Optimal Planning and Operation of Hybrid Energy System Supplemented by Storage Devices

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***Abstract*—This paper presents a two-stage model for optimal planning and operation of a distribution network. Optimal siting and sizing of renewable energy sources (RES) as well as electrical energy storage (EES) systems are considered in the proposed hybrid energy system. In this context, the planning problem is considered as a master problem, while there are different sub-problems associated with the short-term operational problem. To properly handle the uncertainties of forecasted load as well as renewable power generations, fair stochastic models are involved in the sub-problems based on historical data of a real grid. The objective function of this problem consists of total investment cost and total operating costs of installed assets. The proposed scheme is implemented on a distribution test system and the obtained results demonstrate the applicability and efficiency of this model in dealing with the optimal operation and planning of distribution networks in the presence of a large number of decision variables. Moreover, simulation results show that joint utilization of the EESs and RESs reduces the annual operational cost and can handle the fluctuations of RESs power generations and hourly demanded loads.**

Keywords-Energy Storage, Optimal Planning, Stochastic Programming, Two-stage Optimization Model

NOMENCLATURE

Sets

r, N_R	Index and number of RESs
b, N_B	Index and number of EESs
t, N_T	Index and number of time intervals
i	Index for injection nodes
l	Index for distribution lines
ω	Index for scenarios

Parameters

C_r	Installation cost of RES
C_b	Installation cost of EES
ρ^{ω}	Probability of scenario ω
λ	Hourly cost
η	EES charge/discharge efficiency

Variables

TC	Total cost of planning
Inv_Cost	Investment cost
Op_Cost	Expected operational cost
P	Active power
E	Energy stored in EES
f	Power flow through distribution lines
x	Binary variable for investment in RES
y	Binary variable for investment in EES
δ	Binary variable for EES charge and discharge

Symbols

g	Utility grid
$\mathrm{Ch.,Dis.}$	Charge and discharge
$\max, \min$	Maximum and minimum

I. INTRODUCTION

The optimal planning of distribution systems to install renewable energy sources (RESs) based units in the mid-term horizon is of high significance due to ever-increasing penetration of such technologies in power systems [1]. The most severe challenges in developing the required infrastructure for investment in renewable energies are the remarkable capital cost and the uncertainty of renewable power generation in the short-term horizon [2]. However, some solutions have been proposed by governments for the investment in developing renewable energy infrastructure [3]. In this respect, purchasing renewable power at a higher price in the form of guaranteed long-term contracts in the form of Feed-in Tariff as well as the capacity payment are the two examples [4]-[6]. Recently, electrical energy storage (EES) systems have been utilized to mitigate the fluctuations of renewable power generation [7]-[9]. In between, using centralized EES system with large-size batteries or decentralized EES systems using plug-in electric vehicles (PEVs) and plug-in hybrid electric vehicles (PHEVs) have been considered the common solutions to tackle the RESs' uncertainties [10]-[11]. In a multi-lateral radial distribution network, supplying the required energy from the utility grid which is a medium voltage (MV) system imposes a great cost to customers while the system's reliability is highly

impacted by the utility grid due to its radial configuration. Furthermore, the power losses due to the power flow from the utility grid to the low voltage (LV) network result in a remarkable cost in long term. In recent decades, the proximity of power generation and load demand as distributed generation (DG) has turned into an interesting debate. In between, RES-based DGs such as wind turbines (WTs) and Photovoltaic (PV) arrays are more highlighted. Authors of [12] propose a comprehensive survey regarding the optimal site, size and the type of DGs. The presence of EES systems beside RES-based DG would obviously bring too many merits to the system. In this regard, EES systems can be utilized to control the distribution system by proposing some services such as load shaving, joint operation with RES, and accordingly, deferring the system investment (e.g.[13],[14]). Other services supplied by such units include ancillary services such as frequency regulation and voltage support as well as indirect congestion management service. Moreover, the power losses of the system can be mitigated, as well by using EES systems [15]-[17].

