Approaches for Optimal Planning of Energy Storage Units in Distribution Network and Their Impacts on System Resiliency

Balaji Venkateswaran V, *Member IEEE*, Devender K. Saini, *Member*, *IEEE*, and Madhu Sharma

***Abstract*—In the recent decade, a significant increase in the penetration level of renewable energy sources (RESs) into the distribution grid is evident due to the world's shift towards clean energy and to increase the reliability or inboard manner resiliency of electrical distribution system. RES based microgrids are the most favorable option available, especially to enhance resiliency. However, the integration of RES over the distribution grid would hamper the grid stability due to its stochastic nature under normal conditions. During extreme weather conditions, RES behavior is completely uncertain. Hence there is a need to eliminate the adverse effects caused by the RES and make the distribution grid more reliable and stable under normal and resilient conditions. To address these issues, many researchers proposed several methods to place energy storage units (ESUs) and microgrids (RES integrated), which can support critical loads at an optimal location in the distribution system during normal and extreme conditions, respectively. The aim of this article is to consolidate and review the research towards various approaches to formulate the problem (optimal location, allocation, and operation of ESU and microgrids to face regular and extreme weather condition) and tools to solve it for enhanced system flexibility and resiliency. Based on the review, a generalized methodology has been designed to adapt the inputs and address both conditions. At the end of the review, future aspects for ESU to strengthen resistance and resiliency of its own are presented, which can be helpful to further improve the reliability and resiliency of the distribution system.**

***Index Terms*—Energy storage units (ESUs), electrical distribution grid, resiliency, renewable energy sources (RES).**

NOMENCLATURE

ABC	Artificial Bee Colony.
ALOA	Ant Lion Optimizer Algorithm.
ARIMA	Autoregressive Integrated Moving Average.
ARMA	Autoregressive Moving Average.
BBA	Branch Bound Algorithm.
BD	Bender Decomposition.
BFA	Binary Firefly Algorithm.
BIS	Bus Impact Severity.
DG	Distributed Generator.
DI	Direct Impact.
DP	Dynamic Programming.
DRES	Distributed Renewable Energy Source.
DSO	Distribution System Operator.
EDSO	European Distribution System Operator.
ESU	Energy Storage Unit.
FBA	Fischer–Burmeister Algorithm.
GA	Genetic Algorithm.
GDA	Greedy Algorithm.
GWOA	Grey Wolf Optimizer Algorithm.
IDI	Indirect Impact.
IHSA	Improved Harmony Search Algorithm.
IPA	Interior Point Algorithm.
LP	Linear Programming.
MILP	Mixed Integer Linear Programming.
MINLP	Mixed Integer Non-linear Programming.
MIQCQP	Mixed Integer Quadratically Constrained Quadratic Programming.
NDMA	National Disaster Management Authority.
NLP	Non-linear Programming.
NPV	Net Present Value.
NSGA	Improved Non-dominated Sorting Genetic Algorithm.
Op	Operation.
OPF	Optimal Power Flow.
PS	Pattern Search.
PSO	Particle Swarm Optimization.
RES	Renewable Energy Source.
SA	Simulated Annealing.
SAES	Self-adapted Evolutionary Strategy.
Si	Sizing.
SOC	State of Charge.
SOCP	Second-order Cone Programming.
SQP	Sequential quadratic programming.
SR	System Resiliency.
SS	Substation/External grid.
St	Siting.

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I. INTRODUCTION

THE distribution system includes many components like substations, transformers, feeders, branches, nodes, circuit breakers, disconnectors, switches, protection devices, and other mechanisms to keep grid power flowing to consumers.

Conventionally, as shown in Fig. 1(a), power flows from utilities (power generation station) to consumers through a distribution network. In the late 20th century, many researchers have proposed electric power generation within the distribution network via distributed generators (DGs), considering various technical and environmental reasons. Since there was no consistent definition of DG, a definition was stated in [1] based on various issues such as purpose, location, mode of operation, technology, rating, and penetration of DGs. As proposed in the literature, many technologies have utilized both fossil fuel and renewable for decentralized energy generation.

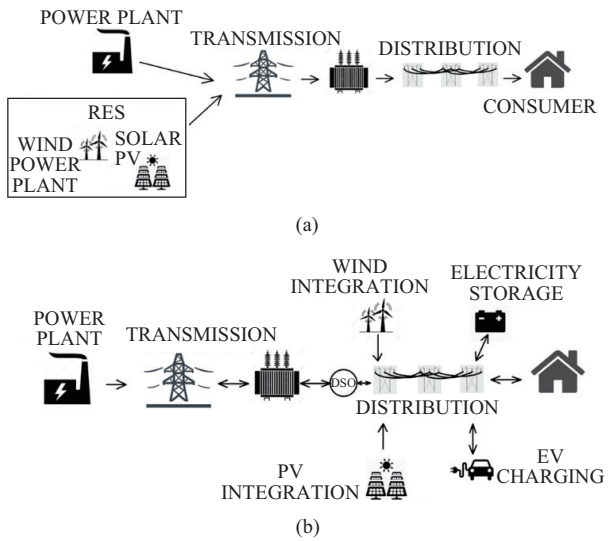

Fig. 1. (a) Conventional Power Distribution System. (b) Future Power Distribution System.

Aiming to decrease the carbon footprint and to create a sustainable environment, the DGs integrated into distribution networks are based on renewable energy, which also keeps a low depletion rate of fossil fuel. In the past decade, many wind farms and solar PV plants were installed to increase renewable energy capacity. The world's largest renewable energy expansion program of India is aiming at introducing 175 MW of energy from RES till 2022 [2]. Implementation of plug and play model has increased 370% capacity of solar PV in the last three years from around 2.6 GW to more than 12.2 GW; also in the financial year 2016–2017, wind capacity of 5.5 GW is added to Indian renewable energy [2]. The introduction of renewables into the distribution grid has increased flexibility. However, it also introduces various issues on the distribution grid, such as stability, voltage deviation, line congestion, reactive power requirement, and other power quality issues. To address such problems and to create an interactive distribution grid, future distribution grid was proposed by European Distribution System Operator (EDSO), as shown in Fig. 1(b) [3]. In Fig. 1(b) it has been proposed that despite wind and PV integration in the distribution grid, electrical storage also plays a vital role in the futuristic distribution grid. E-Vehicle integration on the distribution grid (Fig. 1(b)) is nothing but a portable ESU integration. The integration of ESU directly into distribution grid solves many purposes like peak load shaving, strengthening the grid stability, increasing the probability of survivability of critical loads, which have forecasting deviation errors. More broadly, integration of ESU in the distribution grid is a promising solution to enhance the distribution network's reliability and resiliency. The world aims towards the high number of shares from RES, despite its advantage, these create an adverse effect on the grid which may lead to grid-instability and other power quality issues. A grid-tied PV system produces clean energy and significantly reduces the emission of greenhouse gases. Nevertheless, the power generated from the PV system is highly dependent on weather conditions, which leads to a highly unpredictable and intermittent power generation. Studies in the literature have proved that grid stability is affected by the level of PV penetration into the distribution network [4]. Also, in the literature, authors have suggested penetration level for the problem considered [5]–[7]. Indian state renewable energy authorities have provided guidelines for penetration level of solar PV. The penetration level of various states is shown in Fig. 2; in some states, this limit is not specified. The penetration levels of a few Indian states (which are above 30%), may lead the distribution network to a marginally stable state. For this reason, in the case of solar PV, the stability of the grid is improved by placing ESUs [8]–[11]. In the case of wind electrical systems, the power generated is less compared to the wind potential. The distribution system stability is affected by wind power penetration essentially due to reactive power consumption, change in X/R ratio, short-circuit capacity, energy fluctuations, and power quality [12]–[18]. In [19], the concept of wind rooftop is investigated to serve local demand. The most viable solution proposed is to place ESU in the system, which can store the excess/surplus energy generated from wind and can reduce the power flow congestion in distribution lines, voltage deviations and spillage of wind power [20], [21]. Therefore, it is evident that placing ESUs in the distribution grid can improve the overall performance of grid.

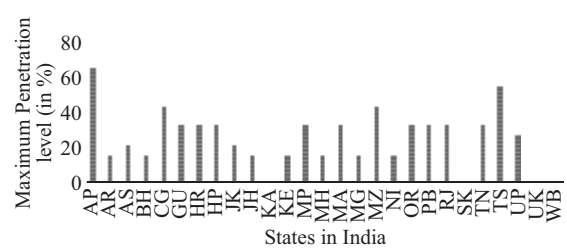

Fig. 2. Solar PV Penetration level of Indian States.

