Battery Energy Storage Optimization in Distribution Power Systems with Distributed Renewable Energy Resources

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Abstract- This paper proposes an improved grey wolf optimization technique to determine the optimal location and the capacity of battery energy storage systems (BESS) in distribution power networks with distributed renewable energy resources. The intermittency in the power outputs of the wind and solar energy conversion systems are taken into account in the proposed approach by means of fuzzy logic representation of the input variables to these systems. The fuzzy rule base developed based on the past history data over a year in the identified geographic area generates the power output probability value of these systems for each hour every day based on the current atmospheric conditions. The algorithm proceeds to find the optimal capacity and location of BESS so as to minimize the net present cost of system power loss and the installation and maintenance of BESS. The effectiveness of the proposed approach is evaluated and established on the standard IEEE 33-bus distribution network with the renewable energy resources at identified buses.

Keywords Battery energy storage systems; renewable energy systems; improved grey wolf algorithm; fuzzy modelling, distribution network, power systems.

1. Introduction

Despite numerous benefits, the high-level integration of renewable energy systems (RES) into a power grid is associated with difficulties in maintaining the power generation-load balance, power quality, system stability and power flow. Researchers have used a variety of techniques to improve RES performance such as low voltage ride through, the addition of a harmonic filter and solar tracking facilities, the utilization of conventional generators with a high ramp rate at the central or distribution level, optimization of the load power flow, and the use of flexible AC transmission system (FACTS) devices. Recently, BESS have been utilized to solve the issues associated with power mismatch, power flow and stability in a system with high-level penetration of renewable energy resources. These can store or release power according to the load demand [2], supply the grid with active and reactive power, or absorb it to overcome these challenges and stabilize the power system. BESS can improve RES efficiency [16]. The location and the capacity of BESS have a major effect on its ability to function optimally and produce the desired results. An undersized system will not have the capacity to meet the demand. However, an oversized system results in unnecessary high costs for the network. BESS investment cost has a linear relationship with its capacity, whereas the operating cost is reduced as the capacity increases. Furthermore, an inappropriate location for the BESS results in an inefficient system and/or the need to increase its capacity in the future. This increases the installation cost of the network and the net present cost (NPC). As a result, the system cannot provide the grid with an optimal outcome, either technically or financially. Several optimization techniques have been developed to determine the optimal capacity and location of BESS, which include iterative methods such as DC optimal power flow [1], adopted optimal power flow on a low voltage network [4], and non-linear programming optimization [8]. Other techniques include multi-objective methods such as the non-dominated sorting genetic algorithm II (NSGA-II) [33], artificial intelligence-based methods utilizing artificial neural networks (ANN)[5], genetic algorithms (GA) [10], HOMER Pro computational engine to optimize the size of BESS and RES[11], gravitational search algorithm (GSA)[31] and particle swarm optimization (PSO) [32] methodologies. However, the outcome of the RES is uncertain by nature [12]. One of the major problems associated with these techniques is

addressing the uncertainty of RES, given that each method requires definite parameters. A few approaches reported in the literature takes the intermittence of the RES into account. An example of this is in ref. [6], wherein the RES intermittence is represented as a through probability, and in ref. [14], in which the intermittence is presented as a scenario-based algorithm. In this investigation, fuzzy logic approach is proposed to represent the intermittence of the solar photovoltaic (PVES) and wind energy conversion systems (WES). In this paper, improved grey wolf algorithm (IGWO algorithm) is utilized for the optimization of the capacity and location of BESS in a distribution network incorporating the RES intermittence through a fuzzy logic based approach. The problem formulation and the fuzzy representation of the intermittence of the PVES and WES are discussed in the following two sections. This is followed by IGWO algorithm for BESS optimization. The test system description and the simulation results are discussed in Section 5 followed by conclusion.

