Optimal Grid-connected Hybrid Renewable Energy Sources with and without EV using Adaptive-Crow Search Optimization

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Abstract- Obtaining the optimum amount of different renewable energy sources to meet demand at the lowest feasible cost and with the highest level of reliability is the primary objectives of this paper. Two different operating modes are taken into consideration for this target: Battery/PV/wind/ and Battery/PV/wind/ EV. In the initial situation the optimal number of components and cost at different levels of dependability has been determined by the suggested algorithm. An EV with predictable and unpredictable condition is introduced to the system in the second situation, and the LPSP is calculated in both modes. EVs have been depicted to enhance system dependability. This study resolves the novel optimum size problem for Hybrid RESs with EVs to reduce costs and improve system reliability by applying the proposed Adaptive Crow Search (Aadp-CSO) algorithm. *The Adap-CSO technique proposed here is a swarm intelligence-based solution influenced by the behavior of the crows that addresses the confines of the standard CSO algorithm.* Additionally, the arrival SOC of the electric vehicle and the arrival and departure timeframes are among the uncertainties related to the EVs that are predicted using Matlab Simulink. According to the results, the designs of both systems are feasible; nevertheless, the first system was more efficient than the second since it used fewer wind units. Lastly, the impact on choice factors of increasing and decreasing wind speed and load demand by 10%, 20%, and 30% was investigated.

Keywords— Wind; Solar Photo Voltaic; Electric vehicle Battery; and CSO

Terminologies

Abbreviation	**Description**
PV	Photo Voltaic
WT	Wind Turbine
RES	Renewable Energy Sources
MG	Micro-Grid
Adap-CSO	Adaptive crow search optimization
TLBO	Teaching–Learning-Based Optimization
LPSP	Loss Of Power Supply Probability
SOC	State Of Charge
DG	Distributed Generations
ES	Energy Storage

ALO	Ant Lion Optimization
EV	Electric Vehicles
RB-EMS	Rule-Based Energy Management Strategy
CSA	Cuckoo Search Algorithm
VAWT	Vertical Axis Wind Turbine
PSO	Particle Swarm Optimization
JLBO	Jaya Learning-Based Optimization
HAWT	Horizontal Axis Wind Turbine
REF	Renewable Energy Fraction
EGC	Energy Generation Cost
TAC	Total Annual Cost
BESS	Battery Energy storage system

I. INTRODUCTION

In order to elude complications, mostly in distribution networks, RESs have established in latest periods. The Hybrid RES idea, which combines RES with DGs and ESSs to meet local demand with acceptable reliability, is selected to address the intermittent character of RESs [1]. Maximizing the sizes of assets required to meet the system's greatest demand while trying to lower the system's overall costs in light of technological constraints is the main problem in these types of systems. On the other hand, road transportation is linked to the world's excessive energy consumption, which results in environmental issues [2]. EVs are marketed as the greatest tools for cutting down on energy consumption and emissions into the atmosphere. Variable performance modification is essential for methodologies to produce optimal outcomes. Optimal solutions with prolonged computation periods could result from improper adjustment of algorithm-specific variables. It is a difficult challenge to use meta heuristic algorithms in planning, sizing [3], and constructing the contemporary optimization approaches of hybrid systems/microgrid systems. The system components that contain PV-WT-BT were sized using ant lion optimization, one of the newest meta heuristic algorithms [4]. To validate the obtained result from ant lion optimization [7], power flow issues are examined utilizing the PSO [5] and CSA [6]. In order to lower costs and improve system availability, this publication must introduce a fresh optimal size challenge for hybrid RESs in the context of EVs.

Using the MOPSO method for one residence, D. Sadeghi et al. [8] developed a novel optimum sizing issue for HRESs in the presence of EVs in 2022 with the goal of minimizing costs and maximizing system dependability. Additionally, MCS is utilized to estimate the uncertainties related to EVs, such as the number of arriving SOC and the dates of arrival and departure. A sensitivity study has been conducted to ascertain the effects of variations in wind speed and load demand on specific criteria, and the proposed framework is applied in probabilistic and predictable scenarios.

