Environmental Constrained Optimal Hybrid Energy Storage System Planning for an Indian Distribution Network

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ABSTRACT In recent days, aiming for power generation with less carbon emission, led to the high penetration of renewable energy into the distribution grid. To improve the intermittency caused by renewables and to increase the grid flexibility, grid integrated Energy Storage Units (ESUs) are proposed as the promising solution in the literature. However, considering the investment cost, ESUs are optimally placed by satisfying the network electrical constraints. On the other hand, consideration of environmental impacts and other practical constraints are also equally important. Therefore, in this article, on top of grid performance parameters, realistic parameters that may affect the location and its size such as (1) environmental impact, (2) land requirement & its associated cost for ESU installation and (3) renewable purchase obligation are formulated in the objective function. Decision making on ESU installation is a planning activity, which follows uncertainty. Consequently, it is essential to model the uncertainty parameters into the objective function, for better planning. In this article, optimal planning of hybrid ESUs based on realistic parameters along with uncertainty is addressed. For this study, a practical 156-bus distribution system of Dehradun district, India is considered. From the results obtained, it is evident that, formulating hybrid ESU constrained with the environmental impact has significantly decreased the emission of CO2 with maximum grid stability.

INDEX TERMS Batteries, distributed power generation, environmental economics, power system planning, sustainable development.

NOMENCLATURE

A. INDICES AND SETS

\( k \) Indices for present year
\( n \) Indices for future year
\( \text{pre} \) Indices for present value
\( i, j \) Indices for bus/location
\( h, t \) Indices for hour and time of a day
\( L_{\text{tot}} \) Index for total number of location for a cluster
\( EV \) Index for electric vehicle
\( PV \) Index for solar photovoltaic power plant
\( D \) Index for general load
\( EV_{\text{Di}} \) Index for electric vehicle distribution
\( N_{c} \) Set of optimal clusters
\( N_{t} \) Set of total time period for this study
\( N_{b} \) Set of system buses

\( N_{l} \) Set of distribution lines
\( N_{\text{ESU}} \) Set of energy storage units to form HESU
\( s_{h} \) Set of hourly scaling factor
\( i_{N_{c}} \) Indices for bus/location in the cluster \( N_{c} \)
\( LCI_{N_{b}} \) Land cost index at bus \( N_{b} \)

B. PARAMETERS

\( C_{h} \) Charging hours of Electric vehicle
\( L_{d_{h}} \) Hourly scaling factor of general load
\( PV_{d_{h}} \) Hourly scaling factor of solar photovoltaic power plant
\( EV_{d_{h}} \) Hourly scaling factor of electric vehicle load
\( P_{\text{pre}} \) Present value of total demand in the distribution network
\( PV_{\text{pre}} \) Present value of total grid – tied solar power generation across the distribution network
\( PEV_{\text{pre}} \) Present value of total electric vehicle load in the distribution network

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C. VARIABLES

- $C^i_{HESU}$: Installation cost of $i^{th}$ HESU
- $C^i_{OM}$: Operation and Maintenance cost of $i^{th}$ HESU
- $C^i_{env}$: Cost of environmental damage due to CO$_2$ emission
- $C^i_{GF}$: Cost of grid performance due to HESU
- $C^i_{land}$: Cost of Land related to the physical size of HESU
- $C_{PI}$: Cost related to the power rating of $i^{th}$ HESU
- $C_{EI}$: Cost related to the energy rating of $i^{th}$ HESU
- $C_{FI}$: The fixed installation cost of $i^{th}$ HESU
- $C_{FOM}$: Fixed operation and maintenance cost of HESU
- $p_{HESU}^{dis,i}$: Discharging power of HESU at time $t$
- $p_{HESU}^{ch,i}$: HESU charging power at time $t$
- $N^i_b$: Total cost of voltage deviation in the network considered
- $LL^i_b$: Total cost of line loading in the network considered
- $C_{Sp}$: Total cost of apparent power loss in the network considered
- $V_{HESU}^b$: Bus voltage after installing HESU in the network
- $P_{rated}^{HESU}$: Total installed capacity of HESU
- $P^{i,t,fn}_D$: Real power of the general load at $i^{th}$ location (bus) at time $t$ of the day in $f^i_n$ year
- $P^{i,t}_N$: Real power of electric vehicle load at $i^{th}$ location (bus) of $N_c$ cluster at hour $C_h$ of the day in $f^i_n$ year
- $P^{i,t}_PV$: Real power generated from solar power plant installed at $i^{th}$ location (bus) at time $t$ of the day in $f^i_n$ year
- $P^{i,t}_HESU$: Real power absorbed or injected by HESU installed at $i^{th}$ bus at time $t$
- $P^{i,t}_grid$: Real power injected from the grid at $i^{th}$ bus during time $t$
- $P^{i,t}_flow$: Real power flow between the bus $i$ and $j$ at time $t$
- $Q^{i,t,fn}_D$: Reactive power of the general load at $i^{th}$ location (bus) at time $t$ of the day in $f^i_n$ year
- $Q^{i,t}_N$: Reactive power of electric vehicle load at $i^{th}$ location (bus) of $N_c$ cluster at hour $C_h$ of the day in $f^i_n$ year
- $Q^{i,t}_PV$: Reactive power generated from solar power plant installed at $i^{th}$ location (bus) at time $t$ of the day in $f^i_n$ year
- $Q^{i,t}_HESU$: Reactive power absorbed or injected by HESU installed at $i^{th}$ bus at time $t$
- $Q^{i,t}_grid$: Reactive power injected from the grid at $i^{th}$ bus during time $t$
- $Q^{i,t}_flow$: Reactive power flow between the bus $i$ and $j$ at time $t$
- $V^b_i$: Bus voltage at time $t$
- $LL^i_l$: Line loading of a line $l$ at time $t$
- $SOC_{HESU}^i$: State of Charge of HESU at time $t$
- $TI$: Binary variable Tourism index
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One of the ways implemented in India to achieve the target of solar PV is through renewable purchase obligation (RPO). Concerning the guidelines from the ministry of new and renewable energy (MNRE), the state electricity regulatory commission (SERC) of Indian states has directed mainly the open access customers having consumed a percentage of its total demand from renewable. For example, in Tamilnadu, India, the RPO has been raised from 9.5% to 14% within two years (from 2016 to 2018) which includes the RPO from solar PV of 0.5% in the year 2016 which is increased to 5% in the year 2018 [2]. Therefore, it is evident that the power injection from renewable is going to be increased drastically in the coming years. Even though high renewable penetration increases flexibility, it introduces significant challenges like voltage deviation, reactive power requirement, power congestion, frequency deviation, and other power quality issues. Besides renewable penetration, the European Distribution System Operator (EDSO) has proposed a future distribution grid with the integration of renewables, ESUs, electric vehicles as a solution for the sustainable network [3]. The ESU integration into the distribution grid can solve many issues like to tackle forecasting errors of renewable plants, voltage deviations, improving grid stability, peak load management [4]–[6]. In [7], the environmental impact created by conventional source and ESU is analyzed by satisfying an energy demand of 1 MWh; where the results are compared based on six ecological parameters such as climate change (kg CO$_2$-eq), Photochemical Ozone formation (kg NO$_x$-eq), Freshwater Eutrophication (kg P-eq), Human toxicity (kg 1,4-DB-eq), Terrestrial acidification (kg SO$_2$-eq) and Fine particle matter formation (kg PM$_{2.5}$-eq). From the results, it is ostensible that the impact created by the implementation of large scale ESU is significant for two parameters. However, the characterization of ESUs is essential to mitigate the hazards created during the failure of cells [8]. Therefore, given the circumstances, ESUs can play a significant role in improving grid performance with a considerable impact on the environment.

