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TOPICAL REVIEW

Applications of BESS in Electrical Distribution Network With Cascading Failures Study: A Review

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ABSTRACT The rise in the growth of renewables in the distribution network introduces several challenges, such as voltage & frequency fluctuation, while the digitization of the network introduces cyber threats and risks like false data injection (FDI), resulting in a cascading network failure. By determining the optimal sitting, size and cost of the Battery Energy Storage Systems (BESS), these power quality issues & threats can be overcome as BESS can rapidly inject or absorb power as needed. In case of any cyber threat, it can supply energy to critical areas, reducing the cascading effect and increasing the survivability of the distribution network. Therefore, this paper provides a review of the existing methodologies used for the optimal placement, sizing, and cost of BESS in distributed networks involving Distributed Energy Resources and Electric Vehicles. Additionally, it provides insights into cascading effects in power systems due to cyber-attack, especially FDI attacks or component failure. After a thorough literature survey of the existing methods utilized for placement, sitting, costing, and modelling techniques, the paper concludes by providing a framework to enhance the grid resiliency against such power quality issues by improving the quality and reducing the minimum disruption area in case of any FDI attack. The proposed framework differs from the existing methodologies as it provides adaptive ancillary services and dynamic BESS response to address the operational and security challenges, based on this framework EV load penetration is estimated. Further to this EV load will be integrated into the dynamic distribution grid to analyze grid parameters including frequency, voltage, and line losses considered to be the future research work of the authors. However, the proposed framework has some challenges, including data dependency for stochastic modelling, computational challenges, and high quality for reliable optimization results.

INDEX TERMS Battery energy storage systems, cascading, cyber-attack, distributed energy resources, distributed networks, uncertainties, false data injection.

I. INTRODUCTION

Due to the rising population and growing demand for electricity, the pressure on generating power plants is increasing significantly. However, this demand puts stress mostly on traditional coal-based power plants because of the abundant coal reserves present today [1]. However, the energy generated from coal-based power plants results in higher emissions of hydrocarbons, which substantially increases global warming levels. Several policies have been created in efforts to reduce carbon emissions, one of them being the Paris Agreement. India, as per the Paris Agreement, is targeting to reduce its carbon emissions by up to 30% - 33% by 2030 [2], [3]. To achieve this, governing bodies are forced to opt for resources that can generate greener energy. These concerns have led to the expansion of independent Renewable Energy Sources (RES) such as solar, wind, small hydro, and other Renewable Energy (RE). These RES technologies are currently used for both DER and power generation. Indian power system, which was more passive, is now undergoing

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significant changes due to the integration of RES into the grid system, which is converting into an active system. India is now rapidly increasing its RE capacity, especially with wind and solar energy. The Indian government has introduced several initiatives to increase the share of renewables in the energy sector. The high-level penetration of the RES into the transmission and distribution network affects demand and generation balance because of its sporadic nature, as well as requiring enhanced flexibility in the power system [4]. The power injection by the distributed RES into the distributed grid sometimes leads to grid problems like frequency fluctuations [5], voltage violation [6], and network congestion [7].

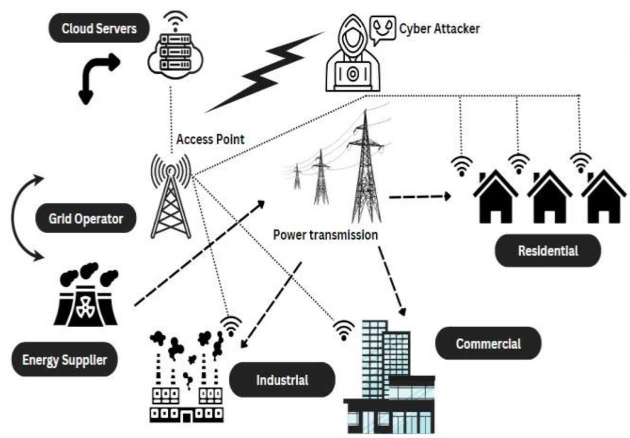

FIGURE 1. Cyber-attack on cyber-physical power system.

A. STORAGE FOR RE INTEGRATED GRID

The challenges introduced by the incorporation of RES in the grid, especially the sporadic nature, can be addressed by integrating Energy Storage Systems (ESSs). In addition, the ESSs can also be utilized to mitigate power quality issues by providing ancillary services to the grid [8], [9]. ESS can provide different services for long as well as short durations; the long-term duration involves services like load levelling, peak shaving, and power smoothing. Meanwhile, the short-term duration includes voltage and frequency regulation along with a black start. ESSs, especially Battery Energy Storage Systems (BESS), are recognized as a potential alternative for providing grid services. BESS can not only store the excessive amount of energy generated by RES but is also able to provide the services mentioned. BESS, compared to other types of ESSs, exhibits geographical flexibility.