The JLBO algorithm, a hybrid of the Jaya and TLBO algorithms, was proposed by Asif Khan and Nadeem Javaid [9] in 2020 as a way to optimize the sizing of a PV-WT battery system in order to service the consumer's load with the lowest TAC. To estimate system consistency, a maximal LPSP model is useful. The results show improved TAC performance, and this model provides a less costly option for all recommended LPSP measures, especially when compared to the WT-battery and PV-battery models. Diab, A et al. [10] proposed a modified farmland fertility optimization algorithm based optimal RES scaling method in 2019 that is very reliable and emits no emissions or pollutants. The optimal component size is determined through the optimization process in order to achieve the lowest cost of power output. Integrating LPSP as a cost consequence within the EGC is the system's objective. Compared to the current SOA and MFFA approaches, the proposed optimization methodology has produced superior results and converged more quickly in terms of accuracy and calculation time.

The Sparrow Search Optimization method, a metaheuristic optimization technique for scaling system components to satisfy load demand by reducing the two objective functions, such as LPSP and Cost of Electricity while maximizing the REF, was developed in 2023 by Mohan.H et al. [11]. Additionally, the RB-EMS is expected to regulate the power flow in the system. The outcomes depict that the performance of the offered scheme is improved in an on-grid structure.

Hyeon Woo et al. [12] developed a method in 2022 for determining the optimal DG unit and EVCS sizing, which aids in accurate power system analysis and ensures EV driver happiness. To minimize loss and harmonics, the optimal size of the system's liabilities problem is proposed using probabilistic second-order conic software development. This convex issue illustrates the unpredictability of AC power flow and can be solved in polynomial time. An enhanced IEEE 15 bus system is used to validate the approach, and simulations with several goals are conducted. Therefore, the results of the recreation show that the recommended approach is effective.

The key effects of this paper are as :

- An Adap-CSO algorithm is given to address the optimal sizing problem of hybrid RESs in electric vehicle systems.
- The quantity of arriving SOC and the uncertainty relating to the EVs contributing to the arrival and departure times are modeled using the proposed algorithm.

The manuscript is organized as follows: Section I provides a summary and review of the hybrid RES system.Modelling of hybrid RES is explained in Section II. The optimal sizing problem is explained in Section III using the suggested Adap-CSO model. The results of the planned work are shown in Section IV, and the conclusion of the paper is explained in Section V.

II MODELLING OF HYBRID RES

A. Solar PV System

An energy system that generates electricity from sunshine without the need of mechanical or chemical processes is known as a photovoltaic system [8]. Stated differently, these technologies generate clean, reliable energy that is independent of fossil fuels. Equation (1) is used to calculate the solar array's output power, as shown below.

$$P_o(t) = P_r \eta \left(\frac{G_C(t)}{G_{st}} \right) \left[1 + \beta \left(T_s(t) - T_{st} \right) \right] \tag{1}$$

$$T_s(t) = T_l + \frac{NOCT - 20}{800} G_C \tag{2}$$

where, P_o denotes the solar output power, P_r signify the rated power, η represents the coefficient of reduction of solar surface module between 0.9 and 0.94, G_{st} is the light intensity, G_c signifies the intensity of light under certain conditions, β represents the temperature coefficient, T_{st} is the temperature standard , T_s is the temperature surface, T_l regards to the temperature of panel position, and $NOCT$ indicates the nominal operating cell temperature that lies between 0 and 2^0C [11].