In the case of grid failure, this area can be operated in an islanding mode having the power supplied from distributed renewable energy sources (DRES) [22], based on its architecture [23]. Considering the involvement of capital investment, the ESUs are placed in the distribution network at optimal locations [24]. Therefore, it is vital to model an optimization function and identify suitable optimization algorithm to solve the objective function having the technical parameters of the grid within its limit. The power outage in the distribution system can happen due to various reasons such as load shedding (due to violations in technical parameters such as voltage and frequency), failure of distribution system components (due to

failure of protective devices installed or due to accidents), and natural calamities affecting the system components. Hence to develop a sustainable distribution grid, it must be reliable and resilient. In other words, it is essential to consider both normal and extreme conditions to be faced by the grid during planning and operation [25]–[28].

In this article, an attempt is made to review various ways in which the optimization problem is formulated, applicable to find the location, allocation, and operation of ESUs in the distribution network for both conditions. Section II elaborates on the concept of power system resiliency. Section III analyses various approaches in which the problem can be formulated. Section IV reviews various procedures applied in the literature to solve the problem and proposes a generalized methodology to deal with system flexibility and resiliency. In Section V, the results of all the techniques are compared. The review is concluded in Section VI with identified potential future direction to enhance grid flexibility and resiliency in line with ESU planning.

II. Power System Resiliency

The electric grid operation must be reliable and secure for any developed or developing country. In recent years the occurrence of natural calamity has increased compared to the past due to many reasons. According to the National Disaster Management Authority (NDMA) of India, the country experienced seven major disasters like cyclone, earthquake, etc., from the year 1972 to 2000. But this number has increased to nine between the years 2001 to 2010 and 19 from 2011 till 2019 [29]. This trend shows that the rate of increase in natural calamities has increased; hence, there is a requirement to increase the resiliency of power distribution systems to face these disasters and to increase the survivability of critical loads at least. In this view, many researchers have attempted to enhance the resiliency considering various disasters such as windstorms, floods, wildfires, earthquakes, and icing [30]–[33]. In some articles, the authors have enhanced resiliency considering a generalized outage due to disaster [34]–[37]. To improve the understanding of power system resiliency, its definition, and parameters which can quantify resiliency, are discussed further. The definition for resiliency given by the IEEE task force is *"the ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to and/or rapidly recover from such an event"* [38]. Since resiliency is an event-based analysis, it is performed based on two aspects (time-dependent) such as short term and long term. Here, the short term refers to operational resiliency, and the long term refers to hardening resiliency. The time of an event for which the resiliency analysis to be performed can be represented as the horizon (time in hours with some interval). Authors of presented paper have conceptualized short-term and long-term resiliency in terms of the system state curve, as shown in Fig. 3. This figure shows two curves, where the red curve represents long-term and green curve represents short-term resiliency. Here, the solid lines (in both the curves) represents the impact on system without resiliency planning whereas the

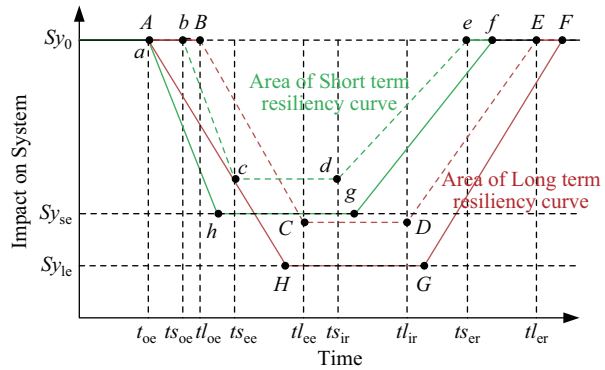

Fig. 3. System state curve for short- and long-term resiliency.

dotted one represents the impact on system with resiliency planning. The presented curve is based on three time zones viz. event time (time of event/disaster), dead time (time for which the system remains degraded after the event), restoration time (time taken to restore the system to normal condition). The line 'ab' to 'bc' represents the system behavior during event occurrence; line 'cd' represents the dead time occurs post event; line 'de' represents the system restoration time.

From Fig. 3, it is evident that short term and long-term resiliency can be enhanced by increasing the area of "abcdefgh" and "ABCDEFGH" respectively. To improve the area, three possibilities are in hands viz. decreasing the slope of line 'bc' & 'BC', increasing the slope of line 'de' & 'DE' and by increasing the length of line 'ab' & 'AB' whereas the length of line 'ef' and 'EF' depends on the slope of 'de' & 'DE' as the position of 'd' & 'f' are constant. The length of line 'ab' can be increased by improving the reliability and stability of power system components, whereas the length of 'AB' can be increased by improving flexibility, reliability, stability, and hardening of the network. The slope of line 'bc' can be made sluggish by satisfying the critical loads during event time (without any disturbances). The slope of 'BC' can be made sluggish by intelligent operation of optimally placed sectionalizers for survival of loads based on priority. Similarly, the slope of line 'de' & 'DE' can be improved by enhancing the developed strategies to be deployed for restoration of the system. To implement the above points for resiliency enhancement of distribution grid, the generalized procedures followed are: 1) distribution grid modeling, 2) modeling of disaster (or event), 3) choice of design to handle the disaster, 4) identifying the best scenario which can handle the disaster using optimization algorithms [39].

A. Modeling of the Distribution System

The distribution system is modeled with buses (nodes), power lines (branches), and transformers. In this system, there may be single-phase, two-phase, or three-phase components, including loads; hence it is essential to consider the flows are unbalanced. Also, it should be noted that, during any failure including failure due to disaster, the flow becomes unequal.

Therefore, the system must be modeled accurately considering the constraints of each phase. The distribution radial architecture must be modified accordingly, to increase the system resiliency using switches/sectionalizers, which can improve the operational resiliency of the system. Linearized power flow equations (DC power flow) are used to analyze the power flow of such a system [39]. Many path optimization techniques are used to decrease the complexity of the distribution system model having switches. In [40], authors have developed a technique based on graph theory to optimize the path for characterizing the distribution network. In [41], authors have developed the structured energy of the grid using graph theory to optimize the path of power flow in the distribution grid to increase resiliency. Therefore, in modeling a distribution system for enhancing the resiliency, it is essential to perform path optimization considering various scenarios.

B. Modeling of Disaster

Modeling of disaster is an important segment in resiliency analysis. This model should provide a clear aspect related to the behavior of the system during the pre-disaster, disaster, and post-disaster. This can be better understood using the resiliency trapezoid, as introduced in [42]. Here, the resiliency of the system is depicted using two indicators: infrastructure resiliency and operational resiliency. Infrastructural resiliency denotes the physical strength of the network. In other words, the ability of the components in the distribution network to withstand the disaster. The operational resiliency indicates the functioning of the grid even during the disaster. In other words, the distribution grid must satisfy the specified demand (at least the critical loads) even during the disaster. The physical strength of the grid is modeled using the fragility curves of various components of the system [31], which are developed using the component failure probabilities. Operational resiliency is modeled by creating different sets of scenarios. These scenarios can be user-defined or can be modeled using the damage model which is developed with the help of probabilistic damage model or forecasting models. Here, each scenario defines the component failure due to the disaster which is damaged and not in operation.

C. Choice of Design to Handle Disaster

In the literature, the main focus to improve the design of the distribution network is by choosing between the following options: 1) hardening of existing components to decrease the probability of failure, 2) installing new components or power lines to increase the redundancy of the network, 3) installing switches/sectionalizers to extend the flexibility, 4) placing either conventional DGs or RES or both, and 5) placing RES and ESU. Many factors/indices are developed in the literature to quantify the power system resiliency. In [32], the authors have presented four indices, i.e. the expected line outages due to disaster, the demand not being supplied during disaster, the probability of loss of load during a disaster, and the difficulty in grid recovery. In [40], authors have developed resistance, recovery, and resiliency indices to quantify the system resiliency. In [42], the indices developed include 1) the slope of physical strength curve/operational curve during phase 1 which can be measured in MW/hours, 2) the difference between the initial level of resiliency and the resiliency level during post-disturbance which can be measured in MW, 3) the time duration for which the network is degraded measured in hours, 4) the slope of physical strength curve/operational curve during phase 3 which can be measured in MW/hours. After creating a suitable index to quantify system resiliency and considering anyone design option from Section II-B and developing various scenarios as mentioned in Section II-C, a combinatorial optimization problem is framed, which can be solved by using optimization algorithms.