Therefore, the demand for BESS is increasing rapidly in large and small-scale systems, providing dependable and sustainable energy management solutions for a variety of applications. Large ESSs are commonly employed with RE sources such as solar and wind to stabilize power generation [10]. Meanwhile, the BESSs for small-scale systems are increasingly heavy as they can be utilized as DER with other renewables to generate energy close to the point of demand [11], [12], [13]. It is preferred to allocate numerous BESS with smaller capacities at different locations in the network rather than deploying the entire available BESS capacity at one location, increasing BESS power reachability. Such a deployment method can aid in mitigating the negative effects of high MW installations on network components located in a single area [14].

B. EMERGING TRENDS IN ENERGY STORAGE FOR POWER SYSTEM STABILITY

ESS, especially BESS, is a key element for maintaining stability, particularly when renewables like solar and wind exist. To cater to the unpredictable power flow due to renewables, BESS is nowadays being used as Cloud Energy Storage (CES). Multiple BESS are installed in space-constrained areas, establishing a distributed, networked area where these storage devices' charging and discharging are controlled and managed through cloud-based platforms [15]. This helps optimize energy across locations to support grid stability, renewable integration, and demand-side management. This strategy is very effective, especially on the distribution side, where renewables and EVs are in existence; managing their uncertainties will eventually provide more stability to the grid. Multiple storage units acting as CES can be a viable solution to enhance the transient and steady stability in the grid network. In case of a sudden fault or load change affecting the grid frequency can be addressed through CES by rapid charging and discharging of storage devices till the frequency lies under the nominal range [16]. By combining and controlling these devices via a cloud-based system, CES can improve the voltage profiles and allow them to inject or absorb reactive power to support the grid [17], [18]. To reduce peak load and instability, CES uses effective energy management and demand response to align real demand with cloud computing [19], [20]. Through distribution energy storage, CES helps avoid cascade failure by providing backup power in emergencies [21]. However, to provide all these services through CES, it is mandatory to check for their secure operations with renewables and EVs. Effective protection schemes are required for grids with CES to manage sudden high current faults that disrupt recloser fuses. Advanced protection schemes in these systems should be integrated to adjust their response according to faults [22].

C. BATTERY STORAGE FOR E-TRANSPORTATION

The integration of renewables has also increased the growth of the electrification of transportation in India. The Indian government has promoted several policies that provide initial incentives and subsidies for Electric Vehicle (EV) buyers, such that encouragement for the use of electric vehicles in India increases. To support this electrification, the Indian government and other entities are regularly investing in the charging infrastructure. Initially, this electrification of the transportation sector was mainly focused on the shift from conventional gasoline two-wheelers to electric two-wheelers, also recognized as e-scooters [23]. These E-scooters provide a more cost-effective and sustainable alternative compared to conventional scooters. For charging these E-scooters, public charging stations are provided in different areas across the cities and highways to improve the charging experience of EV buyers. However, this electrification of the transportation sector puts a burden on the power distribution network.

Forming an interdependency over the distributed network and transportation network [24], [25]. As the mobility of the EV's in the transportation network increases, the overall demand for electricity rises, increasing the peak demand and putting strain on the generation systems and electrical distribution network if the load is not managed properly.

They also introduce variability and uncertainty into the distribution grid due to the varying charging behavior and patterns of EV users. However, to avoid this, effective use of BESS can be implemented, providing load shifting and peak shaving by shifting the charging of EV's during the off-peak periods. The uncertain charging behavior causing voltage and frequency fluctuation in the distribution grid can be ducked using BESS by delivering the necessary ancillary service [26], [27].