Given the capital investment, an optimum number of ESUs are placed in the distribution network [9]. In the literature, ESU planning is formulated as an optimization problem and is solved by using the analytical approach, conventional optimization, and meta-heuristic approach. In [10], [11], RESs and ESUs are optimally placed in a distribution network using meta-heuristic algorithms to face the uncertainty of RESs and also to tackle demand response. In [12], a multi-objective optimization model based on particle swarm optimization (PSO) is proposed considering peak shaving, voltage quality, and dynamic power adjustment. For effective utilization of ESU, the charging and discharging cycle length is optimized for each day using mixed-integer nonlinear programming. This is implemented in two stages where the charging and discharging periods are optimized in the first stage, and the optimal power flow is carried out in the second stage for the flexible operation of ESU [13]. Considering the future expansion of power grids, large scale ESU is optimally

PDF$_D$ Probability distribution of general load
PDF$_{PV}$ Probability distribution of power generation from solar power plant
PDF$_{EV}$ Probability distribution of electric vehicle load

D. ABBREVIATIONS
ESU Energy Storage Unit
HESU Hybrid Energy Storage Unit
PV Photovoltaic
RES Renewable Energy Source
REP Renewable Energy Plant
RPO Renewable Purchase Obligation
MNRE Ministry of New and Renewable Energy
SERC State Electricity Regulatory Commission
EDSO European Distribution System Operator
PSO Particle Swarm Optimization
BPSO Binary Particle Swarm Optimization
LP Linear Programming
MINLP Mixed Integer Non-Linear Programming
TOD Time of Day
LCI Land Cost Index
MSL Mean Seal Level
Li-ion Lithium-ion battery
Na-S Sodium Sulphur battery
CQI Cluster Quality Index
SI Silhouette index
DBI Davies – Bouldin index
DOD Depth of Discharge
UPCL Uttarakhand Power Corporation Limited

I. INTRODUCTION
The world is witnessing climate change, an increase in environmental pollution, global warming, mainly due to the exploitation of energy from fossil fuels. On the other hand, the trend of fossil fuel exploration is decreasing which made to search for pollution less alternative. One such way to produce energy is through renewables. This made people across the world to invest in renewable technologies for power generation. In the earlier days, power generation from wind energy was dominating because of its comprehensive technology. However, in the past decade, the development of solar photovoltaic (PV) technology has paved the way for generating energy simpler compared to other renewables. This made many developed and developing countries like Germany, USA, Japan, Italy, China, India to invest its significant portion of renewable power generation via solar PV technology. In this regard, India has aimed at introducing 175 MW of its power generation from renewable energy sources (RESs) until 2022 [1]. This target was planned to achieve by installing various grid-tied solar PV plants (both rooftop and surface mount), solar thermal plants, wind energy conversion systems, etc. However, the significant share amongst all is solar PV technology. By employing the plug-play model, India has increased its solar capacity up to 370% in the last three years from 2.6 GW to 12.2 GW [1].
placed in the system to meet the required demand profile [14], [15]. For example, in India, TATA power has established an ESU at Rohini substation with a capacity of 10MW to manage the major challenges such as peak management, effective management of renewables, and power quality [16]. The concept of hybrid ESU (HESU) with the combination of super-capacitors or ultra-capacitors and battery storage is proposed for effective grid management [17]–[19].

It is straightforward from the literature survey that, the ESUs are placed in the distribution network to improve the following: (i) fluctuations of renewable energy plants (REPs) [9], [20], [21], [22] (ii) minimization of distribution network loss [23]–[26], (iii) power quality [12], [27], [28], (iv) reliability of distribution network [29]–[32], (v) arbitrage cost (between utility and REPs) [33], [34]. Apart from these parameters, it is also required to consider the uncertainty introduced due to renewables and load. In [35], a novel multi-stage model is proposed for distribution system planning considering the uncertainties introduced due to wind turbines. Here, the uncertainties are modeled based on the operational parameters such as limits of current and voltage by framing chance constraints. It is also expressed here that, assuming a single probability distribution to address wind uncertainty may not be realistic; therefore, the wind uncertainty is represented using ‘distributionally robust’ chance constraints. In [36], the uncertainty of wind generation is addressed based on various probability distribution using the Kullback – Leibler divergence measure. On the other side, clustering techniques are used to decrease the complexity of problems with high renewable uncertainty [37]. However, practical considerations such as the environmental impact of ESUs, land requirement, and its cost and increasing RPOs are yet to be explored concerning optimal planning of ESUs. Since ESU placement is a decision-making problem under planning, this time needs to consider uncertainties related to load growth, load fluctuations, REP fluctuation, the growth rate of grid integrated REP, and the influx of electric vehicles.