III. Problem Formulation

From Section II, it is imperative that the optimal placement, allocation, and operation of ESUs in the distribution system is one of the promising solutions to increase system reliability and resiliency. Hence, this problem is formulated as a constrained, multi-objective optimization problem. In this section, a detailed analysis of various approaches followed in problem formulation is performed by reviewing objective function parameters and their constraints. In the literature, this problem is always formulated generally by keeping the total cost of ESUs as the objective function and the technical parameters such as bus voltage profile, short circuit limit, thermal limit of the feeder as constraints [24]. Later, together with the system complexity, the complexity of the objective function, along with the constraints are increased to find the optimal location, allocation, and operation of ESUs under both normal and extreme conditions. For better understanding, the decision variables and the constraints are classified according to the problem category such as improving the intermittency of RES, network loss minimization, power quality improvement, reliability improvement, increase in arbitrage cost, improving the hosting capacity of grid, and enhancing resiliency, as presented in Table I.

From the summary of parameters considered, it is evident that the placement of ESUs in the distribution system is mainly aimed at reducing the network loss, bus voltage deviation, and line congestion, also, for proper management of integrated RES. It is also evident that only a single technology of ESU may not provide a complete solution. Hence, recently, hybrid configurations of different ESU technologies are proposed to address this problem [90], [99]. To enhance the resiliency of the system, there are various ways suggested in the literature. This can be broken down into the following: 1) improving the current distribution infrastructure to withstand extreme conditions; 2) restoration of load; 3) load shedding; 4) demand response; 5) placement of ESUs [97]. Essential constraints for the optimization problem of ESU considered in the literature to improve reliability and resiliency are listed in Table II. Here, in some articles, the ESU placement can be extended to improve the operational resiliency, as mentioned under short term resiliency in Table II); and in few articles, the ESU placement is performed to enhance the hardening resiliency, as mentioned under long term resiliency in Table II. Analyzing Table II, it is apparent that the technical parameters (such as RES curtailment, load curtailment, and reverse power flow

TABLE I
SUMMARY OF DECISION VARIABLES AND THEIR CORRESPONDING CONSTRAINTS FOR ESU PLANNING

Classification	Objective	Objective function parameters	Constraints
Intermittency	To improve the operational capability of solar PV integrated into the distribution grid [21], [22], [24], [43]–[45]. To store excess wind energy generation [46]–[48]. To increase the lifespan of ESU integrated with the distribution system [49], [50]. To mitigate the risk in the power market of the distribution company [51].	Investment cost of ESU. The operational cost of ESU. Constructional cost. Maintenance cost. Residual of investment. Cost of environmental benefit from ESU. Cost of network loss. Wheeling cost. Voltage deviation and its cost. Network loss and its cost. Investment cost of RES. Revenue generated from RES. The annual cost of excess wind energy. Penalty factor. Real power from ESU. Cost of electricity from the external grid. Cost of wind curtailment. Cost of production and storage.	Power balance equation. Capability curve limits of a conventional generator and ESU. Power factor limits. Charging and discharging limits of ESU. SOC limits of ESU, budget for ESU. The thermal capacity of the feeder. Short circuit limit of current. Voltage limits of the feeder. Reverse power. Network loss with ESU is less than equal to 125% of Network loss without ESU. The maximum number of RES and ESU. Customer satisfaction in kWh/year (amount of energy served per year is greater than 97%). Real power output from RES. Spinning and reserve capacity limits. Ramp-up and down of traditional generators limits. Current limits of the feeder. Depth of discharge of ESU. The minimum level of ESU penetration at the distribution bus.
Loss minimization	To minimize energy loss [52]. To reduce the losses of power distribution [53]. To reduce the distribution network loss [54]. To minimize the loss of the distribution network [55]. To reduce energy loss in the distribution grid [56].	Real and Reactive power from ESU. Real power losses. Total energy loss in a day.	Real and Reactive power balance. Capability curve of ESU. Limits of power factor. Demand satisfaction. Line current limits from ESU. The energy of ESU should be within limits. The sum of energy absorbed and injected by ESU should be zero at the end of the day. Charging and discharging limits of ESU. Power balance equation. Voltage limits of the feeder. Real power from solar PV must be within limits. SOC of ESU must be within limits.
Power quality Improvement	To deliver high-quality power [57]. To improve the quality of bus voltage profile, peak shaving ability, and active power exchange [58]. To improve distribution network management and its power quality [59].	Cost of the aggregate outage: • *The energy capacity of ESU.* • *The power rating of ESU.* Bus voltage quality. Power discharged from ESU. Charging power for ESU. Investment cost of ESU. O&M cost of ESU. Cost of loss due to solar PV and ESU.	The total budget for ESU. Power balance equation. Maximum energy derived from individual ESU. Maximum energy stored in individual ESU. Power injected from solar PV must within limits. Capability curve limits of solar PV. SOC of ESU must be within limits. Power and energy rating must be within limits (solar PV and ESU). The ratio of nominal power to energy must be within 0.1 to 8.
Reliability Improvement	To maximize the support for bus voltage control [60]. To reduce the voltage deviation caused due to the penetration of solar PV [61]. To provide voltage support, reduce energy loss, and the cost of power fed to the grid [62], [63]. To mitigate the vulnerability of the distribution system [64], [65]. To develop a business model based on ESU for an integrated wind system [66]. To address the reliability of RES penetrated distribution grid [67]–[77].To support the operation and control of the distribution system [78], [79].	Bus voltage deviation and its cost. The minimum size of the battery. Distribution Network losses and its cost. Grid electricity cost. Location of ESU. Size of ESU. Expected cost for the interruption. Cost of storage device as a function of its capacity. Cost of generation from RES. Cost of power purchased. Investment cost of ESU. O&M cost of ESU. Residual cost. Cost of line congestion. Cost of DG, including its startup cost. Cost of load curtailment. Discharging and charging the cost of ESU. Net Present Value (NPV) of energy losses, system upgrade, and arbitrage. Cost of undelivered energy: • *Average energy demand.* • *Failure rate.* • *Outage time.* • *Cost of penalty for undelivered energy.* The replacement cost of ESU. Expected cost for daily operation.	Capability curve of ESU and DG. The maximum number of nodes in which ESUs can be installed. The total power rating of ESUs to be installed. The maximum power rating of individual ESU. Voltage limits of the feeder. Balanced Load flow. Power balance equation. Normalized impact factor for outages of generator and line must be within limits. Power generation limits. The increase and decrease of change in power are within its specified limits. Optimization is performed only for a specific number of hours h (time period for which deviation occurs). Current limits of the feeder. Power limits of a substation transformer. Operational limits of DG. Charging and discharging limits of ESU. State of Charge (SOC) limits of ESU. Load shedding limits. Annual benefits of peak shaving and load shifting. Energy stored in ESU per day is within limits. Conventional generator ramp limit. The budget of ESU and its location. Reverse power from ESU must be within limits. Wind power injected must be within limits. Solar power injected must be within limits.