D. DIGITALIZATION AND CYBER THREATS

The addition of RES and battery storage devices provides several advantages: reducing greenhouse gas emissions, enhancing grid resiliency reliability and increasing energy independence [28], [29]. Amidst this integration, digitalization plays a very important role in enabling grid management and control. Digital technologies such as smart meters, advanced sensors, and data analytics provide real-time monitoring and controlling of energy generation, demand, and storage. This data-driven approach helps grid operators make better decisions, optimize energy transfer, and improve efficiency. It also allows coordination between the energy supply chain and demand, increasing the overall potential for flexible grid management. Despite the various benefits digitalization provides in the distribution grid, it also introduces some cyber threat possibilities. Cyber-attacks, especially False Data Injection (FDI), can disrupt the overall distribution grid during its operation and can cause power outages, resulting in widespread cascading effects in the grid [30], [31]. Fig. 1 shows a brief idea of how a cyber attacker can attack a distribution network consisting of different consumers. The data access point is the main point of attack where all the data related to distributed networks like power generation, power transfer, relay and sensor information is stored and can be controlled. Therefore, to avoid such types of attacks, various techniques like data encryption [32], network security [33], and continuous monitoring can be implemented. In addition, BESS can also play a crucial role in minimizing the cascading effect that occurs during the cyber-attack. BESS enhances the resiliency of the overall grid by providing the localized power supply and backup during major blackouts, making the area capable of islanding operation, and providing a black start facility for immediate restoration of an area lying under a critical zone.

The BESS is gradually being integrated into the grid system to improve the stability and reliability of the electrical network. To ensure the stable operation of BESS, various parameters are taken into consideration. They are energy capacity, power rating, round-trip efficiency, depth of discharge, cycling capability, response time, operating temperature range, and safety [34], [35]. Energy capacity refers to the amount of energy that can be stored in the battery, while power rating is the maximum amount of power the battery can deliver [36]. Round-trip efficiency is the efficiency of the battery in converting electrical energy into chemical energy and back [37]. Depth of discharge refers to the amount of energy that can be discharged from the battery relative to its total energy capacity, and cycling capability is the number of charge and discharge cycles the battery can undergo [38]. Response time is the speed at which the battery can respond to a change in the grid system, and the operating temperature range is the range of temperatures within which the battery can operate efficiently and reliably [39]. Safety is also a critical parameter, as the battery should be designed and operated in a way that minimizes the risk of fire, explosion, or other hazardous events. These parameters are essential considerations when designing, operating, and integrating battery storage systems into distribution grid systems.

For utilizing BESS to its maximum capacity and ensuring that the specifications are not affected, consideration of sizing and placement is necessary. Allocation involves the optimal location of the BESS in the electrical grid to address the specific grid challenges and ensure that the grid operators have profited. Strategical placement of BESS results in reduced line congestion, voltage and frequency fluctuation, and reduced line losses, ensuring that the allocation is well-planned and enhancing the performance of BESS. For the enhancement of overall performance, sizing is also equally important. The sizing of BESS involves the selection of the optimal capacity and storage capability of the system. Inaccurate sizing can result in under or oversizing BESS, limiting its performance. Under-sizing the BESS affects its ability to meet the grid's requirements, whereas oversizing increases the unnecessary cost and underutilization of the resources. Optimal sizing of the BESS can be obtained by considering different parameters like peak and energy demand and system specifications. Furthermore, it can result in an optimal balance of supply and demand, easy integration of renewables, and the facility to provide the required grid services.

Section I discusses the critical necessity of integrating RE, E-transportation, and BESS into a distributed network to eliminate the introduced uncertainties. Furthermore, it offers a concise synopsis of potential cyber threats linked to these technologies. Section II examines various ongoing battery initiatives in India. Additionally, it delineates the technical characteristics of diverse battery varieties utilized in BESS.

TABLE 1. Comparison of review articles.

