m \quad (27)$$

$$\Psi_m \in \{0,1\}; \; \forall\, m \quad (28)$$

$$\psi_m, \phi_m \in Z_0^+;\ \forall\, m \quad (29)$$

$$0 \le \psi_m \le \overline{\psi} \cdot \Psi_m;\ \forall\, m \quad (30)$$

$$0 \le \phi_m \le \overline{\phi} \cdot \Psi_m;\ \forall\, m \quad (31)$$

$$C^{ess} \le \overline{B} \quad (32)$$

The cost related to the energy purchased from the EDS operator and consumer-side PV generation are defined in (33) and (34) respectively, where $P_{m,t,y,s}^{tse}$ and $P_{m,t,y,s}^{tpv}$ represent the power purchased from the substation and PV systems, respectively; Δ_t and Δ_y represent the duration of each period of the indexes t and y, ξ_s represent the solar irradiation scenario probability and ς_t^{en} the energy cost.

$$Ce^{se} = \sum_m \sum_t \sum_y \sum_s \Delta_t \cdot \varsigma_t^{en} \cdot \Delta_y \cdot \xi_s \cdot P_{m,t,y,s}^{tse} \quad (33)$$

$$Ce^{pv} = \sum_m \sum_t \sum_y \sum_s \Delta_t \cdot \varsigma_t^{en} \cdot \Delta_y \cdot \xi_s \cdot P_{m,t,y,s}^{tpv} \quad (34)$$

$$A^{pro} = \sum_m \sum_t \sum_y \sum_s \Delta_t \cdot \varsigma_t^{en} \cdot \Delta_y \cdot \xi_s \cdot P_{m,t,y,s}^{ess+} \quad (35)$$

As mentioned, the aggregator can offer voltage regulation in the EDS, for this purpose (36)–(38) are established. First, two new variables are introduced and defined in (36), to represent the positive and negative voltage deviation ($V_{n,t,y,s}^{+}$ and $V_{n,t,y,s}^{-}$ respectively) from the nominal value (V^{nom}), and they are associated to the EDS voltage in (37). The factor to be minimized is defined in (38), as the square of the sum of the new variables with a weight ω^v.

$$V_{n,t,y,s}^{+}, V_{n,t,y,s}^{-} \ge 0;\ \forall\, n,t,y,s \quad (36)$$

$$V^{nom^2} - V_{n,t,y,s}^{sqr} = V_{n,t,y,s}^{+} - V_{n,t,y,s}^{-};\ \forall\, n,t,y,s \quad (37)$$

$$fV = \omega^v \cdot \sum_{n,t,y,s} \left(V_{n,t,y,s}^{+} + V_{n,t,y,s}^{-}\right)^2 \quad (38)$$

Finally, the objective function can be established for the proposed mathematical model, which involves the sum of the previously defined variables representing both investment and operational costs. Defined in (39), the objective function considers an annualization parameter for the investment denoted by

$$\varphi = \frac{\lambda(1+\lambda)^\tau}{(1+\lambda)^\tau - 1},$$

where λ represent the interest rate and τ the planning horizon in years. This part of the model ensures that the investment and cost calculations align with financial constraints and realistic energy pricing.

$$of = Ce^{se} + Ce^{pv} + \varphi \cdot C^{ess} - A^{pro} + fV \quad (39)$$

F. Mixed Integer Linear Programming model

Based on the equations previously presented, it is possible to define the mathematical programming model in (40).

$$\text{minimize } (39)$$
$$\text{subject to: } \begin{cases} (1)\text{–}(3) \\ (5)\text{–}(38) \end{cases} \quad (40)$$

From the defined mathematical model, it is possible to carry out the planning of ESS in the EDS where the growth of PV generation penetration is modeled with a logistic growth function. This model incorporates the relation between the changes between the energy price and the penetration of renewable PV generation.