2. Problem Formulation

Determination of the optimal location and capacity of BESS is attempted through the minimization of the net present cost involving the cost of power loss (TPLC) and the BESS cost (ICESS) thus the objective function is

$$\text{Min} \sum TPLC + ICESS \tag{1}$$

For improved results, in this formulation, the power loss cost corresponding to the daily peak and off-peak times are separately considered. Thus the daily total power loss cost (TPLC) is

$$\sum TPLC = \sum_{h=1}^{24} \sum \text{P}_{\text{loss}}\, \text{C}_{\text{loss-peak}} + \sum_{1}^{24} \text{P}_{\text{loss}} \text{C}_{\text{loss-Offpeak}} \tag{2}$$

In addition to the power loss cost, it is also intended to minimize the annual installation and maintenance costs of the BESS represented by the variables: the capital power cost ($/kW) (CPESS), the capital energy cost ($/kWh) (CEESS), and the annual maintenance cost ($/kWh) (OMESS). Thus the BESS investment cost (ICESS) given by

$$ICESS = (OMESS + CPESS).PESSrated + CEESS.EESSrated \tag{3}$$

Hence, the problem is to

$$\text{Min} \sum TPLC + ICESS \tag{4}$$

subject to the equality constraints

$$\text{PG} - \text{PD} + \text{PBESSch} = \sum_{J=1}^{n} Vi * Vj * Yij * \cos(\theta\, ij + \delta\, j - \delta\, i) \tag{5}$$

$$\text{PG} - \text{PD} + \text{PBESSdis} = \sum_{J=1}^{n} Vi * V * Yij * \cos(\theta + \delta\, j - \delta\, i) \tag{6}$$

$$\text{QG} - \text{QD} = \sum_{J=1}^{n} V\, i * Vj * Yij * \sin(\theta\, ij + \delta\, j - \delta\, i) \tag{7}$$

and the inequality constraints

$$Vimin \le Vi \le Vimax$$

$$S_{BESSi} \le S_{DSBESS}^{MAx}$$

$$E_{BESSi} \le E_{BESS}^{MAx}$$

Where

i : sending bus.

j : receiving end bus.

n : total number of buses.

Y: bus admittance matrix.

Y_{ij} : ijth element of the bus admittance matrix.

θ_{ij}: Angle of ijth element of the bus admittance matrix

V: bus voltage magnitude.

δ : the phase angle.

$\text{P}_{\text{BESS}}^{\text{ch}}$: BESS input power in the state of charging.

$\text{P}_{\text{BESS}}^{\text{dis}}$: BESS output power in the state of discharging.

P_{D} and Q_{D}: active and reactive power demands

P_{G} and Q_{G}: generated active and reactive power generations

S_{BESS}i and E_{BEESi} : BESS power and energy

The major modules in the proposed approach for the determination of the optimal location and capacity of BESS in a distribution network is shown in Fig.1. The charging and discharging of BESS in the system depends to a great extent on the output availability of the renewable energy resources: the wind energy conversion system (WES) and the photovoltaic energy conversion system (PVES). One of the major issues in the BESS optimization in a system with renewable resources is the intermittence of their power outputs. This is overcome in this paper by fuzzy representation of the intermittence in the output of WES and PVES. A fuzzy logic system is capable of accepting delivering the crisp output in spite of the vague, imprecise and uncertain variation a variable. This feature is utilized in this paper to represent the probability of the power outputs of the PVES and WES at any instant of time. The Fuzzy Power Intermittence Module in the figure determines the WES and PVES power output probabilities based on the current values of the wind velocity, change in wind velocity, solar irradiance level, cloud density and cloud size. The actual power outputs of WES and PVES are computed from these probabilities by the Power Computation Module. Once the WES and PVES power outputs are obtained together with the other load flow data of the distribution network, load flow analysis is performed to get the voltages at various buses in the network. With the load flow results together with the cost related data as given by equation 4, the optimal values of the location and capacity of BESS are obtained by the Integrated Grey Wolf (IGW)