The expansion planning of distribution systems taking into account the real conditions of the system, the uncertainties related to the seasonal conditions of power generation by RESs, and the variations of the load profile, is a large-scale optimization problem. Adding EES systems and the necessity to consider the inter-temporal characteristics of such units in day-ahead market lead to more complexity and the computational burden of solving the problem. In addition, it is necessary to consider the load flow equations in each time interval. Thus, the assessment of the objective function over the operation horizon includes the operating point of each generating unit and the EES system along with the power transaction with the MV network to balance the load demand and the power generation at each node of the system during each time interval.

In this regard, this paper presents a two-stage stochastic framework for optimal siting and sizing of renewable resources as well as energy storage units for typical distribution networks based on historical data of a real grid. In order to reduce the computational burden of this large-scale optimization model, the problem is decomposed into two stages. The decision variables of master problem are sizes, locations and types of new assets, i.e. WTs, PVs and EESs, while the decision variables of the sub-problems are determination of operating points of installed capacities in the short-term planning horizons. In the first stage, the optimization model proposes the random string mapping to the location, size and the type of new assets to be evaluated in the second stage. In the second stage, the network topology is reorganized based on the introduced capacity additions from the first stage. The feasibility and optimality criteria of the addressed plan should be checked by implementing optimal power flow (OPF) and charging/discharging determination of the probable energy storage in a daily operational horizon. This procedure should be handled for a set of predefined scenarios in each season considering the load profile and renewable power generation, as well. The computational burden of the second stage is very high and it is necessary to decompose this section into the different sub-problems. The main contributions of the paper can be briefly stated as follows:

- Decomposing the log-term planning problem into a two-stage programming problem,
- Co-optimal siting and sizing of RES and EES in distribution networks,
- Modeling the short-term stochastic optimization problem using mixed-integer programming (MIP) to mitigate the computational burden in the expansion planning sub-problems.

The remainder of this paper is organized as follows: Section II proposes a long-term expansion problem to enhance the performance of the distribution system where the modeling approach is described. Section III is devoted to the modeling of the problem and Section IV presents the simulation results. Lastly, some relevant conclusions are drawn in Section V.

II. Problem Description and Modelling Approach

A. General Structure

Fig.1 illustrates the conceptual framework of the proposed two-stage model for the optimal planning of the RESs and EESs in this study. As shown in Fig. 1, in the first stage the best combination for investment is determined and in the second stage, the suggested plans from the first stage are assessed through stochastic sub-problems. The objective function comprises the expected value of the operating costs in the short-term horizon together with the investment cost over the long-term horizon. As the operating cost of RESs is small, the operating cost reduction would be remarkable. On the other hand, the investment cost to add new assets would be high. Hence, there should be a trade-off between the expansion costs and the costs of such units over the long-term horizon. In other words, the presented optimization problem seeks to find the best expansion plan to supply the customers' load demand over the planning horizon. In this regard, the location of new assets must be optimally determined beside their capacity to this end.

B. Master Problem

There are one master problem and several sub-problems in the proposed two-stage expansion planning of distribution systems. The decision variables of the master problem are integer variables and the problem is modeled using MIP. This stage determines the optimal locations, capacity, and the type of the assets intended to be added to the distribution system. It should be noted that each bus of the system can be a candidate bus to install WTs, PVs or EES systems. After selecting the asset for installation, the investment cost is specified. Briefly, the output of this stage of the problem includes the suggested capacities as well as the associated investment cost.