B. Wind Energy System

Two types of wind turbines, such as VAWT and HAWT, can be distinguished [13]. The HAWT is the most popular kind of wind turbine for a number of reasons, such as its ability to harness significant wind energy, its ability to adjust the pitch angle of its blades to avoid severe windstorms, and its ability to withstand low wind [14]. Thus, the frame, generator with gearbox and controls, and rotor with blade are the three fundamental parts of a wind turbine. Therefore, Equation (3) is used to determine the power produced by the wind turbine [15] [16].

$$P_{wt} = \begin{cases} P_n \dfrac{N_w - N_{ci}}{N_r - N_{ci}}, & N_{ci} \le N_w \le N_r \\ P_n & N_r \le N_w \le N_{co} \\ 0 & N_w \le N_{ci} \; or \; N_w \ge N_{co} \end{cases} \tag{3}$$

Where, cut-out speed, rated speed and cut-in speed of the WT in m/s , P_{wt} signifies the power output of wind; P_n represents nominal power of both turbine's; N_w , N_{co} , N_{ci} and N_r indicates the wind speed,. Figure. 1 depicts the Schematic illustration of the suggested hybrid RES with an EV structure.

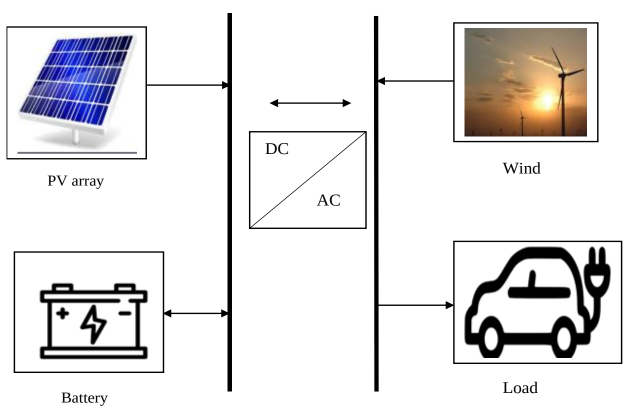

Figure. 1 Schematic diagram of the suggested hybrid RES with an electric vehicle structure

C. Mathematical model of BESS

Power system dependability and electrical power quality are among the problems that arise with the quick expansion of DG resources, particularly with regard to PV and wind turbines. In actuality, the intermittent and sinusoidal behavior throws off the generation-consumption balance, which could cause problems with grid stability. The discrepancy between production and consumption is addressed by the storage systems [17].

When the total power output from WT and PV exceeds the load, the battery is said to be in a charging state, as determined by mathematical calculations.

$$SOC_B(t) = (1-\sigma)SOC(t-1) - P_{charge}(t)\alpha_c \frac{\Delta t}{C_r} \tag{4}$$

The battery's state of charge (SoC) reaches the discharging state if the total power output produced by WT and PV is less than the load requirement. This is determined by

$$SOC_B(t) = (1-\sigma)SOC(t-1) - P_{discharge}(t)\frac{\Delta t}{C_r \alpha_d} \tag{5}$$

Where, C_r indicates the rated capacity; SOC signifies the charging and discharging mode, σ represents the discharge rate , α_c is the charging mode coefficient; α_d is the coefficient of discharging mode; $P_{discharge}(t)$ specifies discharge power and $P_{charge}(t)$ denotes charging power, respectively.

D. Mathematical Model of electric vehicle System

Because of environmental concerns, EVs is being created as an alternative to internal combustion automobiles. EVs may meet and support network operators' objectives in addition to meeting the mobility needs of car owners. They are also economically viable and have a smaller environmental impact. Additionally, when additional variables are present, EV charging and discharging are carried out in the same manner as a regular battery such as $t_{arrival}^{EV}$, t_{depart}^{EV}, $SOC_{arrival}^{EV}$ and SOC_{depart}^{EV}. Similar to this, the arrival time and the entry and leave times of SOC follow a normal distribution function; however, this study addresses a constraint for the EV's departure-time SOC [18] [19].