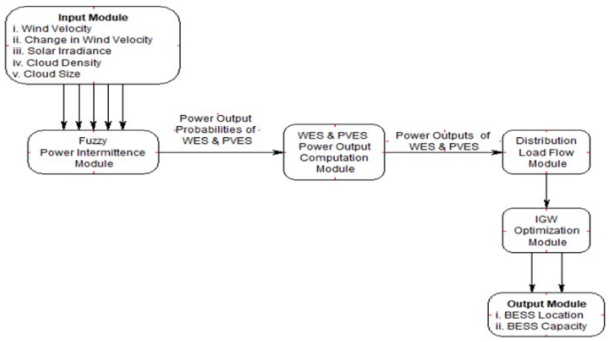


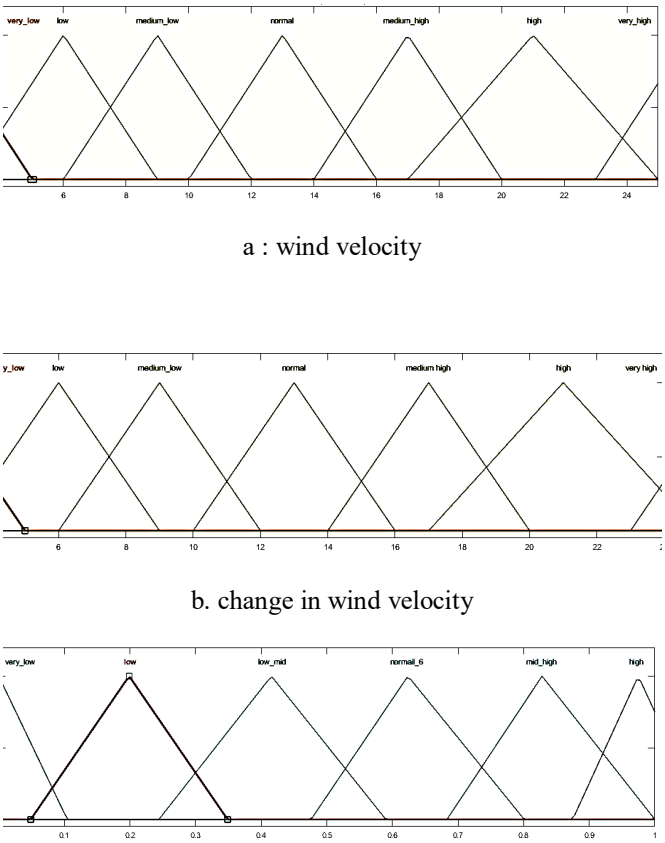
Fig. 1. Schematic diagram of the proposed BESS optimization approach.

Optimization Module. IGW has the ability to keep the diversity of the searching agents. As the following wolf Omega (ω) changes its position not just according to the dominated wolf but also according to its is neighbor Omega wolf. This action prevent the searching agent from falling in the local optimum and thus gives the best possible solution. The details of these modules are discussed in the following sections.

3. Fuzzy Power Intermittence Module

The evaluation of the intermittence in the power outputs of WES and solar PVES involves two steps: first is the development of a scenario based on the historical data, from which an average daily variation of the WES and solar PVES outputs are generated. The power output of WES changes according to the wind velocity starting from cut-in speed at which the power output is zero to the cut-out speed, the maximum limit. The intermittence of the WES output is taken into consideration by the fuzzification of the two input variables, namely, the wind velocity, the change in wind velocity and then the output of this fuzzy module is the WES output probability as shown in Fig.2. The wind velocity and the change in wind velocity are divided into seven fuzzy subsets: very low, low, medium low, normal, medium high, high and very high wind velocity. The change of the wind velocity is classified into the same subsets as the wind velocity. The output variable is divided to six regions, which are very low, low, low_mid, normal, mid_high, high. The rule base formed to generate the output probability from the WES based on the instantaneous values of the wind velocity and the change in wind velocity is shown Table 1.

The solar PVES output depends on three input fuzzy variables solar radiation, cloud density, and cloud size. The PVES output varies according to the cloud's effect. On a cloudy day, the global horizontal irradiation (GHI) decreases dramatically. Therefore, the performance of the PVES is also reduced. On clear days, the PVES output reaches the normal**.** Hence, the solar radiation is divided into four triangular fuzzy subsets, namely, low, medium, normal and high. The cloud density is considered to have three levels: light, medium, and heavy. The variation of the PVES power outputs with the change in cloud density corresponding to small cloud size, medium cloud size and large cloud size considered separately and are given in Table 2.



a : wind velocity

b. change in wind velocity

c. WES power output

Fig. 2. Fuzzification of
a. Wind velocity b. Change in wind velocity
c. WES power output.