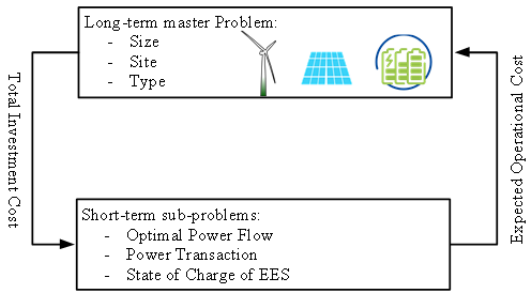

Figure 1. Two-stage model for expansion planning in this study

C. Sub-Problems

The next step after determination of the candidate assets at the first stage, is to assess the suggested plans to specify their effectiveness in mitigating the total cost. The operating cost of the suggested assets is calculated at this stage. The effectiveness of each asset must be determined in the scheduling horizon with respect to the seasonal change and consequently, the RES power output variations as well as the load demand variations. Therefore, it is necessary to implement the OPF based on the load demand, the electric energy price and also, the RES power outputs and the total operating costs of a given time interval, i.e. one year in this paper is calculated. It is essential to use the stochastic OPF and the expected value of the operating cost is determined. It is noteworthy that the total cost includes the aggregated cost of the investments and the expected value of the operating costs in presence of suggested assets. However, each sub-problem must be considered in an hourly-based 24-hour period with respect to the variations of the load demand and the power generation and also the dynamic nature of the stored energy in the battery to highlight the effectiveness of the EES systems in mitigating costs. Accordingly, the operating cost would be calculated for each scenario in a year based on the daily horizon and added to the investment cost of candidate assets obtained from the first stage to derive the total cost.

D. Stochastic Evaluation

To more accurately model the expansion planning problem in the system under study, a set of information as the input data are needed. In the first stage, i.e. determination of the candidate assets, the type of the asset, the capacity of the asset as well as the capital cost of the asset are taken into account as the main data. The operation stage is assessed at the stage of the evaluation of the suggested plans from the first stage. The required data include the technical data of the system under study to be used for the OPF together with the hourly load demand, the forecasted power generation of candidate units as well as the price of energy purchase from the utility grid. Using these streams of data and the site and size determined at the first stage, the optimal scheduling of the available assets over the 24-hour horizon is obtained. In this regard, the scenario-based optimization is used to take into account the forecasting errors of RESs and load demand [18]. In this paper, a scenario is defined as a realization of the hourly load demand and the power output of RESs. Thus, several scenarios are generated at the first stage using Monte-Carlo simulation to characterize such uncertainties according to their related probability distribution functions (PDFs) [19]-[20]. The forecasts of the load demand and wind speed over the scheduling period must be obtained to generate the required scenarios. Furthermore, the historical data are used to specify the associated standard deviations. Afterwards, the wind speed and load demand scenarios at each time of the scheduling period are derived using normal PDF while the mean is equal to the forecasted value and the standard deviation is specified using the historical data [18]-[20]. After obtaining the wind speed scenarios, they should be turned into the corresponding power outputs by fitting them on the power curve of the WT [21]. If the required data of the other types of RESs are available, similar procedure can be taken to generate related scenarios. It is assumed that the uncertainties in the proposed framework are independent [20]. The main challenge regarding the scenario-based optimization relates to the high computational burden, i.e., the higher number of scenarios results in a higher accuracy but at the expense of higher run-times. In this respect, the number of generated scenarios should be decreased to a reasonable number. This paper employs an efficient method named backward scenario reduction technique for reducing the number of the initially generated scenarios [18].

III. Model Formulation

This section includes the presented model for the system expansion-planning problem within a two-stage optimization framework. The mentioned problem is formulated in a single-objective optimization framework in which the objective function is defined as the sum of investment cost and the operating cost subject to several constraints using MIP.