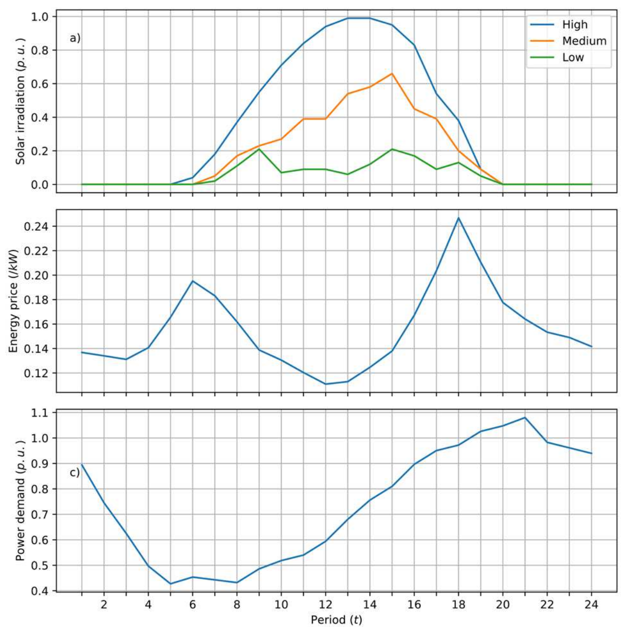

Fig. 2 Data for the case study: a) solar irradiation, b) energy price and c) power demand.

III. Results

In this section of the paper tests and results with the proposed stochastic mixed integer linear programming model will be presented to analyze the influence of the ESS planning in the context where the growth of PV generation is considered facing the influence in the energy price. For this purpose, initially, the input parameters of the case study will be presented, which are based on the IEEE 33 node EDS [13]; in the following subsection, the results are presented.

A. Case Study Description

For the ESS planning, this case study used the IEEE 33 node system [13] which has a nominal voltage of 12.66 kV, with one substation and 32 load buses, and a maximum and minimum voltage limit of 1.03 and 0.95 p.u., respectively. Additionally, for each system node was considered an initial installed PV power.

Three profiles for the solar irradiation coefficient are considered, ranging from a clear day with high irradiation to a cloudy day; the parameter has an hourly resolution ($\Delta_t = 1$ hour) and the possible scenarios have probabilities of 30%, 40%, and 30%, respectively. For the energy prices, was developed a Python-based forecasting model to predict future electricity prices using historical day-ahead prices; was employed the Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) model [14]; the data and the Python script are available at [15]. Additionally, the power demand at the nodes of the EDS also varies hourly. These data are presented in Fig. 2.

The battery considered for the problem is a lithium nickel cobalt aluminum (Li-ion NCA) battery, with a lifespan of 18 years, which exhibits a self-discharge of 0.2%/day, being able to discharge up to 90% of its total charge with an efficiency of charge and discharge of 96%. Also, each module has an energy capacity of 200 kWh and a power of 50 kW. The cost of each module is $15,765, while the annual operation and maintenance costs are 1.5% of the invested value [16].

Finally, the cost of installing a battery system in a node in the system is $5,000, and the investment limit is $500,000. The planning horizon that will consider the growth of photovoltaic generation penetration is five years, with the duration of each annual period (Δ_y) 365 days. The discount rate adopted is 3%. All the data used in the paper is available at [15].

B. Results for the Case Study

With the method presented the result achieved suggest an installation of an ESS in the EDS node 17, with 3 inverters and 39 modules, with an investment of $ 494,795. The profit with energy arbitrage is $ 161M, that comparing to the initial investment is a payback of 300 times greater.

The operation of the ESS prioritized solar generation during the peak generation, which coincides with the lowest energy price. It can be noticed that during the medium and low solar irradiation profiles, the ESS also uses less energy, but in all cases the energy stored is discharged in the EDS during the peak time of power demand, at period 21, making a considerable influence on the voltage of the EDS. This can be observed in the Fig. 3.