To perform the proposed study on the chosen distribution system, a survey was conducted to understand the following parameters: (a) the number of electric vehicles introduced into the distribution grid each year, (b) charging time, (c) density of electric vehicle across the district and (d) number of grid-tied solar power plants installed each year along with its capacity. With this survey data, the growth rate of demand, RES grid penetration rate, and the influx of electric vehicles on the distribution system are calculated considering a time period of five years. Having these data, the distribution system is modified to identify the optimal locations of HESU. The novelty of this study abides in the formulation of ESU planning with parameters such as (i) growth rate of RPO, (ii) growth rate of demand and grid-tied RES, (iii) placing the electric vehicle demand based on the survey conducted, (iv) availability of land and its associated cost to install the ESU and (v) environmental impact of ESU. In the formulated problem, the size of ESU takes a continuous value within limits, its location is decided by a binary variable and the nonlinear power flow equations. This makes the formulated problem as a mixed-integer non-linear problem (MINLP).

To solve the MINLP problem, a methodology is proposed that combines the particle swarm optimization (PSO), binary PSO (BPSO) and linear programming (LP).

DigSILENT and Python 3.7 are linked together to model the system and perform a power flow study as it is more pragmatic in DigSILENT; while Python is used to apply proposed optimization methodology. Section II elaborates on the distribution network modeling, under this, the clustering of distribution network, uncertainty formulation of general load, EV & Solar PV, and the selection of ESU technology are explained. Section III describes REs and load modeling for optimization and how the optimization problem is formulated. Section IV describes the methodology proposed to solve the formulated optimization problem. The results obtained are discussed in section V and the article is concluded in section VI.

II. DISTRIBUTION NETWORK MODELING

The distribution network chosen for this study is spread-out on a mixed terrain which consists of both plain and hilly areas, which also creates various challenges of its own for ESU planning. To understand the importance of practical constraints and the expected influx shortly, a survey has been conducted in Dehradun district. The outcome of this survey derives various parameters such as the number of electric vehicles in operation (yearwise) concerning locality, the source and time of the day (TOD) for charging, the power rating of electric vehicle and number of grid-tied RESs (here solar photovoltaic (PV) is considered) in operation (yearwise). With these data, the average growth rate factors for grid-tied solar PV, electric vehicles, and load demand are calculated using (1). In this equation, \( x \) represents the data corresponding to the number of electric vehicles in operation, total demand, and total grid-tied RES installed at \( k^{th} \) year. Using this growth rate factor (GF), future value (FV) of these parameters are found using (2).

\[
GF = \frac{1}{n} \left[ \sum_{k=1}^{n} \frac{x_k}{x_{k-1}} \right] \quad (1)
\]

\[
FV(x_{pre}) = GF \times x_{pre} \quad (2)
\]

In this equation, \( x_{pre} \) represents the present value, \( f_n \) represents the future number years for which the estimated FV need to be calculated. To verify the reliability of the model represented by (1) and (2), the data is divided into two sets, where one set (70%) is used to develop the GF and the other set (30%) is used to test FV. From the survey, there is a significant difference in the electric vehicle density and the distribution of grid-tied solar PV across the district. These differences were found because of various reasons such as population density, economic status, load density, etc. Therefore, it is essential to incorporate these factors into the optimization model.
A. CLUSTERING OF DISTRIBUTION NETWORK

Based on the survey, the electric vehicles are rarely found at places of high altitudes and mostly found within city limits (at low altitudes). From the experts’ suggestions, and considering the economic status of people, the possibility of electric vehicles at high and medium-altitude regions of the district are low. Therefore, this aspect should be modeled in the system for which planning is to be performed. To introduce this, the chosen distribution system is clustered based on latitude, longitude, mean sea level (MSL), population, Tourism index (TI), and load density using the k-means algorithm [38]. Here, TI takes the value 1 if the $i^{th}$ location is an identified tourist spot and 0 otherwise. Applying k-means clustering is effective, for large datasets. However, the major drawback of the k-means algorithm is the number of clusters for the clustering procedure has to be provided in prior. Therefore, to address this issue, cluster quality index (CQI) is formulated as given by (3), based on popular quality measuring indices for clustering such as Silhouette index (SI) and Davies – Bouldin index (DBI) [39]. Here, $\{w_1, w_2\} \in [0, 1]$ represents the importance factor of SI and DBI respectively. To get the optimal number of clusters for a given data set, a methodology is followed as mentioned in the flowchart shown in figure 1.

$$CQI = SI^{-w_1}DBI^{w_2} \times tSI, DBI \in [0, 1]$$

(3)

The indices represented in (3) are calculated using the equations given below:

$$S (j) = \frac{y (j) - x (j)}{\max (x (j)) \times y (j)}$$

(4)

where $x(i)$ is the average distance between the $i^{th}$ location and all other locations within the cluster $C_k$ and $y(i)$ is the minimum average distance between the $i^{th}$ location and all other locations in different clusters. Therefore, the overall Silhouette index is calculated by using (5).

$$SI = \frac{1}{L_{tot}} \sum_{i=1}^{L_{tot}} \left( \frac{1}{N_c} \sum_{j=1}^{N_c} S(j) \right)$$

(5)

where $L_{tot}$ is the total number of locations in a given set and $N_c$ is the number of clusters. The DBI index is calculated using (6). Where $X (i)$ and $X (j)$ is the average distance between each location of cluster $i$ & $j$ and centroid of that cluster respectively; $d_{ij}$ is the distance between the centroids of cluster $i$ and cluster $j$.

$$DBI = \frac{1}{L_{tot}} \sum_{i=1}^{L_{tot}} \max_{i \neq j} \left( \frac{X (i) + X (j)}{d_{ij}} \right)$$

(6)

B. UNCERTAINTY FORMULATION

Installation of grid-tied ESUs in the distribution network improves its performance in various ways as mentioned earlier. However, without considering the uncertainties introduced mainly due to RESs and load, leading to doubtful results [22]. In this article, the uncertainties of RES and load are modeled on their probabilistic behavior.