Table 1. WES power output probability

Wind Velocity	Chnge in Wind Velocity						
	VL	L	ML	N	MH	H	VH
VL	VL	VL	L	LM	LM	MI	L
L	VL	L	L	LM	N	MI	LM
ML	L	L	LM	N	N	H	N
N	L	LM	LM	N	MI	H	LM
MH	LM	LM	N	N	MI	H	L
H	LM	N	N	MI	H	H	VL
VH	VL	LM	MI	H	H	H	VL

VL:Very Low, L:Low, ML:Medium Low, N:Normal, MH:Medium High, H: High, VH:Very High, LM:Low_Mid, MI:Mid_High

Table 2. PVES power output probability

a. Cloud Size : Small

solar radiation	Cloud Density		
	Light	Medium	heavy
low	very low	very low	very low
medium	low	Low	very low
normal	medium	Medium	low
high	normal	Normal	medium

b. Cloud Size : Medium

solar radiation	Cloud Density		
	light	medium	heavy
low	very low	very low	very low
medium	low	very low	very low
normal	medium	low	low
high	normal	medium	low

c. **Cloud Size**: Large

solar radiation	Cloud Density		
	light	medium	heavy
low	very low	very low	off
medium	low	very low	very low
normal	medium	Low	very low
high	normal	medium	very low

The Bisector of Area (BOA) defuzzification method [30] is used to defuzzy the fuzzy power output probabilities of the WES and PVES. The BOA generates the action that partitions the total fuzzy area into two regions with the same area. In the case of medium and high wind velocity rates, there is no interference from the cut-in and cut-out variables. That means that the outcome depends on only one variable, the wind velocity. In the case of high wind velocity, the cut-out variable is involved. Computing the two variables gives the probability of the WES power output whether it is the rated output or it is set to off. The same approach is applied in the case of low wind velocity, wherein the computation of the cut-in and the low wind velocity gives the probability that the wind turbine is off or yields a low power output.

4. Load Flow Module

A multi-year probabilistic load flow analysis is applied to compute the cost of power losses. Load flow is run for each hour of the day. The cost of power losses is divided into two parts: i. corresponding to peak hour between 17 and 22 hours and the other ii. corresponding to the off peak for the rest of the day. The load flow equations given by eqn. 5 to eqn. 7 are solved for each BESS state assuming that the charging state occurs between 5.00 and 6.00 hours of the day while the discharging state occurs between 20.00 hours and 21.00 hours. The initial location and size of the BESS are chosen randomly and are updated by the IGW optimizer after each iteration.

5. Proposed Improved Grey Wolf Algorithm Based BESS Optimization

In the standard grey wolf algorithm [15-21], first, the wolves find the prey and attempt to get close to it. When the prey tries to escape, the wolves chase and encircle it until the prey stops. The last step is the attack on the prey. The grey wolf optimizer (GOW) is inspired by this process. Alpha (α) is the most dominant wolf, followed by beta (β), delta (δ), and omega (ω), consecutively. Mathematically, alpha presents the fittest solution. Beta (β) is the second-best, and delta (δ) is the third solution. When the hunt begins, the omega (ω) wolves follow the alpha (α), beta (β), and delta (δ) wolves to initiate the encircling process given by

$$D = |C . X p(t) - X(t)|$$
$$X(t+1) X p(t) - A . D \quad (8)$$

Where t is the current iteration, and X p is the prey position. A and C are coefficients computed as

$$A = 2\alpha r1 - \alpha \quad (9)$$

$$C = 2r2 \quad (10)$$

Where r1, and r2 have random values in the range [0, 1]. The parameter α decreases linearly from 2 → 0 throughout the process governed by the equation

$$\alpha = 2\left(1 - \frac{t}{maxIter}\right) \quad (11)$$

Alpha (α), beta (β), and delta (δ) lead the hunt since these are the three best solutions. The position of the Omega agent is updated depending on the position of Alpha (α), beta (β), and delta (δ). given by

$$D\alpha = |C1 . X\alpha - X(t)|$$
$$D\beta = |C2 . X\beta - X(t)| \quad (12)$$
$$D\delta = |C2 . X\delta - X(t)|$$