Classification	Objective	Objective function parameters	Constraints
Reliability Improvement	To improve voltage regulation and perform peak load shaving [80]–[86]. To improve the penetration of wind energy into the distribution system [87]. To support energy management and voltage regulation in the distribution system [88], [89]. To configure hybrid ESU in the distribution system [90].	Cost of reactive power: • *Reactive power loss.* • *Trade-in reactive power.* Cost of feeder loading. Investment cost of the feeder. Cost of interfacing device (needs to interface ESU with grid). Load deviation. The capacity of ESU. Operating cost of distribution network. Benefits due to the deferral of upgrading distribution network. Shaving the peak load. Reduce the negative impact of RES. Reserve capacity of ESU. Line congestion. Cost of delivered energy. Investment cost of ESU. Revenue generated from ESU: • *Real-time electricity price.* • *Revenue from load-shifting.*	Reactive power support from the capacitor bank must be within limits. The transformer tap position must be within limits. Limits of the depth of discharge of ESU. The voltage unbalance factor must be within limits. The power and energy rating of ESU must be within limits. Real and reactive power limits of the feeder. The budget limit for network extension. Real Power balance equation.
Arbitrage cost	To increase the arbitrage benefit of ESU [91]. To reduce the net cash flow [92].	Generation cost. Start-up and shut-down cost of reserve units. Cost of operation of ESU.	Limits if reserve capacity. Limits of ESU capacity. Capability curve limits of both unit reserve and ESU. SOC limits of ESU. Power balance equations. Voltage limits of the feeder. Power and Energy rating of ESU is within limits. Charging and discharging cycle efficiency of ESU is equal to the square root of overall round-trip efficiency.
Hosting capacity	To improve the ESU hosting capability of the distribution grid [93]. To improve the hosting capacity of the distribution grid [94]. To analyze the influence of ESU in the distribution system [95].	Cost of ESU. Cost of network loss. Cost of voltage regulation. Cost of peak demand. Cost of power generation from ESU. Network loss function.	Voltage limits of the feeder. The voltage unbalance index is within limits. Power and Energy rating of ESU is within limits. Real and reactive power limits of ESU. Current limits of the feeder. SOC of ESU is within limits. The discharge rate of ESU is within limits.
Resiliency	To improve the capability of energy sources during grid outages [96]. To enhance the resiliency of the distribution network [33]. To enhance resiliency [36]. To enhance the resiliency of the power grid [35]. To enhance system resiliency during a natural disaster [97]. To enhance the resiliency of microgrids [37]. To enhance resiliency towards wildfire [98].	Cost of interruption due to grid failure. Unreachability of the load center. The investment cost for enhancing resiliency. The operational cost of AC and DC DGs. Start-up and shut-down cost of AC and DC DGs. Arbitrage benefits. The penalty of load shedding. Response during pre-event: • *Price of electricity generation.* • *Cost of load shedding.* Response during the event: • *Load shedding.* During post-event: • *Load shedding.* Estimated load shedding. Estimated buying power from the substation. The estimated cost of power from RES. Estimated cost for hardening power lines: • *Cost of overhead lines.* • *Probability of its failure.* • *Wind load probability.* Cost of load loss. Cost of electricity price. Cost of electricity generation from DGs.	Demand satisfy with PV+ESU. Limits for change of energy stored in ESU. Power generation limits of PV. Limits of the depth of discharge of ESU. Start-up and shut-down of the generator. Limits of feeder capacity. SOC of ESU must be within limits. Charging and discharging limits of ESU. Load curtailment is allowed. A maximum possible real power shift during a time period must be within limits. Operational limits of both DC and AC DGs. The power balance between buying and selling. Survivability of critical loads. Power balance equation. The ramp rate of generators. Power flow limits of a transmission line. Voltage and phase angle limits. Branch currents must be within limits. Load shedding must be less than the maximum demand. The system considered must be radial. Energy exchange between AC and DC DGs must be within limits.

limits), the economic parameters (such as budget limitation), and the environmental parameters (such as adaptability to any situation refers to resiliency and reduction in emission of CO_2) are yet to be robustly incorporated in the problem formulation

for optimal placement of ESUs. Here the resiliency is considered under environmental parameters because it refers to the performance of the network under extreme environmental conditions; while performing resiliency, environmental parameters such as climatic data, system withstanding capability for disaster etc., are considered.

IV. Methodology

In this section, various approaches to solve the formulated problem mentioned in Section III followed in the literature are reviewed. As mentioned, initially, the optimization of ESUs is performed to decrease the spilled energy from renewable [47], later this method is also applied to enhance system resiliency [98]. Hence, various methods employed to solve both kinds of problems are illustrated here. There are various procedures followed in the literature to solve this problem by using analytic, conventional optimization, meta-heuristic, and hybrid combinational optimization.

Based on the formulation of the objective function and its constraints mentioned in Table I; the applicability of various algorithms to solve problems such as siting, sizing, and operation of ESUs is listed in Table III according to the problem categories, as mentioned in Section III. The prime objective under normal conditions is to optimally place ESU by satisfying technical and economic parameters considering various constraints mentioned in Table II. However, the objective function under the disastrous condition is to enhance resiliency by maximizing critical demand satisfaction. Since the objective function in both the scenarios is multi-objective having nonlinear characteristics; the same can be solved using various approaches, as mentioned in Fig. 4. In most of the articles mentioned in Table III, RES is considered during extreme conditions to increase the survivability of critical loads, but considering the most realistic situation during extreme weather conditions, authors of [32] have made RES out of service.

To enhance resiliency, few authors have improved the energy management using the available microgrids under islanding mode to serve the demand by prioritizing it as critical and non-critical loads [34]. As mentioned in Section II, few authors have proposed to change the architecture of the system during

TABLE II
Essential Parameters for Optimal Placement of ESU

Ref.	Technical parameters						Economical parameters				Environmental parameters		
	Real power loss	Power flow constraints	RES/Load curtailment	Capability of RES	Reverse power flow	Capability of ESU	Cost of investment/ replacement	Budget limitation	Outage cost	Arbitrage benefit	Emission level	Short term resiliency	Long term resiliency
[55]	✓	✓	×	×	×	×	×	×	×	×	×	✓	×
[64]	×	✓	×	×	×	✓	×	×	✓	×	×	×	×
[65]	×	×	×	×	×	×	✓	×	✓	×	×	×	×
[67]	×	✓	×	×	×	×	×	×	×	×	×	✓	×
[69]	×	✓	✓	×	×	×	✓	×	✓	×	×	×	×
[78]	✓	✓	✓	✓	×	✓	✓	×	×	×	×	×	×
[80]	×	×	×	×	×	×	✓	×	×	✓	×	×	×
[81]	✓	✓	×	×	×	×	✓	×	×	✓	×	✓	×
[87]	✓	✓	×	×	×	✓	✓	×	×	×	×	×	×
[91]	×	×	×	✓	×	✓	✓	×	×	×	×	×	×
[93]	✓	✓	×	×	×	×	✓	×	✓	×	×	×	×
[48]	×	✓	×	×	×	×	✓	×	✓	×	×	✓	×
[95]	✓	✓	×	×	×	✓	✓	×	×	×	×	✓	×
[50]	×	✓	✓	✓	×	✓	×	×	×	✓	×	×	×
[72]	×	✓	×	×	×	✓	✓	×	✓	×	×	×	×
[82]	×	✓	×	×	×	✓	×	×	×	✓	×	×	×
[45]	×	✓	×	×	×	✓	×	×	×	×	×	✓	×
[73]	×	×	×	×	×	✓	✓	✓	✓	✓	×	×	×
[88]	×	✓	×	✓	✓	✓	✓	✓	×	×	×	×	×
[22]	✓	✓	×	×	×	×	✓	×	×	✓	✓	×	×
[44]	✓	✓	×	✓	×	✓	✓	×	×	✓	×	✓	×
[89]	×	✓	×	×	×	✓	✓	✓	×	×	×	✓	×
[43]	✓	✓	×	×	×	×	×	×	×	×	×	×	×
[90]	×	✓	×	×	×	✓	×	×	×	×	×	✓	×
[76]	×	✓	×	✓	×	✓	✓	×	×	×	×	×	×
[77]	×	✓	×	×	×	✓	✓	×	×	×	×	×	×
[59]	✓	✓	×	✓	×	✓	✓	×	×	×	×	✓	×
[75]	×	×	×	×	✓	✓	×	×	×	×	×	×	×
[54]	✓	✓	×	×	✓	×	×	×	×	×	×	×	×
[21]	×	✓	✓	×	✓	✓	✓	✓	✓	✓	×	×	×
[96]	×	✓	×	✓	×	✓	✓	×	✓	×	×	✓	×
[33]	×	✓	✓	×	×	✓	✓	×	✓	×	×	×	✓
[36]	×	✓	×	✓	×	✓	✓	×	✓	✓	×	×	✓
[35]	×	✓	×	×	×	×	×	×	✓	×	×	×	✓
[97]	×	✓	✓	×	×	×	✓	✓	✓	×	×	×	✓
[98]	×	✓	×	×	×	✓	✓	×	×	✓	×	✓	×
[37]	×	✓	✓	✓	×	✓	✓	✓	×	✓	×	×	✓