$$t_{arrival}^{EV} \sim N(\rho_{EV}, \mu_{EV}) \tag{6}$$

$$t_{depart}^{EV} \sim N(\rho_{EV}, \mu_{EV}) \tag{7}$$

$$SOC_{arrival}^{EV} \sim N(\rho_{EV}, \mu_{EV}) \tag{8}$$

$$SOC_{depart}^{EV} \geq 0.2 \times C_{EV} \tag{9}$$

Whereas, $t_{arrival}^{EV}$ and t_{depart}^{EV} signifies the EV arrival and departure time, $SOC_{arrival}^{EV}$ and SOC_{depart}^{EV} indicate the SOC arrival and departure time, μ and ρ denotes the typical deviation and mean value, and C_{EV} is the capacity of electric vehicle

III PROSOSED ALGORITHM FOR THE CAUSE OF OPTIMAL DESIGNING

In the first scenario, the proposed Adap-CSO method was used to determine the optimal element counts and costs of battery/ PV/wind/ systems at different LPSP ranges. After the EV was linked to the model, LPSP was reassessed using the current EV, and its impact on LPSP was investigated. The suggested Adap-CSO algorithm is used to find the starting count of ideal components and pricing for different LPSP ranges with deterministic and stochastic behavior of the EV in a Battery /PV/wind/EV system taking into consideration the second scenario.

A. Objective Model

(i) Cost: The cost may comprise the systems initialization cost (INC), replacement cost (RPC), and maintenance cost (MAC) that are from the related Equations (10), (11), and (12), respectively

$$cost = RPC + INC + INC \tag{10}$$

$$INC = \left(C_{in,w} \times N_w\right) + \left(C_{in,pv} \times N_{pv}\right) + \left(C_{in,b} \times N_B\right) \tag{11}$$

$$MAC = \left(C_{ma,w} \times N_w + C_{ma,pv} \times N_{pv} + C_{ma,b} \times N_B\right) \sum_{t=1}^{T} \left(\frac{1+IfR}{1+ItR}\right)^t \tag{12}$$

$$RPC = \left(C_{r,b} \times N_B\right) \sum_{t=1}^{T} \left(\frac{1+IfR}{1+InR}\right)^t \tag{13}$$

Where, IfR and ItR are the inflation, N_w, N_{pv} and N_B denotes the count of WT, PVs, and battery in the system respectively and interest rate, T signify the lifetime of the system;

(ii) Reliability:

In the first scenario, uncertainty is assessed without taking EV into account; in the second scenario, EV is taken into account.

Without considering EV

$$LPSP = \frac{\sum_{i=1}^{8760} \left[P_{load}(t) - \left(P_{wind}(t) + P_{pv}(t) + SoC_b(t)\right)\right]}{\sum_{i=1}^{8760} P_{load}(t)} \tag{14}$$

Considering EV:

$$LPSP = \frac{\sum_{i=1}^{8760} \left[P_{load}(t) - \left(P_{wind}(t) + P_{pv}(t) + SoC_b(t) + SoC^{EV}(t)\right)\right]}{\sum_{i=1}^{8760} P_{load}(t)} \tag{15}$$

whereas, $SoC_B(t)$ signifies battery power and $SoC^{EV}(t)$ is the EV output power , $P_{wind}(t)$ indicate wind power, $P_{pv}(t)$ represents PV power , $P_{load}(t)$ represent power of load correspondingly.

(iii) Constraints:

The suggested methodology has been adjusted to meet a number of technical confines. These limitations are seen as the charging and discharging of battery's characteristics, power balance, and the cap on the overall number of WT, batteries, and PVs.

$$SoC_{\min} \le SoC(t) \le SoC_{\max} \tag{16}$$

$$P_{pv}(t) + P_w(t) + SoC_B(t) \le P_l(t) \tag{17}$$

Equation (16) shows that the battery's charging range per hour rises above the maximal value and does not fall below the minimum value. The power limit balancing equation is shown in equation (17).

$$N_{MIN} \leq N_{PV} \leq N_{MAX} \quad (18)$$

$$N_{MIN} \leq N_{W} \leq N_{MAX} \quad (19)$$

$$N_{MIN} \leq N_{B} \leq N_{MAX} \quad (20)$$

As a result, the constraints on the quantity of hybrid energy storage system components are shown by eqns. (18), (19), and (20).