$Xi1\ (t)\ Xi2\ (t)$ and $Xi3(t)$ are the positions of alpha (α), beta (β), and delta (δ) at alteration (t) given by

$$Xi2\ (t) = X\alpha\ (t) - Ai2 . D\alpha\ (t),$$
$$Xi2\ (t) = X\beta\ (t) - Ai2 . D\beta\ (t), \quad (13)$$
$$Xi3(t) = X\delta\ (t) - Ai2 . D\delta\ (t),$$
$$X(t) = \frac{Xi1(t) + Xi2(t) + Xi3(t)}{3}$$

According to Mirjalili, the grey wolf optimization (GWO) procedure can produce a trap in a local optima [22-23]. The behavior of the dominant wolf in the GWO guides the follower wolves to the area that is most likely to yield the optimal solution in the search space. As a result, it may get stuck on the local optimum. In addition, leads to a lack of population diversity as the wolves slowly gather. To address these issues

Mirjalili presented improved grey wolf optimizer (IGWO) in 2020 [1]. The IGWO has the following three stages:

a. Initializing step: In this stage, the IGWO distributes N wolves in the search space in a random action flowing scale of $[l_i, u_j]$ as

$$X\,ij = l\,i + randj\,[0,1].(uj - li), i \in [1,N], j \in [1,D] \quad (14)$$

Where D represents the problem dimension. A matrix of the population is then created.

b. Moving step: In this stage, another movement called dimension learning-based hunting (DLH) [22] is added to the search plane. In DLH, an individual wolf creates a new position that is driven by the knowledge from a neighbouring wolf and a randomly selected wolf. This position can be computed as

$$Ri(t) = ll\,Xi(t) - X\,i_{GWO(t-1)ll} \quad (15)$$

$$Ni(t) = \{X\,j(t)\ \mathrm{I}\ Di(Xi(t), XJ(x)) \leq Ri(t), Xj(x)\ \in pop\} \quad (16)$$

$$X\,i_{DLH,d}\,(t+1) = Xi,d(t) + rand\,.(Xn,d(t) - X\,r,d(t)) \quad (17)$$

c. Choosing and updating step: In this step, a new position is determined as

$$Xi(t+1) = \begin{cases} \{\mathrm{X}i_{GWO}\,(t+1), if\ f(Xi_{GWO}) < f(Xi_{DLH}) \\ Xi_{DLH}\,(t+1) \qquad otherwise \end{cases} \quad (18)$$

If the result is less than Xi (t), a new position is updated. Otherwise, the position for Xi (t) is the same for the population.

The flowchart of the proposed IGW algorithm incorporating the fuzzy representation of the WES and PVES power outputs is given in Fig. 3.

6. Test System and Simulation Results

The effectiveness of the proposed approach is evaluated on the IEEE 33 bus distribution system [28] shown in Fig.4, with a WES on Bus-18 and solar PVES on Bus-33 respectively. WES and solar PVECS are assumed to be rated 1 MW and 500 kW respectively. It is assumed that all the battery considered for capacity and location optimization in the network is sodium-sulfur (Na/S) type. The system data is given in Appendix. The daily load [27] variation is assumed to be as shown in Fig. 5. The average daily variation of the power outputs of a typical WES and PVES. Fig.6.