TABLE III
METHODOLOGY DESIGNED AND TOOLS USED IN LITERATURE FOR ESU PLANNING

Problem Category	Ref.	Test System	Grid setup			Technique					Software Tools
			No. of Primary SS	RES (if integrated)	Capacity of RES	Algorithms	Purpose	Applied for S^i	S^t	O^P	
Intermittency	[24]	17-node system radial system	2	WPP Biomass	2 MW 1 MW	Genetic Algorithm (GA) Dynamic Programming (DP)	For generating the initial population for both sizing and siting To estimate the optimal profile of ESU	✓	✓	×	Not mentioned
	[44]	IEEE 34-node radial distribution system	1	×	×	GA AC – OPF	The initial solution for optimal location size of ESU Evaluate the objective function	✓	✓	×	MATLAB DigSILENT
	[22]	LV distribution system in Yazd, Iran	1	Solar PV	Not mentioned	GA LP	Optimal number and location of ESU Optimal charging and discharging of ESU	✓	✓	✓	DigSILENT MATLAB
	[101]	16-bus distribution system	1	WPP Solar PV	6 MW 2.5 MWp	Wavelet + Neural Network + PSO Wavelet + Fuzzy Wavelet + Fuzzy + Firefly algorithm OPF	Solar power forecast Wind power forecast Load forecast Optimal location of ESU	×	✓	×	MATPOWER V 5.1 MATLAB
Loss Minimization	[102]	41-node radial distribution system	1	WPP	3 × 10 MW	GA Active-Reactive OPF	Optimal charging and discharging hours of ESU Evaluate the objective function	×	×	✓	GAMS MATLAB
	[96]	Ontario distribution system	1	WPP	5 × 1.98 MW	OPF (Sensitivity analysis) PSO	Optimal location of ESU Optimal size of ESU	✓	✓	×	MATLAB
	[55]	CIGRE 14-bus distribution system	1	×	×	Pattern Search (PS) algorithm Mixed integer quadratically constrained quadratic programming (MIQCQP) Sensitivity analysis	The optimal size of ESU Evaluate the network loss Optimal location of ESU	✓	✓	×	MATLAB NEPLAN
	[64]	IEEE 33-bus system	1	WPP Solar PV	2 × 1 MW 3 × 400 kVA 4 × 500 kVA	ABC	Optimal location of ESU	×	✓	×	DigSILENT Python programming
	[54]	CIGRE low voltage distribution grid	1	Solar PV	36 kWp	DP	Optimal operation of ESU via minimum loss	×	×	✓	MATLAB
	[57]	69-bus radial distribution system	1	Solar PV	3 MWp	Improved Harmony Search Algorithm (IHSA)	Optimal operation of PV integrated system	×	✓	✓	MATLAB
	[103]	IEEE 37-bus system	1	×	×	OPF	Optimal operation of ESU	×	×	✓	Not mentioned
Power Quality Improvement	[46]	IEEE 8500-node system	1	Solar PV	Not mentioned	GA Linear Programming (LP)	The initial solution for sizing ESU Evaluate the objective function for optimal siting	✓	✓	×	OpenDSS
	[94]	IEEE 33-bus system	1	WPP Solar PV	2 × 1 MW 3 × 400 kVA 4 × 500 kVA	Interior Point Algorithm (IPA)	Optimal charging/discharging and size of ESU	×	✓	✓	MATLAB
	[53]	15- and 69-bus radial distribution system	1	×	×	User defined analytical procedure based on power loss expression	Optimal location and size of ESU	✓	✓	×	MATLAB
	[60]	69-node distribution system	1	Solar PV	(125 – 1250) kWp	OPF (based on Second Order Cone Programming (SOCP))	Optimal sizing and location of ESU	✓	✓	×	Not mentioned

Problem Category	Ref.	Test System	Grid setup			Technique					Software Tools
			No. of Primary SS	RES (if integrated)	Capacity of RES	Algorithms	Purpose	Applied for S^i	S^t	O^p	
Reliability Improvement	[63]	IEEE 13-node system	1	Solar PV	Not mentioned	GA AC-OPF	Initial optimal sizing and location of ESU Evaluates the objective function	✓	✓	×	MATLAB
	[77]	Modified IEEE 33-bus system	1	WPP Solar PV	400 kW 420 kWp	Multi-subgroup hierarchical chaos hybrid algorithm	Optimal capacity of ESU	✓	✓	×	Not mentioned
	[104]	94-node Portuguese radial distribution system	1	×	×	NSGA-II	Improved reliability parameters such as MAIFI and SAIDI by optimal siting and sizing of ESU	✓	✓	×	Not mentioned
	[105]	Spanish distribution system	1	×	×	ARMA Genetic Algorithm	Electricity price forecasting Optimal operation of ESU	×	×	✓	MATLAB
	[85]	IEEE 34-bus system	1	Micro-wind Solar PV	Not mentioned	Clustering and Sensitivity analysis	Optimal sizing of ESU	×	✓	×	SeDuMi V 1.02 MATLAB
	[81]	Modified – GE power distribution system	2	Solar PV	2 × 250 kWp	User-defined analysis	Sizing strategy	✓	×	×	MATLAB
	[62]	8-node radial system	1	Solar PV	10 kWp 50 kWp 100 kWp	Artificial Bee Colony (ABC)	Optimal size of ESU	✓	×	×	Not mentioned
	[61]	IEEE 13-node system	1	Solar PV	4 × 400 kWp	Bender Decomposition (BD)	Optimal location and size of ESU	✓	✓	×	MATLAB and GAMS interface
Arbitrage Cost	[66]	13-bus distribution system	4	WPP Solar PV	Not mentioned	PSO	Optimal capacity of ESU	✓	×	×	DIgSILENT
	[65]	IEEE 30-bus system	1	×	×	Bus Impact Severity (BIS) analysis GA	Better location of ESU Optimal location and size of ESU	✓	✓	×	Borland C++
	[92]	IEEE 34 bus system	1	WPP	2 × 300 kW	Branch Bound Algorithm (BBA)	Optimal siting, sizing and operation	✓	✓	✓	YALMIP MATLAB
	[93]	IEEE 33 bus system	1	WPP Solar PV	3 × 200 kW 2 × 100 kW 200 kWp 250 kWp 300 kWp 350 kWp	GA OPF	To determine the optimal location and size of ESU (framed as outer optimization) To evaluate the inner objective function	✓	✓	×	HOMER MATLAB
Hosting Capacity	[106]	IEEE 14 bus system	1	WPP	Not mentioned	OPF with quadratically constrained	Optimal location of ESU	×	✓	×	MATLAB YALMIP
	[67]	IEEE 24 bus system	1	WPP	1500 MW	GA	Optimal location of ESU	×	✓	×	MATLAB
	[107]	69 bus distribution system	1	WPP Solar PV	(1.5 – 1.6) MW (122 – 187) kWp	Loss sensitive factor approach Ant Lion Optimizer Algorithm (ALOA) Grey relation projection method	Optimal location of DGs (thereby ESUs) Optimal capacity of DGs Optimal capacity of ESU	✓	✓	×	Not mentioned
	[108]	Hybrid microgrid (user-defined)	1	WPP	3 MW	Fischer–Burmeister Algorithm (FBA)	Optimal sizing of WPP and ESU	✓	×	×	MATLAB
	[109]	IEEE 33 bus system	1	Solar PV	8 × (500 – 800) kWp	OPF Sensitivity analysis	The optimal size of ESU Optimal location of ESU	✓	✓	×	Not mentioned
Resiliency	[36]	Hybrid microgrid system	1	✓	Not mentioned	MILP	Optimal operation of microgrid	×	×	✓	Not mentioned
	[35]	IEEE one & three – area RTS – 96 system	1	×	×	Nested Column and Constraint generation decomposition framework (Robust MILP)	Optimal operation of power grid	×	×	✓	Gurobi 6.5 PSS/E

Problem Category	Ref.	Test System	Grid setup			Technique					Software Tools
			No. of Primary SS	RES (if integrated)	Capacity of RES	Algorithms	Purpose	Applied for S^i	S^t	O^P	
Resiliency	[32]	IEEE 30 & 118 bus system	1	×	×	Markov Chain Monte Carlo Simulation	Optimal operation of power grid during extreme condition	×	×	✓	MATPOWER MATLAB
	[98]	IEEE 33 bus system	1	WPP	5 × 1 MW	Mixed Integer Non-linear Programming (MINLP)	Optimal Placement of WPP	×	✓	✓	GAMS
	[37]	User-defined Microgrid	1	Not mentioned	×	Two-step adaptive robust optimization	Optimal operation of the microgrid	×	×	✓	Java NetBeans IDE
	[99]	IEEE 33 bus system	1	WPP Solar PV Micro-turbine	3 × 0.8 MW 0.5 MWp 2 × 3 MW 2 × 2 MW	MIQCQP	Optimal operation of the power grid during natural disaster (wildfire)	×	×	✓	GAMS

the disaster to increase the survivability of critical loads. The most common architectures applied to improve the system resiliency by energy management found in the literature are centralized, decentralized, and hierarchical architectures [109]. In [33], [97], [98], authors have specified the requirement of these switches/sectionalizers to change the architecture of the network, which is controlled by the distribution system operator (DSOs) as per the need to ensure the survivability of critical loads. In [110], authors have used electric vehicles to improve the resiliency of the smart grid.