B. Adaptive Crow search Optimization (Adap-CSO) Algorithm

The Adap-CSO [20] is a swarm intelligence-based method for determining the optimal solutions to real-time problems. Additionally, the Adap-CSO expands exploration and exploitation comportment. It may converge at the local optimal solution, as shown by the traditional CSO constraints. The environment is the search space, the crows are the searchers, and every location in the environment corresponds to an appropriate optimization outcome. Faster convergence and escapes from local optima are two benefits of the suggested approach. CSO provides a good equilibrium between severity and biodiversity. Simply modifying the setting for Awareness Probability (AP). The CSO attempts to harness the crows' ingenious behavior to find the best solution to the problem based on similar criteria. In order to create the suggested Adap-CSO Algorithm, an enhancement is made to the traditional algorithm CSO. Below is a model of the features of crows.

Step 1: Initialize the parameters: The optimization is done to get optimum solution and the fitness function is taken for unconstrained multivariable function. The number of search agents(SAs) (r), population size (R), and the maximum number of iterations ($iter_{max}$) are also initialized. The awareness probability (P_A), and flight length ($J^{s}_{m,n}$) are chosen from the valuated benchmark functions as cited in [20]. The standard equation of the CSO is given in Equation (21) as,

$$X^{s+1}_{m,n} = X^{s}_{m,n} + p_m \times J^{s}_{m,n} \times \left(d^{s}_{v} - X^{s}_{m,n}\right) \quad (21)$$

where, $X^{s+1}_{m,n}$ is the position of the m^{th} crow in n^{th} dimension at $(s+1)^{th}$ iteration, $X^{s}_{m,n}$ is the position of the m^{th} crow in n^{th} dimension at s^{th} iteration, p_m is the random number between '0' and '1', d^{s}_{v} is the memory of v^{th} crow in s^{th} dimension, and $J^{s}_{m,n}$ is the flight length of m^{th} crow at s^{th} iteration.

Step 2 : Initialize memory and position: The location and the memory of the Search Agent (SA) in n-dimensional space is specified in Equation (22) & (23) correspondingly as,

$$SA=\begin{bmatrix} C_1^1 & C_2^1 & \dots & C_n^1 \\ C_1^2 & C_2^2 & \dots & C_n^2 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ C_1^R & C_2^R & \dots & C_n^R \end{bmatrix} \tag{22}$$

$$memory=\begin{bmatrix} S_1^1 & S_2^1 & \dots & S_n^1 \\ S_1^2 & S_2^2 & \dots & S_n^2 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ S_1^R & S_2^R & \dots & S_n^R \end{bmatrix} \tag{23}$$

The SA have no involvements in the first iteration, therefore the search starts from the beginning at iteration t=0.

Step 3 : **Estimate fitness function:** For the entire SA, the location superiority is esteemed using the decision variable in the fitness function.

Step 4 : **Develop new location:** Each of the SA develops new location within the search space using the fitness function. The state to update position is done with the value of awareness probability and updated using the Equation (24).

Step 5 : **Evaluate the possibility of new locations:** The possibility of a new SA location is evaluated. The SA updates its location if the new location is feasible; else, it remains in the current location.

Step 6 : **Estimate the objective function of new locations:** The optimal value of the new location of every SA is evaluated.

Step 7 : **Updating memory:** The SA updates the memory as in Equation (24),

$$S_{m,n}^{s+1}=\begin{cases} X_{m,n}^{s+1} & f\left(X_{m,n}^{s+1}\right) \text{ is better than } f\left(S_{m,n}^{s}\right) \\ S_{m,n}^{s} & \text{otherwise} \end{cases} \tag{24}$$

where, $f\left(X_{m,n}^{s+1}\right)$ specifies the value of objective function. When the objective function for the new location is best compared to the objective function for the memorized location, then the SA's memory is updated with the predicted new location.