The investment cost relates to the RESs and EES systems while the operating costs comprise the expected value of the operating cost of new assets along with the cost of power transaction with the utility grid that these costs form the total cost (TC) as below:

$$Min\ TC = Inv\_Cost + Op\_Cost \tag{1}$$

where

$$Inv\_Cost = \sum_{r=1}^{N_R} x_r C_r + \sum_{b=1}^{N_B} y_b C_b \quad r \in \{\text{Wind}, \text{PV}\}; x, y \in \{0,1\} \tag{2}$$

$$Op\_Cost = \sum_{\omega} \rho^{\omega} \left(\sum_{t=1}^{N_T} P_{g,t}^{\omega} \lambda_{g,t}^{\omega} + \sum_{r=1}^{N_R} \sum_{t=1}^{N_T} P_{r,t}^{\omega} \lambda_{r,t}^{\omega} + \sum_{b=1}^{N_B} \sum_{t=1}^{N_T} (P_{b,t}^{\omega,\text{Ch.}} \eta_{b,t}^{\omega,\text{Ch.}} + P_{b,t}^{\omega,\text{Dis.}} / \eta_{b,t}^{\omega,\text{Dis.}}) \lambda_{\text{b},t}^{\omega} \right) \tag{3}$$

It is worth noting that the investment cost includes the annual capital cost of RESs and EES systems as denoted by the first and the second terms in (2), respectively. In this respect, the installation costs of RESs and EESs are indicated by C_r ad C_b, respectively, while the binary decision variables relating to RESs and EES systems are denoted by x_r and y_b, respectively.

The operating cost represented in (3) consists of three items. The first item presents the cost of energy purchase from the utility grid. The second item indicates the generation cost of RESs while the third term includes the operating cost of EESs in both charging/discharging modes. It should be noted that the expected value of the operating cost is obtained for different scenarios over a one-year horizon. In this respect, a day in each season of the year is selected and different scenarios are generated for the wind speed, solar irradiation as well as the load demand with respect to the seasonal conditions. In other words, the total number of hours in this study is 8760 hours over a year considering four seasons and a 24-hour horizon.

The constraints of the problem are as follows:

$$P_{i,t}^{\omega} = P_{g,t}^{\omega} + P_{r,t}^{\omega} + P_{b,t}^{\omega,\text{Ch.}} - P_{b,t}^{\omega,\text{Ch.}} \quad ; i \in \{g, r, b\} \tag{4}$$

$$P_{i,t}^{\omega} - \sum_{l:s(l)=n} f_{l,t}^{\omega} + \sum_{l:e(l)=n} f_{l,t}^{\omega} = P_{d,t}^{\omega} + P_{loss,t}^{\omega} \tag{5}$$

$$-f_l^{\max} \le f_{l,t}^{\omega} \le +f_l^{\max} \tag{6}$$

$$V_i^{\min} \le V_{i,t}^{\omega} \le V_i^{\max} \tag{7}$$

$$0 \le P_{g,t}^{\omega} \le P_g^{\max} \tag{8}$$

$$0 \le P_{r,t}^{\omega} \le P_r^{\max} x_r \tag{9}$$

$$0 \le P_{b,t}^{\omega,\mathrm{Ch.}} \le P_b^{\max,\mathrm{Ch.}} \delta_{b,t}^{\omega,\mathrm{Ch.}} y_b \tag{10}$$

$$0 \le P_{b,t}^{\omega,\mathrm{Dis.}} \le P_b^{\max,\mathrm{Dis.}} \delta_{b,t}^{\omega,\mathrm{Dis.}} y_b \tag{11}$$

$$0 \le \delta_{b,t}^{\omega,\mathrm{Ch.}} + \delta_{b,t}^{\omega,\mathrm{Dis.}} \le y_b \tag{12}$$

$$E_{b,t}^{\omega} = E_{b,t-1}^{\omega} + P_{b,t}^{\omega,\mathrm{Ch.}} \eta_b^{\mathrm{Ch.}} - P_{b,t}^{\omega,\mathrm{Dis.}} / \eta_b^{\mathrm{Dis.}} \tag{13}$$

$$E_b^{\min} y_b \le E_{b,t}^{\omega} \le E_b^{\max} y_b \tag{14}$$

$$E_{b,0}^{\omega} = E_{b,24}^{\omega} \tag{15}$$

The net power injection of bus i is stated in (4) which is equal to the energy purchased from the utility grid denoted by $P_{g,t}^{\omega}$. Wind and solar power generation are indicated by $P_{r,t}^{\omega}$ and the discharged power and charged power of the ESSs are denoted by $P_{b,t}^{\omega,\mathrm{Dis.}}$ and $P_{b,t}^{\omega,\mathrm{Ch.}}$, respectively. Also, the power flow equations are represented in (5)-(7). The upper and lower bounds of the power transaction with the utility grid and the power generation of RESs are stated in (8) and (9), respectively.