ESU planning must be done to improve the overall performance of the distribution grid during any situation (both normal and extreme conditions). This is essential because in the literature the resiliency enhancement using ESU placement can satisfy critical loads only for a particular horizon (mentioned in Table IV), after which ESUs may not be able to satisfy the demand. On the other hand, conventional ESU planning for improving the stability, loss minimization, arbitrage cost, etc., may not operate as desired during extreme conditions. Considering this, a generalized methodology is proposed which can be applied to solve both kinds of the problem (normal and extreme condition) for a system, which is shown in Fig. 4. The proposed conceptually designed steps to enhance flexibility and resiliency are hereunder:

Step 1: Collecting the distribution system data required for load flow, e.g. bus data, line data, capacity, and location of RES installed, if any, etc.

Step 2: Modeling of the system load and load variations by using IEEE RTS-96 [111], CREST demand model [112], or by considering a fixed range of demand.

Step 3: Designing the system for normal condition and extreme condition, if for normal condition go to step 9 and for extreme condition designing (resilient system) go to step 4.

Step 4: Collect weather data, disaster data (number of collapsed lines, poles, transformers, substation equipment, etc.), capacity and location of critical loads, and budget limits for the normal and resilient condition.

Step 5: Develop system hardening strategies to enhance system resiliency by introducing switches (to create adaptive system architecture), parallel lines, enhanced communication, etc.

Step 6: Evaluate the different strategies and identify a better suitable system architecture concerning the disaster.

Step 7: Choose any approach (as mentioned in Fig. 4) to solve objective function of the optimization problem (under extreme condition) for identifying potential location and allocation of ESUs to maximize the survivability of critical loads constrained with electrical parameters and budget limitation (as shown in Table 1).

Step 8: Update the optimal results in the database concerning disaster.

Step 9: Collecting the interruption data (i.e., outage time of the distribution system's component), budget limitation of ESU.

Step 10: Perform load flow/OPF studies to calculate different objective function parameters (mentioned in Table I).

Step 11: Choose any approach (as mentioned in Fig. 4) to solve the objective function of the optimization problem (under normal condition) for identifying optimal location and allocation of ESUs to enhance the flexibility of the system constrained with electrical parameters (as shown in Table I).

Step 12: Update the optimal results in the database.

The input data required for the proposed methodology are distribution system data, load model (as mentioned in step 2 of the algorithm), bus at which critical loads are connected, weather data, system withstanding capability for a particular disaster, budget limits, and location of switches/sectionalizers. With the help of this data, firstly, load flow is performed to create a base case for the system's performance during normal conditions. Based on the objective function parameters and the constraints chosen (from Table I), a suitable optimization algorithm (as mentioned in Fig. 4) is used to minimize/maximize the optimal size, location, and operation of ESU to address normal conditions. The obtained result is stored in a normal condition database. Various sets of strategies are created to address various events, assuming this as the base case. Later, all these strategies are evaluated to minimize/maximize the objective function using a suitable optimization algorithm (as mentioned in step 7 of the algorithm) to obtain the best possible strategy to face a particular event/disaster. The obtained results are stored in extreme condition database. In this way, a robust database is created using the proposed methodology, which can improve the flexibility and resiliency of distribution grid.

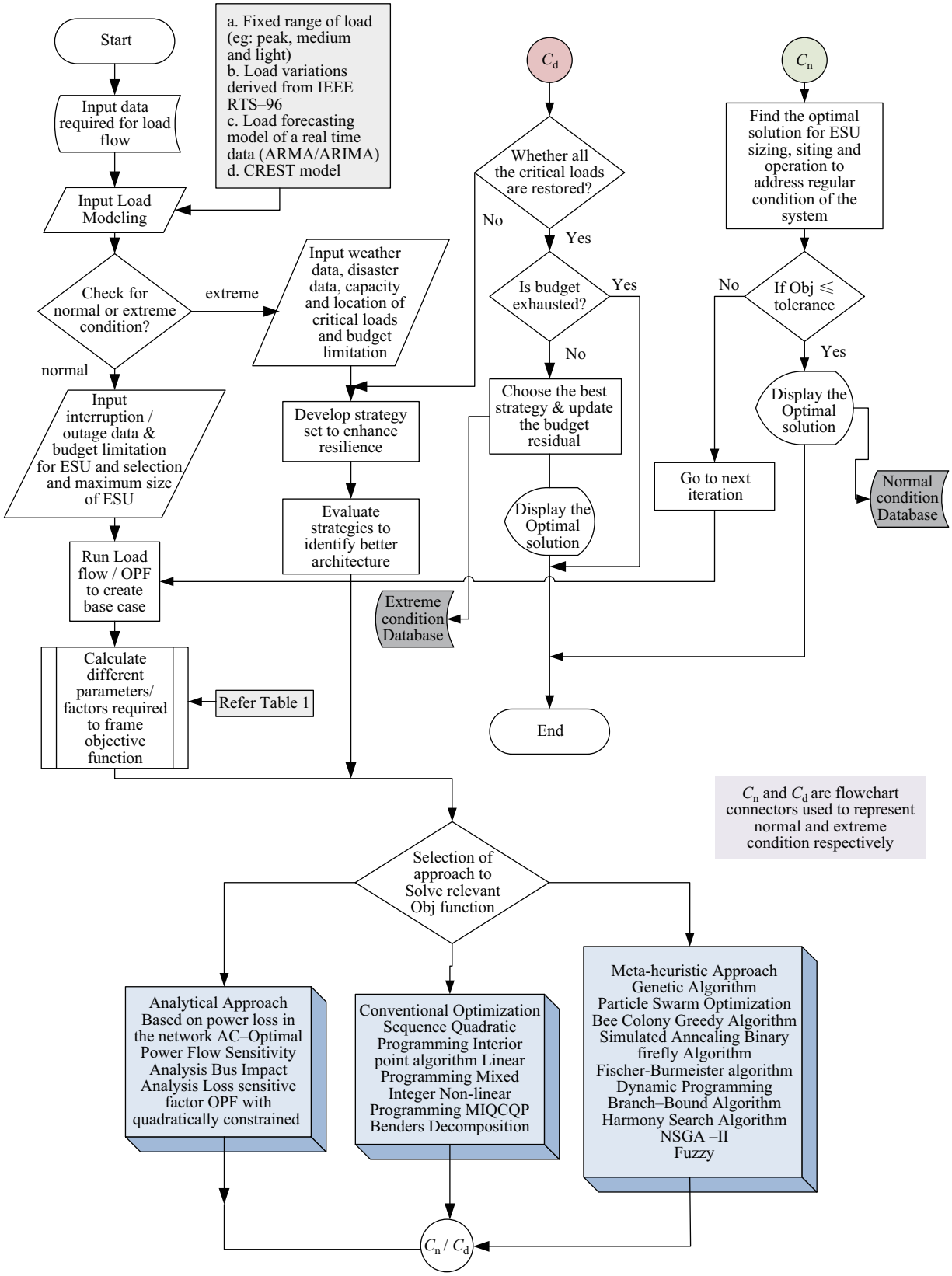

Fig. 4. Proposed generalized flowchart of methodology to enhance system flexibility and resiliency.

V. Results and Discussion

In this section, the performance of procedures mentioned in Section IV is reviewed based on the value of objective function parameters. From the results of the literature, these parameters can be broadly clustered into the technical and economic parameters. Major variables under *economical* are investment cost, cost of energy imported and exported, cost of outages,

arbitrage cost, under *technical* are the number of optimal locations to place ESU, total energy loss, voltage deviation, loss reduction. To understand the problem towards system resiliency, two parameters are proposed by the authors, namely direct impact (DI) and indirect impact (IDI). These parameters are used to identify the impact created by the optimization of ESU to enhance system resiliency. The parameter DI is defined as *"distinct efforts towards improving the survivability of the load and disaster data along with the restoration strategy applied is fed back for further analysis which can be utilized for future purpose"* and the parameter IDI is defined as *"considering the generation and demand level part of the load is curtailed to ensure the system stability and reliability. This is termed as IDI because, during the event (any outage), a part of the system load is satisfied"*. The results of the optimization problem from various research articles based on DI and IDI are listed in Table IV, along with the horizon (time of event/operation) considered.