1) UNCERTAINTY OF SOLAR PV GENERATION

The output power of the solar power plant majorly depends on solar irradiance. This parameter is modeled using a beta distribution function as given by (7).

$$PDF_{PV} (x_i) = \begin{cases} \frac{1}{B(\alpha, \beta)} \times x_i^{\alpha-1} \times (1 - x_i)^{\beta-1}, & \text{if } x_i \in [0, 1] \\ 0, & \text{otherwise} \end{cases}$$

(7)

where $x_i$ is the solar irradiance at the $i^{th}$ location in W/m², B is the beta function and $\alpha$ and $\beta$ are the shape parameters of probability density function taking values greater than zero.

2) UNCERTAINTY OF LOAD

Load variations are mostly modeled using a normal probability distribution. In this study, the real power demand is distributed using a normal probability distribution, whereas the reactive power is calculated using the average power factor of $i^{th}$ location (obtained from the survey). The probability distribution function of real power demand located at the $i^{th}$
bus is calculated using (8). The influx of electric vehicles into distribution is increasing with the market scenario and environmental policies. In this study, the number of electric vehicles connected to the distribution network (or the corresponding demand) is distributed within a region using normal probability distribution given by (9).

\[
PDF_D(P_i) = \frac{1}{\sqrt{2\pi}\sigma[P_i]} \times e^{-\left(\frac{P_i - E(P_i)}{\sqrt{2\sigma[P_i]}}\right)^2}
\]

\[
PDF_{EV}(P_{EV}) = \frac{1}{\sqrt{2\pi}\sigma[P_{EV}]} \times e^{-\left(\frac{P_{EV} - E(P_{EV})}{\sqrt{2\sigma[P_{EV}]}\right)^2}
\]

where \(P_i\) represents the real power demand at the \(i^{th}\) bus, \(P_{EV}\) represents the total electric vehicle demand in a particular region/cluster, \(E[]\) and \(\sigma[]\) denoted the expected or mean value and standard deviation respectively.

C. SELECTION OF ESU TECHNOLOGY

Estimate from expert reveals that nearly 55% of ESUs installed in the world for peak management is mainly based on lithium-ion technology considering its round trip efficiency, depth of discharge (DOD), and energy to power ratio [8]. In general, the choice of ESU technology is only considered based on the electrical requirement, ignoring the environmental impact created by it while planning ESU [26]. However, the ecological impact due to Li-ion technology compared to other technologies is significant. Therefore it is essential to consider the climatic impact parameter for ESU planning along with other parameters mentioned in Table 1 [40], [41]. It is evident from Table 1 that; Li-ion battery can deliver high power to meet peak management requirements. However, the CO₂ emission of Li-ion solvent is 12.5 kg CO₂-eq, whereas for Na-S battery the CO₂ emission level is 1.2 CO₂-eq indicating high environmental damage [42]. Since both the battery technologies are commercially available in the market, it is essential to redesign the ESU planning problem based on environmental constraints. Therefore, it is required to find a hybrid combination of battery technologies, which can satisfy the electrical requirement with a minimized impact on the environment. Thus, in this article, ESU technology is modeled with a hybrid configuration of Li-ion and Na-S.

III. PROBLEM FORMULATION

A. RESs AND LOAD MODELING

For better accuracy in optimal planning, it is essential to combine, time-variation, GF, and uncertainty to create RES and load model. Here, the hourly time-variation of general load and solar PV are introduced by scaling factors constructed using the historical data. The real power of the general load and power generated from solar PV plant connected at the \(i^{th}\) location (bus) at hour \(h\) of the day in \(f_n^{th}\) year is given by (10) and (11) respectively. As mentioned earlier, the reactive power is calculated using the power factor. Also, it is assumed that the solar power plants are operated at a constant power factor.

\[
p^{i,h,fn}_{\text{D}} = PDF_D\left(\text{FW} (P^D_{\text{pre}}(i)) \times L_{s_i}\right)
\]

\[
p^{i,h,fn}_{\text{PV}} = PDF_{\text{PV}}\left(\text{FW} (P^{PV}_{\text{pre}}(i)) \times PV_{s_i}\right)
\]

where, \(P^D_{\text{pre}}(i)\) and \(P^{PV}_{\text{pre}}(i)\) represents the present value of real power demand and power generated from solar power plant respectively at the \(i^{th}\) location, \(L_{s_i}\) and \(PV_{s_i}\) represents the hourly scaling factor of general load and solar PV respectively. As mentioned earlier, the distribution of electric vehicle load on the distribution system depends on the clustering. From the survey and the outcome of clustering, it is apparent that the cluster with a higher population and load density has comparatively more electric vehicles. Therefore, in this article, the electric vehicle loads are distributed in the cluster having a high population and load density as given by (12).

\[
p^\text{Nc,Ch,fn}_{\text{EV}} = PDF_{\text{EV}}\left(\text{FW} (P^{\text{EV}}_{\text{pre}}(i_{Nc})) \times EV_{s_i}\right)
\]

where, \(P^{\text{EV}}_{\text{pre}}(i_{Nc})\) represents the present value of electric vehicle power demand at \(i_{Nc}\) location, \(EV_{s_i}\) represents the hourly scaling factor of electric vehicle load, and \(C_h\) represents the charging hours of EV. This power is distributed within a cluster about the EV distribution index (EV_{DI}). As mentioned earlier, this index is the ratio of the number of EVs in operation for the selected cluster to the total number of EVs in operation. It is assumed that the electric vehicle load is operated at a constant power factor.