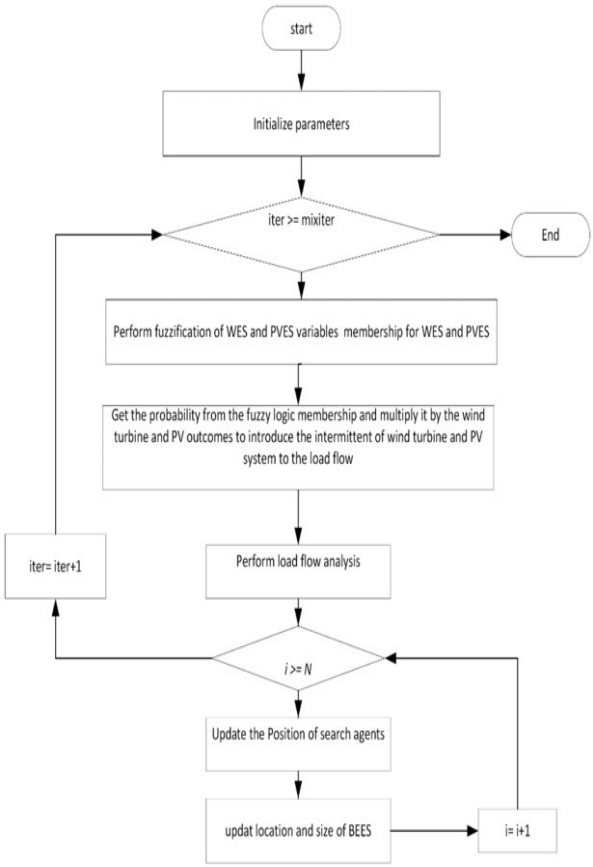


Fig. 3. IGWO algorithm for determining the optimum location and size of BESS.

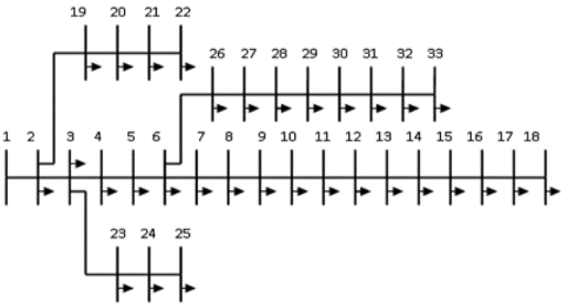


Fig.4. IEEE 33 bus distribution network.

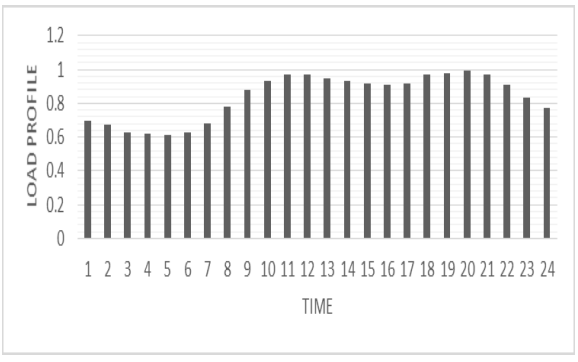


Fig. 5. Daily load curve.

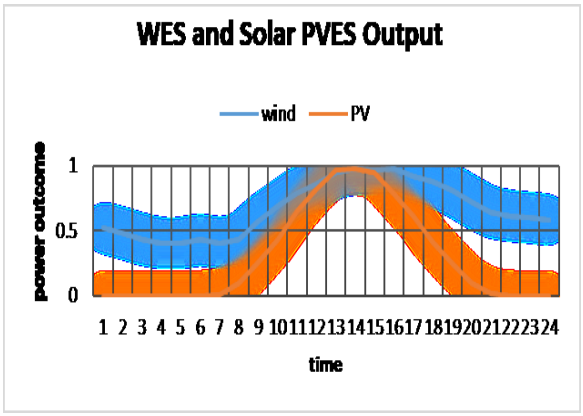


Fig. 6. Average daily variation of the power outputs of a typical WES and PVES.

The value of the wind velocity for each hour over a day is taken as a random number generated in the range from 0 m/s, which represents no wind, to 29 m/s, to show the cut-out velocity. The cut-in and cut-out ranges are between 0 and 1. The value of the change in wind velocity for each hour over a day also has been generated in the range from 0 m/s, which represents no wind, to 29 m/s. The fuzzy intermittence module thus gives the output probability of the WES located at bus 18 corresponding to each hour of the day as shown in Table 3.