The optimization results of various methodologies mentioned in the literature are categorized in terms of system resiliency using two impact parameters as defined above, from which it will be easier to identify the best suitable approach to enhance system resiliency. For easing the comparison, Table IV is clustered into three categories, namely standard bus system, user-defined bus system, and real-time bus system. From the point of the optimal number of ESUs considering the standard bus system, with 13 to 15 nodes, the optimal number of ESUs is 5, which obtained using BDA [60]. For 30 nodes the optimal number of ESUs is 6, which obtained using a combinatorial optimization with BIS analysis and GA [64]. The optimal number of ESUs for 33 nodes is 3, obtained by using the genetic algorithm and optimal power flow [92]. For a high number of buses, the optimal number of ESUs entirely depends on the various circumstance considered. For instance, in [49], IEEE 906-bus system is considered; where the optimal number of ESUs obtained is two (note: along with these two ESUs, RES is also operated to satisfy the required demand). In a few articles, the maximum number of ESUs is fixed by the authors; for example in [62], the maximum number of ESUs to be installed is set as 3. However, the optimal locations of three ESUs are found using genetic algorithms. From the sizing point of view, the optimal size of ESUs varies in the literature even for the same system because of the different load being considered. Also, in a few articles, authors have limited the size of ESU by assuming maximum and minimum limits. For example in [62], the authors have assumed that the total power of ESUs (sum of the power level of all ESUs) is equal to 600 kW, and its energy storage capacity is considered to be 3 MWh. From Table IV and the above discussion, for small system (with fewer nodes), benders decomposition algorithms prove to be promising in obtaining an optimal number of ESUs; whereas, for a larger node system, the genetic algorithm combined with optimal power flow algorithm and NSGA-II algorithm is more suitable in finding the optimal location of ESUs. This is evident from the literature that BD technique is applied to solve ESU planning problem for standard system with less complexity because this technique will get converged only if the subproblems are convex in nature. For a larger system it is complicated to decompose the primary function into subproblems, which may be convex in nature. Also, it is apparent from the literature that NSGA II sorts the population into various non-dominated levels, which reduces the complexity of the problem. Hence it can be better suitable to solve larger systems. For optimal allocation of ESUs in a small network, genetic algorithm and mixed-integer programming are best suitable; whereas for a larger system, combinatorial algorithms (combining two algorithms) are more suitable. For optimal operation, conventional optimization algorithms (as mentioned in Fig. 4) are more appropriate. As discussed in Section II, the resiliency is quantified based on indices/factors. The resistance index determines the power transfer capability of the system even during the disaster. The recovery index (determines the expected energy recovered after disaster) obtained from the method in [40] for the system without tie line is 0.18, and for the system considering the tie line is 0.28; whereas in [113] the recovery index is 0.16 without any tie lines, and in [114] it is 0.23 with tie lines. After reviewing the articles in the literature, it is proposed that these indices namely resistance, recovery, and resiliency can be improved by decreasing the dependency on grid by installing local ESUs at optimal locations which can serve either clustered or local loads, increasing the penetration level and capacity of RES [40] and placing both RES and ESUs at optimal locations respectively.

VI. Conclusion and Future Directions

In this article, a brief review of optimal location, allocation, and operation of RES and ESUs under the ordinary and disastrous conditions concerning the approaches (problem formulation and methodology) is performed. The role of ESU to enhance the flexibility and resiliency of the system with and without RES is analyzed. By analyzing the objective function parameters and its constraints, it is identified that in the literature, the problem has been formulated to minimize the cost function or network loss having constraints related to electrical parameters. Even though ESUs are placed to enhance resiliency, it is essential to frame an interdisciplinary objective function to solve the problem of this kind. Although an adequate number of scenarios and strategies are available in the literature to enhance power system resiliency, still there are several challenges that need to be incorporated in the resiliency model to improve the system performance during major disasters. Based on the review, some of the challenges and its solutions are summarized as follows:

- In case of a flood disaster, water evacuation strategies must be planned. For example, during Chennai floods, (Tamilnadu, India) the water level has reached to 11.5 feet at SRCM Headquarters, Manapakkam ($80°11'0.23''$ E and $13°1'15.74''$ N), and it has been drained using pumps [115]. Until the power is restored, the water is logged in these regions which may cause social and environmental problems. Captive generation units or sufficient ESU capacity should be available to supply these auxiliary water pumps for evacuating the water during the flood disaster event.
- A location-based robust disaster model is to be developed,

TABLE IV
OPTIMAL SOLUTIONS FOR LOCATION AND ALLOCATION OF ESU AND THEIR EFFECT ON SYSTEM RESILIENCY

Ref.	Test system	Optimal no. of ESUs	Optimal location of ESU	Objective fun value		Size of ESUs	Algorithms applied	SR		Horizon	Remarks
				Without ESU	With ESU			DI	IDI		
[61]	IEEE 13-node system	5	671, 684, 633, 645 675	×	Total voltage deviation with an amplitude of 13400	631 kVA, 290 kVA, 365 kVA, 250 kVA, 464 kVA	BD algorithm	×	✓	Not mentioned	In the first half of the year, the capacity required from ESU is 0 kVA at bus 633, whereas, in the second half, 408 kVA capacity is required. Hence, the optimal size of ESUs varies in the year.
[63]	IEEE 13-node system	3	3, 7, 8	During winter: cost of energy is 84.2 p.u.$/day and energy loss is 3.1 MWh/day. During summer: cost of energy is 79 p.u.$/day and energy loss is 2.8 MWh/day.	During winter: cost of energy is 23.4 p.u.$/day and energy loss is 2.9 MWh/day. During summer: cost of energy is 15.6 p.u.$/day and energy loss is 2.1 MWh/day.	66 kW, 200 kW, 334 kW	GA + AC-OPF	×	✓	24 hours with an interval of 2 hours	The number of ESUs to be installed is capped to 3 with total ESU capacity of 3 MWh.
[67]	IEEE 24-bus system	1; 2; 3	For scenario II: 13; 14, 23; 14, 23, 11	×	Cumulative arbitrage revenue under scenario II is 171.11 k$; 342.15 k$ and 342.15 k$.	1200 MWh and 1000 MWh	Probabilistic OPF + GA	×	✓	24 hours with an interval of one hour	There are two scenarios considered: unlimited ESU capacity and limited ESU capacity. The optimal location and size of ESUs are based on the scenario.
[65]	IEEE 30-bus system	6	6, 10, 18, 19, 23, 24	×	Predefined BIS is 18 with NISF of 1.29577.	0.1 MW, 0.025 MW, 0.025 MW, 0.075 MW, 0.05 MW, 0.05 MW	BIS analysis + GA	×	✓	Not mentioned	Since the pre-defined value of BIS forms the base for selection of optimal number of ESUs, defining suitable BIS value is a challenge.
[93]	IEEE 33-bus system	3	17, 32, 31	×	Revenue from load shifting and loss reduction is 312.57 k$ and 271.09 k$ respectively.	426 kWh, 379 kWh, 277 kWh; 522 kWh, 513 kWh, 435 kWh	GA + OPF	×	✓	24 hours with an interval of one hour	The NPV of the distribution network increases as the number of ESUs installed in the system increases. Two optimal solutions for ESU capacity is obtained.
[64]	IEEE 33-bus system	8; 11	9, 14, 25, 28, 29, 30, 31, 32; 8, 10, 13, 16, 17, 20, 22, 25, 30, 31, 32	% index of VD and LLT are 89.73 and 269.81 respectively	For uniform ESU size of 0.724 MVA the % index of VD and LLT are 75.753 and 241.128 respectively. For non-uniform ESU size, the % index of VD and LLT are 72.162 and 240.039 respectively.	0.724 MVA; 0.335, 0.378, 0.383, 0.823, 0.1, 0.128, 0.1, 2, 1.442, 0.725, 0.781 (MVA)	ABC algorithm	×	✓	24 hours with an interval of one hour	The simulations are performed for various cases such as 1) no ESU, 2) ESU with uniform size (0.724 and 1.974 MVA are considered, in this case, the only optimal location is found), 3) ESU with non-uniform size (in this case optimal size and location of ESU is found).
[33]	IEEE 33-bus system	2	3, 29, 16, 22	×	Restoration of disconnected loads is increased by 31.6%. The emission level is reduced by 26.6 % for case 2.	100 kWh and 400 kWh	Greedy Search algorithm	✓	×	5 hours with one-hour interval	There are three cases considered: 1) no strategy, 2) SS is vulnerable for 20% scenarios, 3a) SS is not vulnerable for all scenarios, 3b) SS is vulnerable for all scenarios. The ESUs are replaced by fuel-based DGs to reduce the emission level.
[21]	IEEE 33-bus system	5	21, 22, 30, 32, 33 (case 2) 21, 22, 32, 33 (case 3)	Total system cost in $/year is 11,543, 945.642.	Total system cost in $/year is 9,625, 602.547 (for case 2) and 9,335, 552.338 (for case 3).	2424, 2731, 18312, 15196, 5739 (kWh) (for case 2); 2590, 2537, 7117, 2954 (kWh) (for case 3)	MILP	×	✓	24 hours with an interval of one hour	The ESUs are placed near WPP and far from the main substation to improve the voltage profile and to reduce the line congestion. The optimal number of ESUs are case dependent. The various cases are 1) no ESUs, 2) ESUs exchange only real power, 3) ESUs exchange both real and reactive power.
[92]	IEEE 34-bus system	3	810, 816, 850	The reserve capacity is insufficient to trace the demand.	The required reserve capacity is satisfied. Depending on demand the ESUs are placed at 2 to 5 buses to with the per-unit cost of load ranging between 663.6 $/MWh to 1012.7 $/MWh.	3 × 0.6 MWh	BBA	×	✓	24 hours with an interval of one hour	The optimal number of ESUs are derived based on three wind penetrations (10%, 15%, and 20%) and three load levels (0.6 p.u, 0.9 p.u, and 1.08 p.u). The mentioned one is for a 15% penetration level and 1.08 p.u load level.
[58]	IEEE 123-node distribu-tion system	1	M1	Outage cost $ 155060	Outage cost $ 86555	625 kVA	GDA + SA	×	✓	8 hours with an interval of one hour	IEEE 123-node system is divided into four majors, and in the upstream node, the ESU is placed to serve the load during a grid outage.
[50]	IEEE 906-bus European LV distri-bution system	2	802, 511; 694, 587; 690, 503	Cost saving is $ 52081 for the system with only Solar PV and WPP.	Cost saving is $ 394290 (for case 5), $ 346718 (for case 6), $177982 (for case 7).	60, 67 (kWh); 40, 59 (kWh); 24, 33 (kWh)	Improved Non-dominated Sorting Genetic Algorithm (NSGA II)	×	✓	24 hours with an interval of 4 hours	The location and size mentioned are for case 5 (Solar PV and ESU), case 6 (WPP and ESU), and case 7 (Solar PV, WPP, and ESU).
[108]	Hybrid microgrid (user-defined)	1	1	×	Total hybrid system cost varies between 6.15 to 7.69 M$.	Varies between 838.96 to 1101.6 kWh	ARMA+ Self-adapted evolutionary strategy (SAES)+FBA	×	✓	Not mentioned	Simulations performed for various assumed EENS and the capacity of ESU vary depending on the assumption of EENS.