It should be noted that power generation of RESs is a function of the generated scenarios and it is taken into account in the power flow, provided that the candidate unit is selected at the first stage of the model. This issue is applied to the model by introducing the binary variable, a_r. The constraints related to the EES system are represented in (10)-(15).

Constraints (10)-(12) relate to the charging/discharging power of the EES system. The binary variables $\delta_{b,t}^{\omega,\mathrm{Ch.}}$ and $\delta_{b,t}^{\omega,\mathrm{Dis.}}$ are presented to avoid the conflict between different modes. The constraints of the EES system are applied to the problem, providing that this unit is selected at the first stage, i.e. y_b=1. Constraint (13) depicts the dynamic of the energy stored in the battery at each hour that should be in the permitted range as stated in (14).

One of the most significant constraints in such problems in the presence of batteries relates to the initial and the final energy storage of such systems at the beginning and at the end of a day. In this regard, the initial and the final energy stored in the batteries must be equal so that the required energy is available for the next day (15).

IV. Simulation Results

A. Test System

This section presents the simulation results obtained by implementing the proposed framework on a 30-bus distribution system [22]. The forecasted values are obtained from the real data reported in [23] taking into account the scaling factors for the distribution system. Also, the simulation is done for a typical day in each of the four seasons over the year.

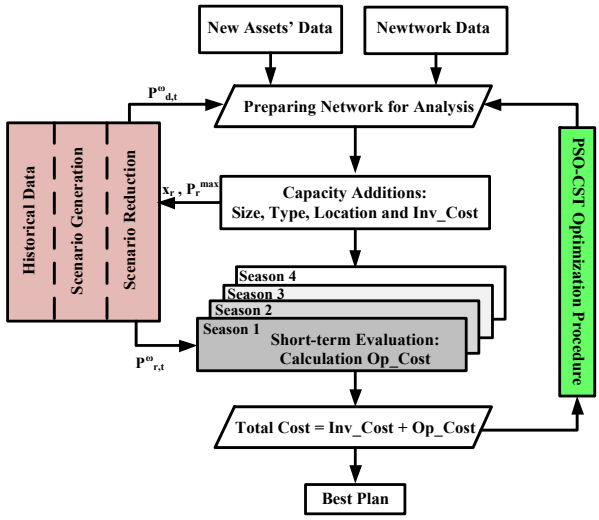

Figure 2. Two-stage flowchart for evaluation the planning framweork

The Intelligent Particle Swarm Optimization Augmented with Chaotic Searching Technique, PSO-CST [26], is used to solve the proposed problem. In this respect, solving the sub-problems leads to the optimal daily generation scheduling with respect to the capacities determined by the master problem. These sub-problems are modeled as MIP and solved by CPLEX. Fig. 2 illustrates the two-stage framework for evaluation the mentioned optimization problem. Moreover, forecasted power outputs of WTs and PVs are normalized on the basis of each asset's rated capacity. The average daily power output of PVs for each season has been represented in Fig. 3. The maximum number of candidate assets possible to be installed, are three storage devices that the capacity of each one is 500 kWh, 1000kWh and 1500 kWh. Furthermore, ten PVs with the rated capacity ranges from 20 kW to 400 kW along with five WTs with the rated capacity of 250 kW to 1250 kW can be installed in the mentioned system. The initial energy stored in the Lithium-Ion-based EES is assigned as 50% of the rated capacity considering the characteristics of such batteries [24]. It is noteworthy that this paper does not consider the degradation cost. Table I represents the required data of the EES system from [26] while includes the energy tariffs used for this study. Besides, [27] comprises the operating cost coefficients pertaining to RESs and EES systems.