Feature	This Paper	[40]	[41]	[42]	[43]	[44]	[45]
Primary Objective	BESS Placement, Sizing, and cost related to power quality and cyber threat resulting to cascading failures	BESS model benefit to residentials grid	ESS technologies and trend	BESS enhancing grid stability by ancillary service	ESS grid support under renewable penetration	Functionalities and impact of ESS in grid	Advancement and challenges in BESS
Scope	BESS placement, grid resilience, cyber security, cascading failure	DSM, storage sharing technologies	Review ESS technologies and Hybrid Storage	BESS service and grid support	Variability management for High Renewable Penetration systems.	ESS evaluation and grid impact.	Explores new mechanical, thermal, electrical, and chemical storage technologies.
Methodology	Literature review, probabilistic modeling, and resilience frameworks.	Optimization techniques like MILP and GA for DSM.	Statistical and comparative review of ESS technologies.	LMP-based dynamic pricing and reserve sizing.	Case studies on renewable grid balancing.	Functional and lifecycle analysis of ESS technologies.	Analyzes trends in multiple ESS types and identifies technological gaps.
Key Findings	Introduces cyber-resilient BESS framework to enhance reliability.	Demonstrates financial benefits from shared storage.	Hybrid ESS adoption is increasing.	BESS improves emergency services and grid stability.	ESS mitigates variability in HRP systems.	ESS enhances peak shaving, load management, and grid reliability.	Identifies emerging technologies, including sodium-sulfur and thermal energy storage.
Contribution to the Field	Provides cybersecurity-focused BESS strategies.	Promotes DSM and shared BESS models.	Identifies hybrid ESS trends across sectors.	Emphasizes dynamic BESS for grid management.	Guides storage planning for HRP systems.	Assesses emerging technologies for future energy needs.	Proposes strategies for enhancing ESS adoption and sustainability.
Limitations and Future Directions	Framework proposed requires high quality reliable data for consistent optimization results	Real-time DSM and shared storage optimization needed.	Calls for regional studies on hybrid ESS.	Recommend risk-based management strategies.	Focus on long-term energy storage for HRP.	Testing of emerging ESS technologies recommended.	Recommends further research on environmental impacts of ESS technologies.
Focus on Cybersecurity	Central theme addressing FDI mitigation.	Minimal; focuses on DSM and operations.	Not discussed; system reliability emphasized.	Introduces penalties to ensure reliability.	Operational reliability emphasized.	No direct cybersecurity focus.	No direct cybersecurity emphasis, more focus on technology trends.
Case Studies	BESS projects in Indian grids.	Shared BESS systems in residential communities.	ESS adoption statistics worldwide.	IEEE 30-bus system integration for ancillary services.	HRP grid case studies in U.S., U.K., and China.	Hybrid storage models with molten metal and hydrogen technologies.	Multiple case studies showcasing mechanical and chemical energy storage.
Cost-Benefit Analysis	Focus on the economic impact of BESS sizing and placement.	Highlights financial gains from shared storage.	Compares efficiency of various ESS technologies.	Explores LMP-based revenue for BESS.	Examines economic feasibility of HRP system storage.	Provides detailed financial metrics for emerging storage.	Compares economic and environmental benefits of various ESS systems.
Emerging Trends	Highlights smart grids and cyber-resilient storage.	Growth in DSM programs and shared storage.	Expansion of hybrid ESS and microgrids.	Adoption of real-time ancillary services.	Increased focus on cloud energy and seasonal storage.	Identifies molten metal and hydrogen-based storage technologies.	Highlights sodium-ion, vanadium-redox, and thermal storage as emerging technologies.

TABLE 2. Battery storage projects in india.

S. No	Plant	Status Commissioned	Under Construction	Tendering Stage	Type of Battery	Installed Location	Level of Connection	Rated Capacity (Power/Energy)
	Modhera Sun Temple Town Solar PV Park-BESS	2021			Li-ion	Mehsana, Gujarat	Distribution	15 MW
	Nexcharge: TPDDL 150KW/528KWh Community Energy Storage System (CESS) Project.	2021			-	Rani Bagh, New Delhi	Distribution	150KW/528KWh
	Applied Energy Services (AES) Mitsubishi-BESS	2019			Li-ion	Rohini, NCT, India	Distribution	10 MW
	Andhra Pradesh State Electric Utility	2019			-	Makkuva, Andhra Pradesh		4MWh
	200kWh flow battery, 300 kWh Advanced LAB, 500kWh Li-Ion (Hyderabad- BHEL)	2021			Flow, Advance LAB, Li-ion	BHEL R&D, Campus, Hyderabad, Telangana	Distribution	1 MW
	160 kWh advanced lead acid, and 350 kWh Li-ion			✓	-	Central Electronics Limited, Sahibabad	Distribution	0.51 MW
	Solar Energy Corporation of India (SECI) Himachal Pradesh Solar-Storage Hybrid		✓		-	Kaza, Himachal Pradesh		1 MW
	SECI			✓	-	Lakshadweep	Standalone	60 MWh
	Tamil Nadu Generation and Distribution Corporation Ltd.			✓	-	Virudhunagar, Tamil Nadu	Distribution	3MWh/1MW
	BESS Pilot Project by Power Grid Corporation of India Limited (PGCIL)	2017			Advance Lead-Acid, Li-ion	Puducherry	Distribution	500 KW (advanced lead-acid), 500 KW (Li-ion)
	Neyvelli Lignite Corporation (NLC) 20MW solar with 16MW/8MWh BESS	2020			Nickel Manganese Cobalt (NMC)	Port Blair, Andaman	Standalone	16MW/8MWh
	National Thermal Power Corporation	2019			-	Chidiyatapu, Andaman & Nicobar Islands	Standalone	3.2MW/3.2MWh
	Phyang Solar PV-BESS			✓	-	Phyang, Leh		50 MW
	Pavagada Ultra Mega Solar Park			✓	-	Pavagada, Karnataka		4.5 MW
	Makkuva Solar PV Park-BESS			✓	Li-ion	Makkuva, Vizianagaram, Andhra Pradesh		1,000 KW