B. OPTIMIZATION PROBLEM

The objective function of the optimization problem comprises of five parameters namely the capital investment of HESU, operation and maintenance cost of HESU, land required to install the optimal HESU & its associated cost, price of environmental impact due to HESUs and the grid performance parameters such as voltage deviation cost, cost of line loading, cost of apparent power loss are represented from equation (13) to (22).

\[
P_{\text{Obj}} = \left[C^HESU_I + C^HESU_OM + C^{HESU}_{\text{land}} + C^{HESU}_{\text{env}} + C^G_P\right] \times 365
\]

\[
(13)
\]
where

\[
C_{HESU}^t = \sum_{i=1}^{N_{ESU}} \left[ C_{ESU,i}^t + C_{ESU,i}^{\text{ESU}} + C_{ESU,i}^{\text{ESU}} \right]
\]

(14)

\[
C_{OM} = \sum_{i=1}^{N_{ESU}} \sum_{j=1}^{N_{P}} \left( [P_{\text{sell},ij} + T_{\text{sell},ij}] - P_{\text{pur},ij} \right) \times C_{\text{ESU,OM}} + p_{\text{ESU,OM}}
\]

(15)

\[
p_{\text{rated}} = \sum_{i=1}^{N_{ESU}} \left[ p_{\text{ESU,i}} \right]
\]

(16)

\[
c_{\text{land}} = \sum_{i=1}^{N_{ESU}} \sum_{j=1}^{N_{N_b}} \left( L_{\text{Cap}} N_b \times C_{\text{land}} \times A_{\text{ESU,i}} / \sqrt{N_b} \right)
\]

(17)

\[
c_{\text{env}} = \sum_{i=1}^{N_{ESU}} \sum_{j=1}^{N_{N_b}} \left( p_{\text{dist},ij} \times C_{\text{ env}} \times \text{env} \right)
\]

(18)

\[
C_{P}^t = C_{\text{VD}}^t + C_{\text{LL}}^t + C_{\text{SP}}^t
\]

(19)

\[
c_{\text{VD}}^t = \sum_{b=1}^{N_b} \left( V_{\text{Rated}} - V_{\text{HESU}} \right) \times C_{\text{VD}}
\]

(20)

\[
c_{\text{LL}}^t = \sum_{l=1}^{N_l} \left( \%_{\text{LL}} C_{\text{HESU}} \right) \times C_{\text{LL}}
\]

(21)

\[
c_{\text{SP}}^t = \sum_{l=1}^{N_l} \left( P_{\text{Loss,LL}}^2 + Q_{\text{Loss,LL}}^2 \right) \times C_{\text{SP}}
\]

(22)

The first term of the objective function presents the installation cost of HESU, which includes power rating cost in $/kW-day, energy rating cost in $/kWh-day and fixed installation cost in $/kW-day. The second term presents the operation and maintenance cost of HESU, which comprises two components, such as the cost of energy trade and the fixed price. The energy trade cost (in $/day) is defined as the difference in cost between the energy sold and the energy purchased at any time \(t\) of a day. As the city or an area witness the development, the value of the land and its availability plays a vital role in the installation of HESUs, which is represented in the third term of the objective function. The same is calculated based on the price of the land in $/sq.m multiplied by the physical size of HESU in sq.m. The value and the availability of land are modeled with land cost index (LCI) which denotes the category for the location of the land. Here, the original data of land cost (in $/sq.m) is considered [43]. A significant part of the economy of a country is spent on compensating the climate-driven damage [44]. Therefore, it is essential to consider the cost of environmental damage created by HESUs, which is represented in the fourth element as the cost of damage created by CO\(_2\) emission from HESUs in $/day. The last term of the objective function deals with the cost involved in HESU affecting the grid performance. The time limit considered here is one day on \(f_{\text{in}}\) year, and the operation cost is calculated for one day with an interval of 15 minutes. However, the total cost is calculated for \(f_{\text{in}}\) year.

The proposed objective function is subjected to the following constraints:

1) GRID OPERATIONAL CONSTRAINTS

The power demand at any time \(t\) at \(f_{\text{in}}\) bus must be satisfied by power from the grid, RPO based REPs, power loss, and the power injected or absorbed by HESU [45]. When any energy source or storage system is integrated with the grid, the performance of the grid is affected [46]. The operational constraints of the distribution network are given by (23) – (28), which includes, the real and reactive power balance, power flow equations, voltage limits, and line loading limits.

\[
p_{\text{D},t}^{f_{\text{in}}+} + p_{\text{EV}}^{f_{\text{in}}+} = p_{\text{PV}}^{f_{\text{in}}+} + p_{\text{HESU}}^{f_{\text{in}}+} + p_{\text{grid}}^{f_{\text{in}}+} + p_{\text{loss}}^{f_{\text{in}}+}
\]

\(\forall \ t = 1, 2, 3, \ldots, N_i\)

(23)

\[
Q_{\text{D},t}^{f_{\text{in}}+} + Q_{\text{EV}}^{f_{\text{in}}+} = Q_{\text{PV}}^{f_{\text{in}}+} + Q_{\text{HESU}}^{f_{\text{in}}+} + Q_{\text{grid}}^{f_{\text{in}}+} + Q_{\text{loss}}^{f_{\text{in}}+}
\]

\(\forall \ t = 1, 2, 3, \ldots, N_b\)

(24)

\[
p_{\text{flow}}^{f_{\text{in}}+} = V_{\text{flow}}^{f_{\text{in}}+} \times \sum_{i,j \in N_b} V_{i,j}^{f_{\text{in}}+} (G_{ij}\cos\theta_{ij,t} + B_{ij}\sin\theta_{ij,t})
\]

(25)

\[
Q_{\text{flow}}^{f_{\text{in}}+} = V_{\text{flow}}^{f_{\text{in}}+} \times \sum_{i,j \in N_b} V_{i,j}^{f_{\text{in}}+} (G_{ij}\sin\theta_{ij,t} - B_{ij}\cos\theta_{ij,t})
\]