Step 8 : **Validate the termination Condition**: Repeat steps 4–7 until ITmax is achieved. If the termination conditions are satisfied, the better memory location is taken as the solution of the optimization issue.

IV. Results and Discussions

A. Simulation method

The Adap-CSO methodology for Battery/PV/Wind/ and Battery/PV/Wind/EV system was executed in MATLAB Simulink and an examination was done. Any of the learning's significant influences is the quantity of PV, battery and wind. The wind and PV variables have a quest space of 0 to 100 kW, and the battery variables have a quest space of 0 to 100 kWh.

B.CollectedInformation

Figures 2, 3, and 4 depict the one-day load power, solar irradiance, and wind speed values for January. The data was gathered from [21] according to the latitude and longitude of the area.

(i) Battery /PV/Wind/

A Battery /PV/wind/ system is the one that was designed. Results of the study depending on the suggested Adap-CSO approach are shown in Fig. 5, which also shows that the best price and reliability results are obtained by non-dominated measures, which are represented by red-colored dots. The figures illustrate that when the LPSP declines, the cost increases. We must investigate more additional components, which come at a considerable cost, in order to improve system reliability.

(ii) Deterministic behavior of EV and MG operation

Here, the only possible arrival and departure times, together with arrival SOC, are examined, and the vehicle's behavior is expected to be predictable. In Fig. 6, the Adap-CSO calculations are shown. It appears that the red-dot methods provide the best balance between reliability and cost. Figures 10 and 11 show the best and worst LPSP results for the solar panel, battery, WT, and EV in this scenario. As can be observed, the battery and EV will start charging between 1 and 8 and between 17 and 20 hours, and they will start discharging between 1 and 8 hours, when the power exceeds the load. The EV shuts off after eight hours if the electricity exceeds or falls short of the demand. From 8 to 17 hours, the EV is shut off when the electricity exceeds or falls short of the load, and the battery will start charging and discharging on its own.