Section III of the paper discusses the multiple modelling methodologies and distribution functions used to represent Photovoltaics (PV), BESS, and wind energy sources within the distributed networks. In addition, a literature review of diverse BESS technologies utilized for various ancillary grid applications is provided. Section IV describes the existing methodologies for optimizing the different parameters associated with BESS. Section V presents a comprehensive examination of the cascading effects that occurred in the power system either due to component failure or due to targeted attacks. A framework for the optimal allocation of BESS is presented in Section VI, which offers an optimal resolution to the uncertainties inherent in the distributed network. The suggested approach would result in minimal fluctuations in voltage and power, and it demonstrates resilience against potential cyber threats by focusing on the most vulnerable segments of the network to prevent a chain reaction of failures, the validation of this framework is future research work. The overall investigation is summarized, and the work is concluded in Section VI.

The paper offers a comprehensive analysis of the integration and optimization of Battery Energy Storage Systems (BESS) in modern power grids. Through an extensive literature survey and critical examination of existing methodologies, the paper addresses the technical and economic challenges associated with BESS deployment. A comparative analysis of this review paper is shown in Table 1, with several other key review papers covering different aspects of BESS.

TABLE 3. Characteristics of different battery technologies.

Type	Capacity (MW)	Charging & Discharging Cycles	Efficiency (%)	Specific Energy (Wh/L)	Energy Density (W/L)	Response Time	Charge Time	Discharge Time	Cost		Environmental Impact
									Power ($/KW)	Energy ($/KWh)	
Lead-Acid[46]	0-40	300-3000	70-90	35-40	80-90	5-10ms	Min-days	sec-hrs	300-600	200-400	Medium (substances coming out from exhaust)
Li-ion[46]	0-100	3000	75-90	100-265	250-693	ms	Min-days	Min-hrs	1200-4000	600-2500	Medium
LFP	0.001-10	2000-10000	85-95	90-120*	120-160*	ms		min-hrs			
NMC		1000-2000		150-220*	275-350*	ms					
LTO		≥4000		50-80*	125-200*	ms					
LMO		1000-2000		100-150*	125-200*	ms					
Na-S[47]	0.05-8	4500	80-90	150-300	10000	ms	sec-min	<15min	250-350	1000-14000	Medium
Ni-Cd[48]	0-40	3000	60-80	46-60	50-150	ms	min-days	sec-hrs	500-1500	800-1500	Medium
Flow battery[47]	0.03-3	2000-20000	65-90	40	-	ms	min-days	sec-hrs	600-1500	150-1000	Medium
Ni-MH[47]	-	2000	66-92	60-120	140-300	-	-	-	-	150-200	-
$NaNiCl_2$[47]	0.004-0.025	1500-3000	85-95	90-120	150	-	-	-	-	-	-
Ultra-battery [46]	0-36	3000	-	-	-	5ms	min-days	sec-hrs	-	200	Mostly Chemical Waste

* Wh/Kg

This paper covers critical gaps related to intersection of the cybersecurity, operational, and economic considerations in BESS placement for providing ancillary services, which are not comprehensively addressed in other articles. Additionally, it delves into the implications of cybersecurity threats and proposes innovative strategies to enhance grid resiliency. Below are the key contributions made by this review paper:

- Presents a comprehensive discussion of alternative techniques for optimizing BESS placement, size, and cost. It examines analytical, mathematical, probabilistic, meta-heuristic, and artificial neural network approaches, providing a thorough assessment of each method's advantages and disadvantages. This comprehensive evaluation is an invaluable resource for researchers and practitioners working to improve the economic and technical performance of BESS in electricity grids.
- The paper discusses various technical characteristics and applications of BESS, including frequency support, active and reactive power support, black start capabilities, and their use in load levelling and peak shaving. This provides a detailed understanding of how BESS can be utilized for different ancillary services.
- The study tackles modern power grid cybersecurity, FDI attacks. It addresses cascade failures from such attacks and how BESS can mitigate them.
- Based on a literature review, this study suggests a framework for improving grid resilience against power quality concerns and cascading failures caused by FDI assaults. This framework intends to improve power quality and reduce disruptions caused by cyber-attacks, so contributing to the creation of more secure and resilient power systems.