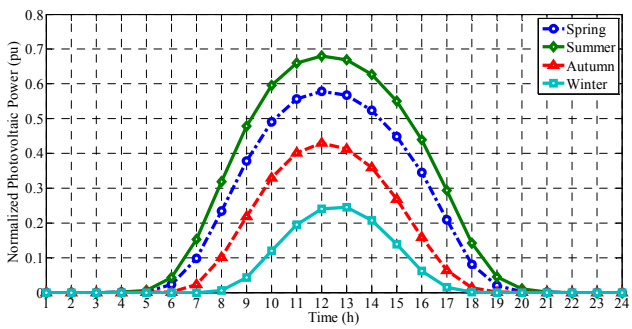

Figure 3. Expected PV generation (pu) based on the historical data

TABLE I. Energy Storage Characterristics

$E_b^{\min}$ (pu)	$E_b^{\max}$ (pu)	$P_b^{\max,\mathrm{Ch.}}$ (pu)	$P_b^{\max,\mathrm{Dis.}}$ (pu)	$\eta_b^{\mathrm{Ch.}}$ (pu)	$\eta_b^{\mathrm{Dis.}}$ (pu)
0.1	1.00	0.1	0.1	0.85	0.80

B. Simulation Results

The distribution system considered in this study has 30 buses beside four laterals fed by the MV system in the base case. The total load demand of the system is 8.7MW+*j*5.37MVAr . The power flow results show that the power losses are equal to 0.874MW+j0.26MVAr and the minimum voltage level occurs at bus 27 by 0.883 p.u. The simulation results of the base case presented in [22] are in accordance with the obtained results for constant power loads. In the next step, the following results are derived by rescaling the technical data of the real system for the planning study. The annual operating cost of the distribution system in the base case without any system expansion is 14.1867 million USD. The distribution system is connected to the MV network through one connection point. If RESs and EES systems are utilized, this cost will reduce to 13.4599 million USD. It is noted that 3.34547 million USD relates to the investment cost of the mentioned assets and as the operating cost of such systems is very low, the total cost has been remarkably reduced. In other words, the annual economic efficiency is equal to 20% of the capital cost having a rational rate of return (RoR) with respect to the life time of WTs, PVs, and EES systems. It can be stated that RoR would be satisfying over a 5-6 year period and the income would outweigh the cost.

Table II represents the combination of the suggested units while the optimal capacities of WT, PV, and EES to be added are 1060 kW, 5250 kW and 1000 kWh, respectively. The optimal locations of these assets are illustrated in Table II and Fig. 4 depicts these locations on the single-line diagram of the system. Fig. 5 indicates the amount of the energy purchased from the utility grid for the ten reduced scenarios in Fall.

TABLE II. OPTIMAL SIZE, TYPE AND LOCATION OF NEW ASSETS

Bus	PV (kW)	WT (kW)	Battery (kWh)
1	60	-	-
2	-	1250	-
5	-	500	-
10	180	-	-
11	160	1000	-
14,20	20	-	-
15	140	-	-
17,18	-	1250	-
22	120	-	1000
23	200	-	-
26	160	-	-
Total	**1060**	**5250**	**1000**