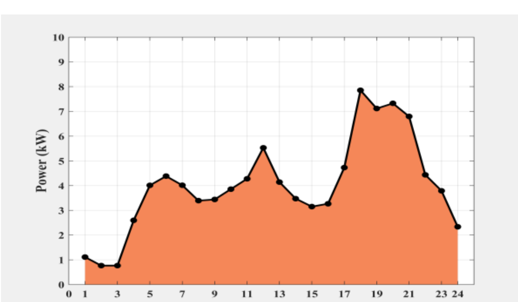

Figure.2 Load Requirement

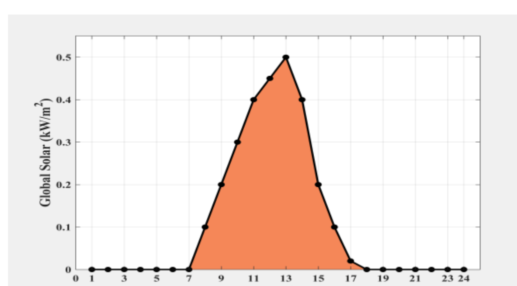

Figure.3 Regional Solar Profile for the Day

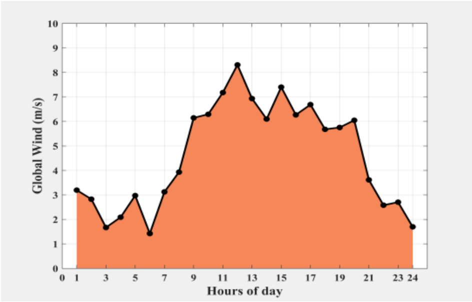

Figure.4 Regional Wind Profile for the Day

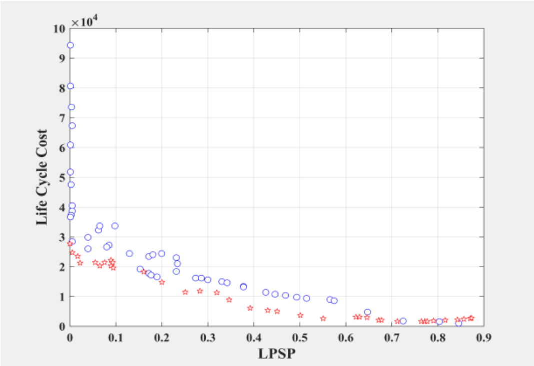

Figure.5 *Equilibrium region of battery /PV/wind*

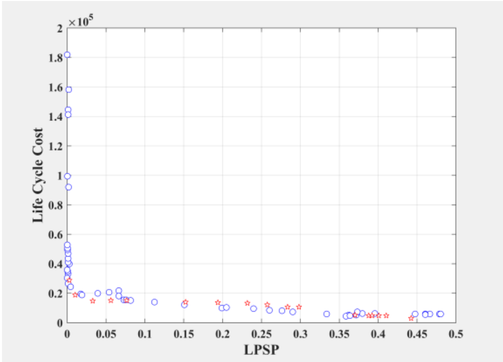

Figure. 6 Equilibrium region of Battery /PV/wind/ /EV

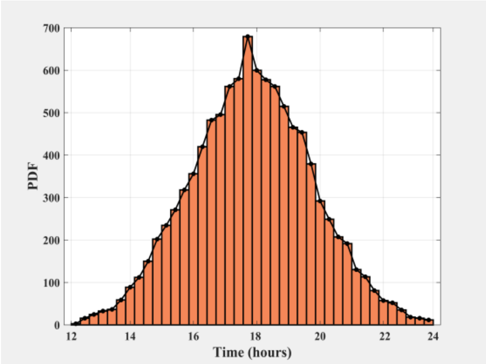

Figure. 7 Electric vehicle Arrival time under Normal distribution function

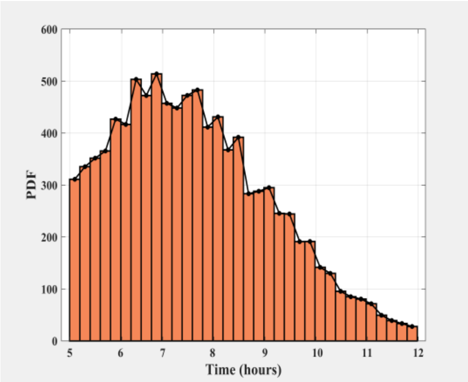

Figure. 8 Electric vehicle Departure time under Normal distribution function

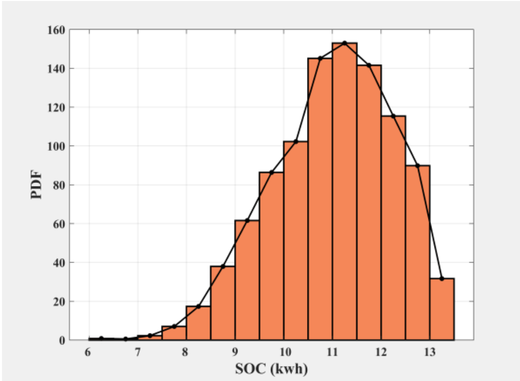

Figure. 9 Electric vehicle Arrival Power under Normal distribution function

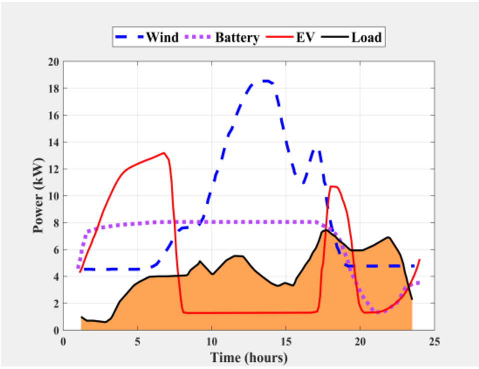

Figure.10 Simulation output for the optimal LPSP

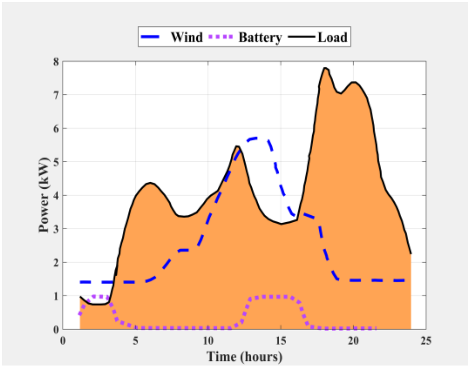

Figure.11 Simulation output for worst LPSP

Figures 7 and 8 depict that the electric vehicle leaves at 7 p.m. and arrives at 18 p.m., with a typical variation of 2 p.m. It is anticipated that the electric vehicle will reach SOC at 80% of its power. With a standard deviation of 10% as in [22], the EV capacity operated according to the normal distribution, as presented in Figure. 9.

(iii) Sensitivity analysis