II. BATTERY ENERGY STORAGE SYSTEMS

A. TYPES OF BATTERY ENERGY STORAGE SYSTEMS

BESS has emerged as a revolutionary technology in the domain of energy storage, offering an efficient means of storing surplus energy from renewable sources. These cutting-edge systems provide a reliable and sustainable solution for meeting peak energy demand without overburdening the grid infrastructure. Due to the growing RES, electrification in the transportation sector and requirements for backup power increase the overall demand for BESS in India. Table 2 shows some of the ongoing battery storage projects in India for standalone as well as in integration with DERs. For battery storage applications a variety of types are available, including lead acid, Lithium-ion (Li-ion), Sodium Sulphur (Na-S), Nickel Cadmium (Ni-Cd), Flow battery, Nickel Metal Hydride (Ni-MH), Sodium Nickel Chloride (NaNiCl2), and the ultra-battery (also known as the advanced lead acid battery), each variant possesses unique features and applications.

To better understand the diverse landscape of Battery Energy Storage Systems (BESSs), a comprehensive Table 3 is presented, highlighting the crucial attributes of each battery

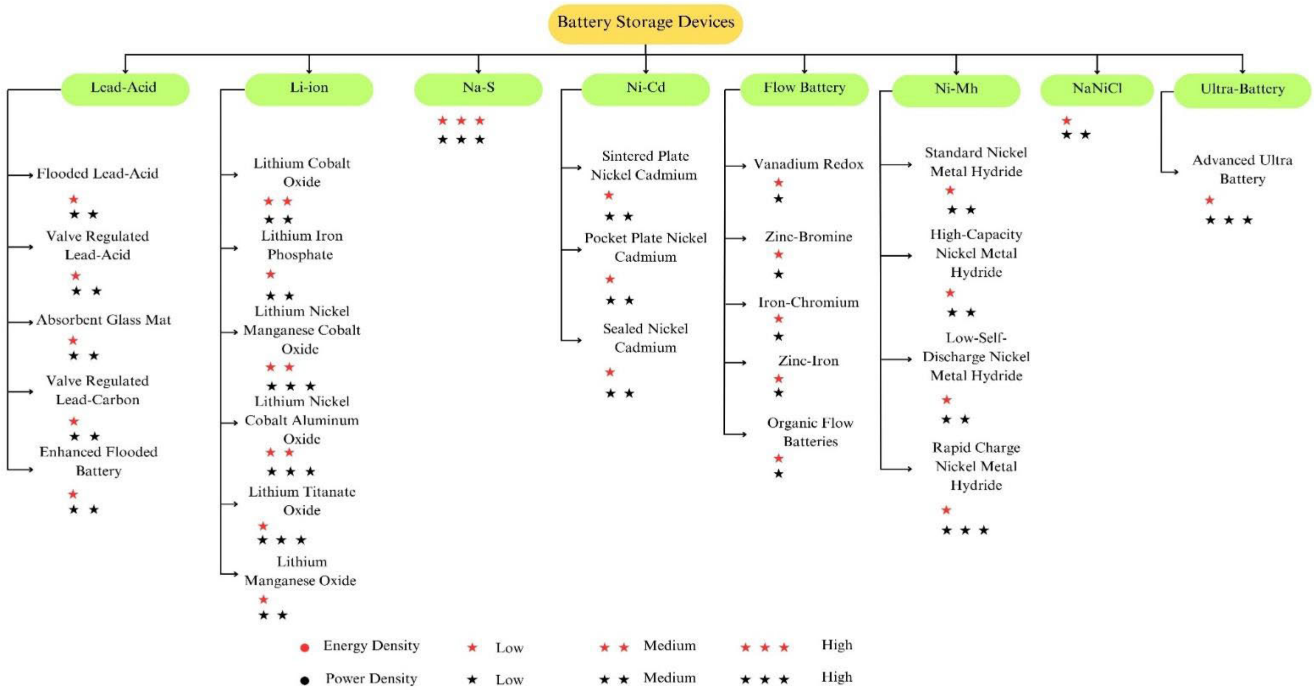

FIGURE 2. **Different types of battery storage technologies.**

type, such as capacity, depth of discharge, efficiency, specific energy density, energy density, response time, charge time, discharge time, cost of generation, and environmental impact. Table 3 serves as a useful tool for making informed decisions about selecting the appropriate battery technology for specific energy storage requirements. Additionally, for a more comprehensive assessment of energy and power density across different technologies, Fig. 2 can be considered. This Fig. 2 provides a comparative visualization of various battery technologies, categorized by their high, medium, or low energy density ratings. This information collectively aids in a complete evaluation of BESS options, empowering stakeholders to make well-informed decisions associated with their energy storage needs.