Ref.	Test system	Optimal no. of ESUs	Optimal location of ESU	Objective fun value		Size of ESUs	Algorithms applied	SR		Horizon	Remarks
				Without ESU	With ESU			DI	IDI		
[36]	Hybrid microgrid (user-defined)	2	AC and DC bus	×	Load shedding is reduced by 63.03% (assessing feasible islands) and 68.15% (assessing the survivability).	200 kW (DC-ESU); 100 kW (AC-ESU)	MILP	✓	×	2 & 5 hours with 15 minutes interval	The simulations are performed for both normal and emergency operation. During normal operation, the ESU will be charged during off-peak load, and discharged during peak demand and during emergency operation ESU along with another available RES critical load survivability is maximized. There are two cases considered under resiliency: 1) operational window of 2 hours, 2) operational window of 5 hours.
[37]	Hybrid microgrid (user-defined)	2	AC and DC bus	×	An average increase of 17.4% in the budget to meet the operational uncertainty during the event.	800 kW, 980 kW, 300 kW, 350 kW, 40 kW, 50 kW	Two-step adaptive robust optimization	✓	×	5 8 & 10 hours with a time interval of 2 hours	There are three cases considered based on event occurrence time, SOC level of ESU, targeted SOC, and power available. Here, the backup is created during normal operation (resiliency-cuts) used to increase the survivability of critical loads after the occurrence of an event.
[8]	17-bus system	Case 1: 0 Case 2: 1 Case 3: 2 Case 4: 2	16; 7, 16; 5, 16	×	Daily losses in MWh are 1.417 (case 1), 1.394 (case 2), 1.287 (case 3), and 1.297 (case 4).	Case 2: 1 × 250 kW; Case 3: 3 × 500 kW 1 × 500 kW; Case 4: 3 × 500 kW	GA + SQP-OPF	×	✓	24 hours with an interval of one hour	This problem is solved under four cases: 1) only arbitrage cost, 2) along with case 1) special tariff for balancing, 3) along with case 1) capital grant for new ESUs, 4) along with case 3) additional benefit for reactive power support.
[47]	41-node rural distribution system	5	4, 9, 28, 39, 40	5.11 million dollars	4.68 million dollars	19.48 MWh, 12.99 MWh, 8.44 MWh, 4.55 MWh, 6.49 MWh	ARMA + OPF	×	✓	24 hours with an interval of one hour	Among various ESU technologies, Zn-Br is chosen considering its economic feasibility.
[102]	41-bus rural distribution system	3	4, 9, 39	×	Revenue generated is 1298 $/4-days, 1277 $/4-days, 918 $/4-days.	1.948 MVA, 1.299 MVA, 0.455 MVA	Search algorithm + OPF	×	✓	24 hours with an interval of one hour	The objective function is solved under three different tariff models, i.e. two-tariff price, three-tariff price, 24-hour tariff price. (Based on these models the objective function values are mentioned.)
[68]	69-bus radial distribution system	1	61	The significant deviation is seen at bus 61.	Voltage deviation is zero at bus 61.	2 MW	BFA	×	✓	Not mentioned	Comparison of voltage deviations at all other buses near bus 61 would have highlighted the performance of ESU.
[81]	Modified GE distribution system	7	201 to 207	Operation time of OLTC and SVR is close to 4000.	Operation time of OLTC and SVR is between 1500 to 3500 depending upon the capacity of ESU.	Varies between 0.5 p.u to 5 p.u	OPF	×	✓	5 hours with an interval of one hour	The operation time is less when 5-hour, ESU capacity is installed whereas the same increases (close to 3250) with 0.5-hour ESU capacity.

which can predict the possible damage and its severity. This can provide an approximation of the time of occurrence of disaster and possible clearance time with the available resources.

- While placing the ESUs or any type of DGs, it is essential to consider the hardening of its mounting structures, and the cost involved in hardening must be included in the resiliency model. Also, the same has to be extended to mounting structures where RES systems are installed.
- During a disaster, the communication network (either wired via optical fibers or wireless) may get damaged (considering the impact of surrounding infrastructure). Therefore, it is essential to plan a decentralized communication line compared to a centralized one. For example, the SOC status of the ESU/status of sectionalizers is crucial in preparing to serve critical demand. If the condition is unknown, this may affect the resiliency of the system.
- After a disaster (before supply restoration), it is essential for DSO to ensure the capacity of ESU, which is placed to charge the protection system; thereafter, the power restoration process can be restored. The size of these ESUs must be included in the optimization problem.
- Most of the researchers have assumed the maximum horizon for resiliency as one day, and the algorithms are also formulated accordingly. This may lead to the off-resiliency state after the horizon (one day), which may result in the shedding of critical loads. Therefore, it is essential to raise the horizon based on disaster and past data and schedule the available resources accordingly.
- In addition, it is essential to create a market to install ESUs in the distribution system. For example, in India, TATA power has installed an ESU at Rohini SS at Delhi province with 10 MW capacity to address the key challenges such as peak management, grid stability, flexibility, reliability improvement, and frequency regulation [116]. The same ESU can be utilized to satisfy the critical loads by optimal switching of sectionalizers during an event.
- Creating energy policies related to ESUs similar to grid-tied RES can help to create a market place to increase the installation of ESUs at optimal locations to address the grid flexibility and resiliency.

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