This portion provides a sensitivity analysis to investigate the impact of two crucial variables, namely wind speed and demand based on results. As a result, by comparing them with fundamental measurements, the amounts of both variables are adjusted to ± 10%, ± 20%, and ± 30%. Figure 12 illustrates the impact of LPSP and LCC variation with changing wind and load.

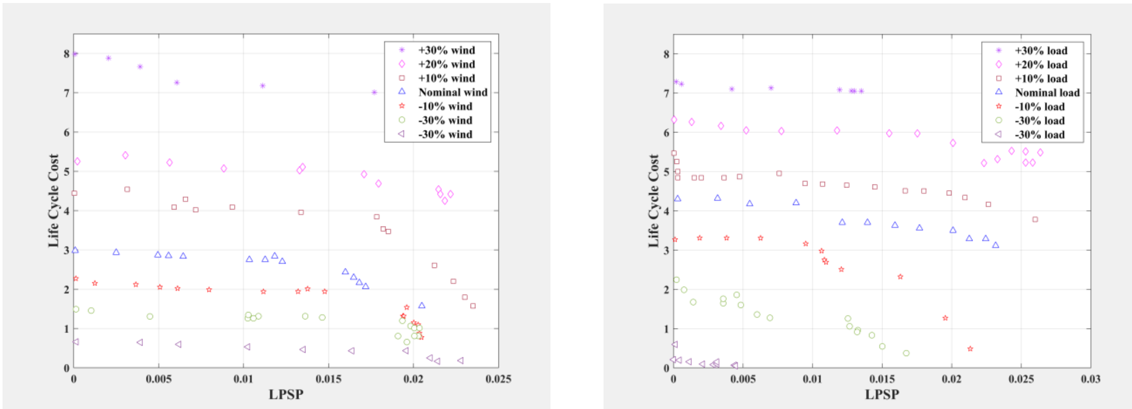

Figure. 12 Effect of equlibrium region by (a) varying wind (b) varying load

V. CONCLUSION

The purpose of this research is to use the Adap-CSO Algorithm to create a single MG that uses RES in two distinct modes, with and without the use of EV, in order to save costs and improve reliability. The capacity to store EV mitigates the risks brought on by RES. Two approaches are used to study the impact of an EV on LPSP: (i) when the behavior of the EV is predictable, and (ii) when the behavior of the EV is considered unpredictable. According to the data, the EV lowers the LPSP in both situations. Additionally, sensitivity analysis was carried out to investigate the effects of altering the wind speed and load demand on the results utilizing the suggested system. Accordingly, outcomes illustrate that altering these values significantly affects the variables used to determine the ideal size of Grid-connected hybrid renewable energy source. In the future, hybrid RES components will be sized effectively using deep learning design.

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