1) LEAD-ACID BATTERY

A French physicist, Gaston Plante, invented the lead acid battery in the 1850s. These batteries were the first rechargeable battery technology and are now considered one of the most mature technologies existing [49]. They are the first batteries used for energy storage applications. It exhibits many specific attributes like robust operation, easy control, low cost, easy maintenance, and less response time. These specifications make it suitable for stationary energy storage applications [50]. However, they suffer from some limitations, like low specific energy density, poor operation during low temperatures, short depth of discharge, and exposure to corrosion, leading to their limited usage.

2) LITHIUM ION (LI-ION) BATTERY

The first commercialization of lithium-ion batteries was done in the year 1991. These batteries possess several properties, such as high round-trip efficiency, high energy and power density, and long life [51]. Due to their high energy power density properties, these batteries have transformed the energy storage and EV industry. It exhibits high specific energy density compared to other existing battery technologies, making it lighter and suitable to be used for mobile energy storage applications. However, safety is the main concern for these types of batteries. Many cases have occurred over the period regarding its flammability problem. The reserves of lithium in the earth's crust are limited, resulting in a difficult and costly extraction process compared to other battery technologies [47], [52]. To further enhance its energy density and to mitigate its flammability apprehension, many types of lithium-ion batteries are developed like lithium-ion phosphate (LFP), lithium manganese oxide (LMO), Nickel Manganese Cobalt (NMC), and lithium titanate oxide (LTO).

3) SODIUM SULPHUR (NA-S)

Na-S battery was invented in the year 1996 by Ford Company, but it was first commercialized by Tokyo Power Corporation and NGK Insulators in the 1990s [53]. They are also known as high-temperature batteries. From an energy storage point of view, these batteries play a very crucial role as they parade high efficiency, energy density, and high depth of discharge [54]. The only issue associated with these batteries is that they require very high temperatures for their operation, which is difficult to achieve. This increases the overall cost of the system and poses a threat to the atmosphere if not operated properly.

4) NICKEL CADMIUM (NA-CD)

The nickel Cadmium battery was invented in the year 1899 by Swedish inventor Waldemar Jungner. The battery is constructed by using nickel oxide as the positive terminal and cadmium as the negative electrode, resulting in the creation of a rechargeable battery possessing stable voltage output and high energy density [55]. These batteries offer very similar properties to lead acid batteries but have a superior depth of discharge and energy density. It is used for various electronic applications like a lead acid battery. The primary drawback of these batteries is they are very expensive due to the high cost involved in the manufacturing process. These batteries also suffer from a term called the ''memory effect'', which usually happens when recharging a battery before it is fully discharged. This results in less capacity than it does, and it will discharge more quickly than anticipated [56].

5) FLOW BATTERIES

The concept of flow batteries was proposed by German scientist Friedrich H. Karl in the 1930s, while the first practical battery was developed by a team of NASA scientists in the 1970s. These batteries are constructed by dissolving two chemical components in a liquid separated by a membrane. The main advantages of these batteries are they can be packed in immense volumes for storing a large amount of energy, fast recharging by changing the liquid electrolyte, quick response time, and no harmful emission into the environment [57]. The only limitation of these batteries is the capital investment required due to the high cost of materials used for their construction [58]. Hybrid Flow batteries (HFBs), Redox Flow batteries, and Membrane-less flow batteries are the three types of flow batteries used for energy storage and other renewable applications [50]. The redox flow and hybrid flow batteries are based on the principle of the flow of electrolytes, a process through which energy is stored and released in the battery. It involves the pumping of two different electrolyte solutions in the cell, where they endure different chemical reactions that generate electricity. During the charging process, one electrolyte gets oxidized while the other electrode reduces, storing the electrical energy in the form of chemical energy. During discharge, the process gets reversed. The main difference between the two-flow batteries is the active material used and the chemical reactions they undergo, whereas membrane-less batteries use an ion-selective membrane instead of the traditional membrane used by redox and hybrid flow batteries.