(26)

\[
V_{\text{min}} < V_{i,j}^{f_{\text{in}}+} < V_{\text{max}} \quad \forall b = 1, 2, 3, \ldots, N_b
\]

(27)

\[
LL_{i,j}^{f_{\text{in}}} < LL_{\text{max}}^{f_{\text{in}}} \quad \forall l = 1, 2, 3, \ldots, N_l
\]

(28)

2) HESU CONSTRAINTS

The absorbed or injected power from HESU depends on its mode of operation, namely charging and discharging mode [47]. This mode of operation is constrained concerning the energy capacity limits, charging power and discharging power limits, limits of the state of charge (SOC), apparent power to be delivered, the maximum budget allocated, and the energy to power ratio of individual HESUs. Then summation of these constraints is considered as the constraints of HESU. Therefore, the constraints of HESU are modeled as: both charging and discharging mode of operation are represented by (29) to (42), and budget limits, energy to power ratio & apparent power are represented in equation (43), (44) & (45) respectively.

**Charging mode:**

\[
E_{\text{HESU}}^{f_{\text{in}}+} = \sum_{i=1}^{N_{ESU}} E_{\text{ESU}}, t^{f_{\text{in}}+} \quad \forall t = 1, 2, 3, \ldots, N_t
\]

(29)

\[
E_{\text{ESU}}, t^{f_{\text{in}}+} = \min \left[ \left( E_{\text{ESU}}, t^{f_{\text{in}}+} - \Delta t \times \frac{P_{\text{ESU},t}^{f_{\text{in}}+}}{\eta_{\text{ch},t}} \times \frac{1}{F_{\text{max}}^{f_{\text{in}}+}} \right), E_{\text{ESU},t}^{f_{\text{in}}+} \right]
\]

(30)

\[
P_{\text{ESU},t}^{f_{\text{in}}+} < P_{\text{ESU},t}^{f_{\text{in}}+} \quad \forall t = 1, 2, 3, \ldots, N_t
\]

(31)

\[
E_{\text{ESU},t}^{f_{\text{in}}+} = \min \left[ \left( E_{\text{ESU},t}^{f_{\text{in}}+} - \frac{\Delta t \times P_{\text{ESU},t}^{f_{\text{in}}+}}{\eta_{\text{dis},t}} \right), E_{\text{ESU},t}^{f_{\text{in}}+} \right]
\]

(32)

**Discharging mode:**

\[
E_{\text{HESU}}^{f_{\text{in}}+} = \sum_{i=1}^{N_{ESU}} E_{\text{ESU}}, t^{f_{\text{in}}+}
\]

(33)

\[
E_{\text{ESU}}, t^{f_{\text{in}}+} = \max \left[ \left( E_{\text{ESU}}, t^{f_{\text{in}}+} - \Delta t \times \frac{P_{\text{ESU},t}^{f_{\text{in}}+}}{\eta_{\text{dis},t}} \right), E_{\text{ESU},t}^{f_{\text{in}}+} \right]
\]

(34)

\(\forall t = 1, 2, 3, \ldots, N_t\)
where

\[ P_{\text{ESU, max}} = \min \left\{ P_{\text{ESU, max}}, \frac{\left( E_{t, \text{ESU}} - E_{t, \text{ESU}} \right) \times \eta_{\text{dis}, i}}{\Delta t} \right\} \]

\[ \forall t = 1, 2, 3, \ldots, N_t \]  

\[ P_{\text{ESU, min}} = \max \left\{ P_{\text{ESU, min}}, \frac{\left( E_{t, \text{ESU}} - E_{t, \text{ESU}} \right) \times \eta_{\text{ch}, i}}{\Delta t} \right\} \]

\[ \forall t = 1, 2, 3, \ldots, N_t \]  

\[ \text{SOC}_{\text{min}}^{\text{HESU}} \leq \text{SOC}_{1}^{\text{HESU}} \leq \text{SOC}_{\text{max}}^{\text{HESU}} \]  

Equation (47) describes the total charging and discharging power flow into the ESU in a day must be equal. This equality constraint is relaxed by using a factor \( D_f \). The total charging and discharging energy must be less than or equal to the maximum energy capacity of ESU, represented in (48) and (49).

Equation (50) represents the sum of discharging power in a day must be less than the total energy demand of that day at the bus where ESU is placed.

To optimize the stated problem (both primary and secondary objective function), a methodology is proposed as mentioned in figure 2. The steps followed in this proposed methodology are as follows:

Step 1: Obtain the optimal number of clusters for the chosen distribution network as shown in figure 1.

Step 2: Calculate the FV of electric vehicle demand using (2) and distribute it uniformly across the cluster in which both the population density and load density are high.

Step 3: Obtain the probability distribution of general load and electric vehicle load using (10) and (12) respectively and the power generated from solar power plant using (11).

Step 4: Develop the DigSILENT PowerFactory model of the distribution network using the data from step1 to step3.

Step 5: Read the parameters of the optimization algorithm, maximum iteration, and the data obtained from step1 to step3.

Step 6: Randomly initialize the position (size and location vectors) and its velocity for all the particles. Generate the location array \( \ell \) of size \( N_b \) with values of 0s and 1s and the size array of HESU (takes continuous values between the limits).

Step 7: Generate an array, representing the size of Li-ion ESU and Na-S ESU where the sum becomes the size of HESU generated in step5.

Step 8: Check the condition for elements in \( \ell \) equal to 1. If yes, place the HESU with size obtained from step5; else skip the bus location.

Step 9: Perform probabilistic load flow (PLF) using probabilistic analysis tool of DigSILENT PowerFactory.

Step 10: Check for the violation of constraints mentioned from (23) to (45). If violated, go to step6; else go to the next step.