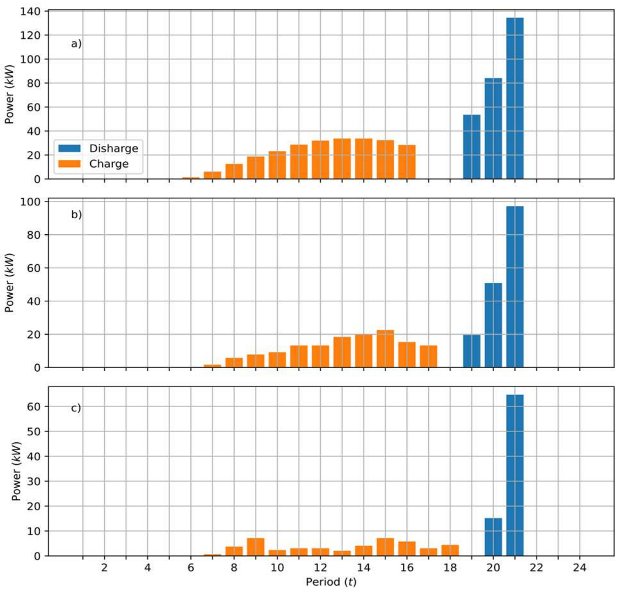

Fig. 3 Battery operation during the solar irradiation profiles: a) high, b) medium c) low.

Comparing the voltage improvement (fV) of the system operation when the EDS does not have ESS and after their allocation, it is observed an improvement of 0.55%, meaning that basically the voltage profile was improved. The minimum voltage is observed in node 17 when there are no batteries in the EDS, with the allocation the observed voltage has an improvement, in all scenarios of solar irradiation, which can be observed in Fig. 4; it's worth mentioning that this improvement is related to the battery placement, first because the batteries are placed in the same node and because the improvement in the voltage happens in the same period that the ESS discharges (between periods 19 and 21, as observed in Fig. 3)

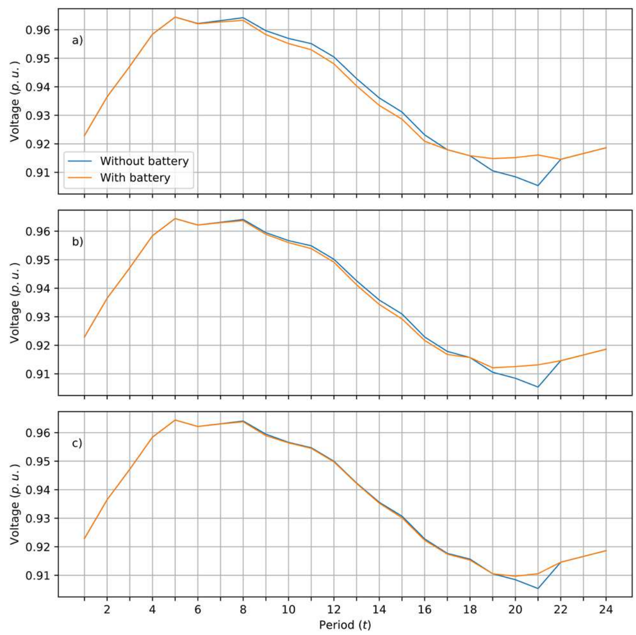

Fig. 4 Voltage observed at node 17 during the solar irradiation profiles: a) high, b) medium c) low.

IV. Conclusion

The results found within the presented method illustrate the possibility of investors to plan energy storage systems (ESS) into the electric distribution system in order to participate in the electricity market marking profits with energy arbitrage taking advantage of the optimal placement to participate in energy markets. By analyzing the investment in ESS across selected nodes and examining the associated costs and energy losses, it becomes evident that ESS plays a crucial role in enhancing the efficiency and sustainability of power distribution networks.

In conclusion, the strategic integration of battery storage into electrical systems presents a viable pathway toward achieving more efficient, sustainable, and cost-effective energy distribution. The findings advocate for the continued exploration and adoption of ESS technologies as integral components of modern power systems, paving the way for a more resilient and sustainable energy future.

Related to the logistic growth model, future works may consider the social aspects of the different clients connected to each node of the system, which can lead to different rates of growth for the penetration. Also, future works can address different types of markets where the investor in ESS can participate, like the frequency control or the peak shaving markets, in which the optimal allocation of the ESS can be influenced by these different markets.

V. References

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