The output from the solar PVES is assumed to be available for 15 hours of a day, the power output from PVES in the remaining hours, being night, is zero. The value of solar irradiance level for each hour of these 15 hours is taken as a random number generated in the range from 0 % and 100% . A zero value indicates the absence of solar radiation due to the clouds, whereas 100 % represents a *normal* amount of solar radiation. The range for the other variables is between 0 and 1, to represent the cloud dynamics. For cloud density, 0 represents light cloud density, whereas 1 indicates heavy density. Cloud size 0 represents a small cloud size, and 1 indicates a large cloud size. The fuzzy intermittence module thus gives the output probability of the PVES located at bus 33 corresponding to each hour of the day as shown in Table 4. For each hour over a day, output probability obtained from the fuzzy logic module is multiplied by the rated power of WES and PVES respectively to determine the actual power output from these renewable energy resources as shown in Table 5. Table 6 shows the optimal size and the location of the BESS obtained through the application of IGWO algorithm. Table 7 and Fig.7 show the load flow results for the system with WES at bus 18 and PVES at bus 33, obtained at the end of IGW optimization process.

7. Conclusion

This paper has proposed the application of improved Grey Wolf algorithm for the optimization of the locations and the capacity of the battery energy storage system in a distribution network with solar and wind energy conversion systems installed at various identified buses in the grid. The objective function has taken into consideration the cost of the power loss in the network in addition to cost of installation and maintenance of the battery. The output intermittence of the renewable energy resources have been incorporated through the fuzzy logic modelling and interfacing of these uncertainties with the optimization algorithm. The investigations reveal that the proposed approach is simple and effective in the determination of the optimal locations and capacity of battery energy storage systems in a distribution network.

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Appendix: System Data

Table A1. Line data for IEEE 33 bus system

Branch No	Start Bus	End Bus	Line Resistance pu	Line Reactance pu
1	1	2	0.0922	0.0470
2	2	3	0.4930	0.2511
3	3	4	0.3660	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.8190	0.7070
6	6	7	0.1872	0.6188
7	7	8	0.7114	0.2351
8	8	9	1.0300	0.7400
9	9	10	1.0440	0.7400
10	10	11	0.1966	0.0650
11	11	12	0.3744	0.1238
12	12	13	1.4680	1.1550
13	13	14	0.5416	0.7129
14	14	15	0.5910	0.5260
15	15	16	0.7463	0.5450
16	16	17	1.2890	1.7210
17	17	18	0.7320	0.5740
18	2	19	0.1640	0.1565
19	19	20	1.5042	1.3554
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3083
23	23	24	0.8980	0.7091
24	24	25	0.8960	0.7011
25	6	26	0.2030	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.0590	0.9337
28	28	29	0.8042	0.7006
29	29	30	0.5075	0.2585
30	30	31	0.9744	0.9630
31	31	32	0.3105	0.3619
32	32	33	0.3410	0.5302

Table A2. Load data for IEEE 33 bus system.

Bus No	Real Load (kW)	Reactive Load (kVAR)	Injected Q (kVAR)
1	0	0	0
2	100	60	0
3	90	40	0
4	120	80	0
5	60	30	0
6	60	20	0
7	200	100	0
8	200	100	0
9	60	20	0
10	60	20	0
11	45	30	0
12	60	35	0
13	60	35	0
14	120	80	0
15	60	10	0
16	60	20	0
17	60	20	0
18	90	40	0
19	90	40	0
20	90	40	0
21	90	40	0
22	90	40	0
23	90	50	0
24	420	200	0
25	420	200	0
26	60	25	0
27	60	25	0
28	60	20	0
29	120	70	0
30	200	600	0
31	150	70	0
32	210	100	0
33	60	40	0

Table A3. Wind turbine data

Cut-in wind velocity	4 m/s
Rated wind velocity	14 m/s
Cut-out wind velocity	25 m/s

Table A4. Electricity price ($/MWh) during peak and off-peak periods

Off-peak	Peak
18	27

Table A5. Cost of BESS

Maintenance and capital cost	Na/S Battery
Capital energy cost ($/kWh)	500
Capital power cost ($/kW)	1000
Annual O&M cost ($/kW)	20

Table A6. PV cell parameter

Short-circuit current	78 mA
Open circuit voltage	2.1 V
Maximum power point voltage	1.4
Maximum power point current	7 mA
Optimal resistance	20Ω