Step 11: Initialise the state of HESU as an idle state. Read the time of day (TOD) characteristics and its tariff details, size of HESUs, Investment cost (using (14)), Energy demand at which the HESU is placed, energy to power ratio of Li-ion & Na-S ESUs and its charging and discharging efficiencies.

Step 12: Check for the conditions of TOD to obtain the state of HESU. If TOD refers to Off-peak, Normal, and Peak hours (Morning/Evening) then change the state of HESU to Charging, Inactive, and Discharging state respectively.

Step 13: Obtain the optimal charging and discharging characteristics of HESUs by maximizing the equation (46) constrained from equation (47) to (50) using LP.

Step 14: Calculate the value of an objective function using (13).

Step 15: Update the local and global best for all the PSO’s particles concerning the value of objective function calculated in step14.

Step 16: Update the velocity vectors of PSO & BPSO as follows:
Step 16a: Update the velocity corresponding to size using (51).

Step 16b: Update the velocity corresponding to the location using sigmoid-function based BPSO [49].
Step 17: Update the new position (size and location) vector based on the velocity calculated in step 16.

Step 18: Check for maximum iteration/convergence criteria. If achieved, display the optimal results else update the iteration counts and go to step 6.

Even though the PSO algorithm is widely applied in various optimization problems, it can get weak in finding a global optimal solution as the PSO particles may converge prematurely around the local minimum. From the literature, it is evident that the PSO algorithm fails to converge at a global minimum or ends up with premature convergence when the velocity parameter approaches a value very near to zero. In other words, if the velocity vector is very close to zero, the position vector cannot move from its previous position significantly and therefore resulting in premature convergence or settling at a local minimum. To address this problem, the average absolute value of the velocity vector is calculated at the end of every iteration and this can be
utilized to improve the exploratory ability of PSO. However, to increase the strength of the exploration ability of the algorithm, it is desirable to have a high average velocity for a longer duration in the initial stage of optimization. During the ending stage of optimization, the average velocity must take small value for a longer duration to obtain the optimal solution. Therefore to avoid such types of results, the authors have applied a methodology proposed in [50]. Here, the velocity of PSO is calculated using a nonlinear function as given below:

\[
v_{new}(t) = v_{initial} \times \frac{1 + \cos \left( \frac{t \cdot \pi}{2.95 \cdot T_{max}} \right)}{2}
\]

where \(v(t)_{new}\) is the updated velocity for PSO particle, \(v_{initial}\) is the initial velocity (generated randomly), \(T_{max}\) is the maximum number of iterations.

The inertia weights of PSO are calculated using (52) and (53) depending on the conditions specified.

\[
w(t + 1) = \max (w(t) - \Delta w, w_{min}) \text{ for } v_{avg}(t) \geq v_{new}(t + 1)
\]

\[
w(t + 1) = \min (w(t) + \Delta w, w_{max}) \text{ for } v_{avg}(t) < v_{new}(t + 1)
\]

V. RESULTS AND DISCUSSION

In this study, the optimal planning of HESU is performed for a practical 156-bus system of Dehradun district, Uttarakhand, India. The DigSILENT PowerFactory model of this system is shown in figure 3. All experiments of this study are conducted on a computer with Intel i7-4510U CPU and 8 GB RAM. A survey is conducted mainly to recognize the uncertainty and growth rate of general load, electric vehicle load, and solar power generation. It is observed that the electric vehicles are regularly charged between 9 PM to 7 AM (for about 10 hours). For that reason, the hourly scaling factor of EV is given as \(EV_{sh} \in [0, 1] \forall h = 1, 2, \ldots, 7, 21, 22, \ldots, 24\). The hourly scaling factor of general load (for summer and winter) and solar PV are shown in figure 4 and figure 5 respectively. Other input parameters are shown in Table 2.

As discussed in section II, the electric vehicle loads are mostly distributed in regions where the population and load density are high. As mentioned before, the optimal number of clusters is obtained by CQI. After applying the methodology shown in figure 1, the optimal number of clusters will be six. Consequently, the curve of CQI shown in figure 7 has attained its peak value at 6, which shows that the Dehradun district is clustered into six numbers of regions. The distribution network nodes (bus) located in these clustered regions are shown in figure 8. This figure also depicts the spread of the distribution network over mixed terrain. The distribution of electric vehicle load on these regions was carried based on \(EV_{DI}\) as shown in Table 3. For better understanding, the cluster color used in figure 8 is presented in this Table.
The characteristics of HESU charging and discharging obtained by maximizing the secondary objective function (arbitrage cost) for summer and winter are shown in figure 9 and figure 10 respectively. By incorporating the input parameters (shown in Table 2) to the proposed methodology (shown in figure 2), the optimal results obtained are shown.
in Table 4. It is evident from the cluster no represented in Table 4 that, the sixteen optimal locations of HESU are widely spread across the network. Since the HESUs are distributed completely throughout the network region, these can serve critical loads (or part of load connected) in case of grid failure. After placing the HESUs at optimal locations with the size mentioned in Table 4, the bus voltage profile has significantly improved. This is shown in figure 11, as a comparison of bus voltage profile with and without HESU in terms of percentage. From the obtained results, the one having global minima and also converged with less number of iterations is shown in figure 12. From this, it is evident that the proposed methodology converges to a global minimum at around 110th iteration count.