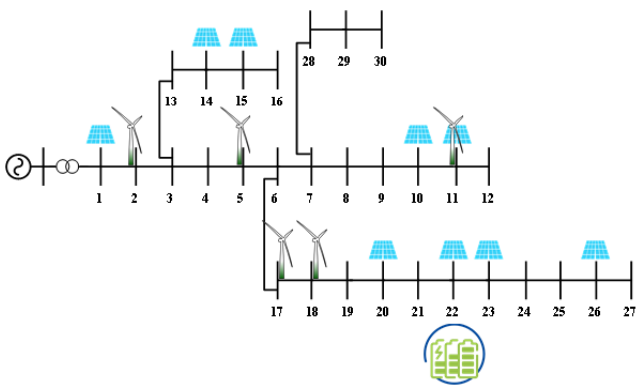

Figure 4. Single-line diagram of 30-bus distribution network

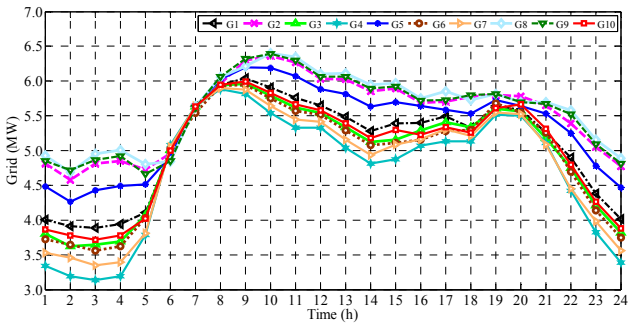

Figure 5. Grid injected power for 10 scenarios in Fall

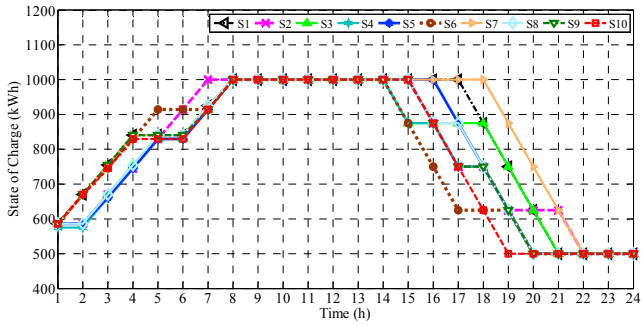

Figure 6. The SOC for battery installed at bus 22 in Fall

As can be observed from this figure, the rate of energy purchase from the utility grid is high over the off-peak hours due to the low energy price during the early hours in the morning. The EES systems absorb power during these hours to deliver it to the system over the peak hours with high energy prices. Fig. 6 depicts the energy stored in the EES system for the ten scenarios in this season. PVs have an acceptable power generation over the day beside WTs and supply a remarkable fraction of the load demand. It is noted that the energy stored in the EES system remains at its highest level during the day to supply the load demand mainly due to the lighting systems at the beginning of the night with high energy prices. Ultimately, the level of the energy stored in the EES system reaches 50% of the rated capacity at hour 24 to be ready for the next day. It is worth mentioning that the operation conditions vary with the energy price, load demand, etc. over different seasons. Here, only the operation conditions in Fall has been investigated as a sample.

V. CONCLUSUION

In this paper, a two-stage optimization framework is proposed to find the optimal plan for a hybrid energy system. This framework consists of a master problem for determining the best assets mix and different sub-problems for short-term evaluation of suggested assets. In order to reduce the computational burden, the sub-problems are defined as standard MIP. The adopted methodology based on scenario generation and then, scenario reduction algorithms are considered based on real data for load and renewable generation profiles. The obtained results from this methodology illustrate that this procedure can find the optimal planning scheme including the optimal size, location and type of each asset for distribution networks.

The proposed two-stage model can be developed to evaluate other objective functions in the framework of a multi-objective programming. Since the combination of

assets are provided at the first stage, other objective functions, such as reliability and voltage stability index as well as minimization of total losses can be analyzed.

Moreover, with adoption of the sensitivity analysis at the operational horizon, the optimal state of charge of battery can also be achieved in order to minimize the total cost and to extend of life cycles of the storage devices. In addition, by considering the role of electric vehicles as decentralized storage devices in distributed parking lots in real networks, the optimal scheduling for these storage devices can be attained by implementing the proposed framework.

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