As mentioned earlier, recent studies prove that Li-ion ESU contributes to CO₂ emission significantly. Also, it is nearly impossible in today’s scenario to completely replace this technology as it has shown promising results in terms of
TABLE 4. Optimal results on dehradun distribution network from proposed methodology.

| Location Name | Latitude  | Longitude | Cluster No | Optimal Size of HESU | Optimal Size of Li | Optimal Size of NaS | Optimal value of Objective Function |
|---------------|-----------|-----------|------------|----------------------|-------------------|-------------------|-------------------------------------|
| Anarwala      | 30.3657   | 78.0445   | 2          | 1.5219               | 0.9769            | 0.5450            | 164638252.424480                    |
| Araghar       | 30.3069   | 78.0499   | 2          | 0.9603               | 0.2452            | 0.7151            |                                     |
| Bindal        | 30.3305   | 78.0297   | 2          | 1.4004               | 0.7797            | 0.6207            |                                     |
| Dakpatti      | 30.3916   | 78.0944   | 3          | 1.4151               | 0.5194            | 0.8957            |                                     |
| ITpark        | 30.3015   | 78.0583   | 2          | 0.5376               | 0.5188            | 0.0188            |                                     |
| Landour       | 30.4555   | 78.1023   | 1          | 1.1377               | 0.8634            | 0.2743            |                                     |
| Miyawala      | 30.267    | 78.0909   | 4          | 0.9331               | 0.1464            | 0.7867            |                                     |
| Nagarpalika   | 30.10647  | 78.28156  | 0          | 0.6385               | 0.5835            | 0.0550            |                                     |
| Naghat        | 30.5721   | 77.9721   | 5          | 1.1453               | 0.2682            | 0.8771            |                                     |
| Nirjanpur     | 30.2967   | 78.0141   | 4          | 0.717                | 0.6975            | 0.0195            |                                     |
| Raipur        | 30.309    | 78.0948   | 2          | 0.8413               | 0.7894            | 0.0519            |                                     |
| Raiwala       | 30.0222   | 78.2147   | 0          | 1.1595               | 0.4960            | 0.6635            |                                     |
| Sahaspur      | 30.3927   | 77.8096   | 4          | 0.579                | 0.4826            | 0.0964            |                                     |
| Savra         | 30.82238  | 77.8546   | 5          | 1.0249               | 0.9858            | 0.0691            |                                     |
| Tuini         | 30.9429   | 77.8496   | 3          | 1.7432               | 0.9160            | 0.8272            |                                     |
| VasantVihar   | 30.3226   | 78.0037   | 2          | 0.778                | 0.1340            | 0.6440            |                                     |

FIGURE 13. Comparison of CO2 emission with only Li-ion and HESU.

TABLE 5. Damage cost comparison with only Li-ion and HESU in Dehradun distribution network.

| ESU with only Li-ion | HESU |
|----------------------|------|
| Damage cost due to CO2 emission (in $) | 259902.7 | 159543.9 |

VI. CONCLUSION

In this article, the HESU planning for an Indian mixed terrain distribution grid is carried out by modeling the problem with practical constraints such as RPO, land required to install HESU & its associated cost, CO2 emission from ESU affecting the environment. Apart from this, a survey is conducted from which the uncertainty parameters related to general load, EV load, and Solar PV generation are calculated and introduced in the model. From the survey, it was concluded that the EV loads are not connected throughout the distribution network. Therefore, the distribution network is clustered based on load density, geographical data (latitude, longitude, and MSL), TI, and population. After this, the EV loads are placed on clusters where both the population and load density are high. Within the cluster, the EV loads are distributed using EVDI (obtained from the survey). Having these data, the distribution system is modeled in DigSILENT PowerFactory and the optimal planning of HESU is obtained from the proposed methodology. Although the ESU planning in literature did not consider the environmental impact, it has the utmost importance for sustainable planning. To minimize the emission level from ESU, a hybrid combination of popular Li-ion battery along with Na-S battery technology has been implemented using the proposed methodology. The optimized results paved a way towards reduced damage cost due to CO2 emission significantly, by considering other components such as uncertainty (of load and solar PV), grid performance cost, land cost index, operation and maintenance cost, arbitrage cost, and capital investment. The studied region in this article is situated in the Uttarakhand state of India; the state has witnessed the frequent natural calamities in the past including the horrific incident at
Kedarnath, Uttarakhand in 2013. From the results obtained, it is also evident that the HESUs are widely spread across all the clusters of the distribution network. Therefore, the same HESUs can be utilized to form microgrids to satisfy critical demand during grid failure.

**ANNEXURE - I**

see Table 6.

**TABLE 6. General load data of each substation in Dehradun distribution network.**

| Substation | General Load in MVA | Substation | General Load in MVA |
|------------|---------------------|------------|---------------------|
| Jabalpur   | 14.9163             | Nagarpalika| 9.043938            |
| Anarwala   | 14.37119            | Naghat    | 1.87563             |
| Araghar    | 34.63952            | Natraj    | 12.76062            |
| Bairaj     | 5.971476            | Niranjanpur| 22.84524            |
| Bhaniyawala| 8.424491            | ParadeGround| 25.76903           |
| Bindal     | 16.72509            | PatellRoad| 16.62598            |
| Chatraka   | 8.052823            | Raipur    | 7.185594            |
| Dakpatti   | 12.88451            | Raiwala   | 9.55583             |
| Ganeshpur  | 7.557264            | RammagarDanda| 4.212245           |
| Govindgarh | 9.73772             | Rudrapur  | 2.339902            |
| Harbertpur | 10.53061            | SIDCUL    | 24.77791            |
| Hathibakaraka| 11.49695           | SaharanpurRoad| 13.05796          |
| HimalayanHospital| 0.991117        | Sahaspur  | 13.0084             |
| Gpark      | 11.59606            | Safastraehara| 18.03832           |
| Jollygrant | 6.251237            | Sahiya    | 2.329124            |
| Kargi      | 15.80831            | Savra     | 0.099112            |
| Kaulagarh  | 22.64701            | Selaqui   | 27.85038            |
| Kunjabhavan| 9.316495            | Selaqui2  | 15.11453            |
| Kyarkuli   | 5.748475            | ShantiKunj| 5.451141            |
| Lachiwala  | 9.440385            | SportsCollege| 5.946699           |
| Lakhmandal | 1.561009            | TransportNagar| 15.85787          |
| Laltapper  | 6.194479            | Tuini     | 4.088356            |
| Landour    | 8.306061            | TurnerRoad| 16.99765            |
| ManeriBhal | 1.313229            | VasanVihar| 12.83496            |
| Miyawala   | 13.97474            | VikasNagar| 16.10564            |
| Mohanpur   | 19.20288            |           |                     |

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