6) NICKEL METAL HYDRIDE (Ni-MH)

Ni-MH batteries were developed by a team of researchers in an institute in Ohio, United States, led by Stanford Ovshinsky in the 1980s. The Ni-MH battery consists of an anode of hydrogen-absorbing alloy (MH), a cathode of nickel hydroxide (Ni $(OH)_2$), and a potassium hydroxide (KOH) electrolyte [59]. These batteries were recently used for many electric and hybrid electric vehicle applications, as they do not have oxidizing properties and provide a safer environment compared to lithium-ion and nickel-cadmium batteries [60]. The main disadvantages of these batteries are their high self-discharging rate, low energy density, and reduced voltage per cell [61].

7) SODIUM NICKEL CHLORIDE ($NaNiCl_2$)

$NaNiCl_2$ battery was developed by a group of researchers from the French National Centre for Scientific Research (CNRS) in the 1980s. They are also known as ZEBRA (Zero Emission Battery Research Activity) and are a type of high-temperature battery [62]. It uses two types of electrolytes, namely sodium chloride (NaCl) and nickel chloride ($NiCl_2$). They are recognized because of their high operating temperature, high energy density, long life, and very low environmental impact. Due to these properties, it is applicable to use for electric transportation, stationery grid systems, and energy storage. However, it suffers from low power density, resulting in a longer charging time, limiting its practice.

8) ULTRA-BATTERY

The Ultra-battery was developed jointly by Commonwealth Scientific and Industrial Research Organization (CSIRO) of Australia and Furukawa Battery Company of Japan. It is a type of advanced battery that combines the features of a lead-acid battery and a supercapacitor [63]. The two components are connected in parallel, in which the positive terminal of the lead acid battery is made up of lead oxide, while the negative terminal is constructed of porous lead material. During high charging and discharging rates, the supercapacitor can provide high power to limit the current and prevent the lead-acid battery from any damage. Ultra-battery has several advantages, such as a long-life cycle, high efficiency, and a safe operating environment compared to the traditional lead-acid battery [64].

B. EMERGING TRENDS IN BESS TECHNOLOGY

For grid applications, Li-ion batteries are widely accepted as they have an inherent high energy density, faster response time, and high efficiency in absorbing and releasing energy. They are used for services like peak shaving, load levelling, frequency regulation, and the integration of intermittent renewable sources like solar and wind. However, these batteries suffer from thermal risks, material availability, and environmental impact during production. LFP, one type of Li-ion, could be preferred because of its longer life span, cheaper manufacturing cost, and improved safety [65], [66]. Liquid electrolyte batteries are now being replaced by Solid State Batteries (SSBs), eradicating the hazards involved with the traditional liquid electrolyte. Using SSBs enables fast charging, due to their high energy density making them suitable for large scale applications in storage and EVs. The risks of thermal runaway decrease as flammable components are substituted with solid materials, increasing the overall energy density allowing them for longer operations. However, SSBs commercialization suffers from high production cost, complexity in manufacturing, and low efficiency at low temperatures. SSBs will play a significant role in future grid services as they are well suited for cases requiring fast cycling and high energy output [66], [67].

Regardless of the advantages the SSBs possess, redox flow batteries are another alternative becoming popular for grid applications because of their scalability and capability to store large amounts of energy for long duration with low leakage and less environmental impact [68]. All these advancements in battery technologies will make the modern grid more resilient, reliable and efficient.

III. MODELS OF BESS, EV, PV, & WIND FOR DISTRIBUTION GRID

A. EV LOAD MODELS

The growth and development of EVs have significantly brought many changes in the energy sector, and now EVs are playing a very crucial role in shifting the transportation sector towards a sustainable environment. As the adoption of EVs increases exponentially, the impact of EV charging on the electric grid is one of the major concerns of grid operators. In [69], several models are created for EV charging that are suitable for power flow operation.

The model represents both coordinated and uncoordinated charging of the EVs and also includes parameters like battery size, charging level, arrival time, and energy consumption. The models are integrated into the power system production cost model (PCM) to analyses the influence of EV's in the power system. Another model [70] for analyzing the impact of EV charging is proposed; the model considers different charging scenarios, including uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging, and publicly controlled domestic charging. The model also considers the initial state of charge along with the starting charging time of the EV, helping to better analyze the load demand. There are several other models which can be employed to better understand the impact of EV's on the distribution grid.

It is observed that EV charging is an unpredictable load and depends upon various factors like charging infrastructure, charging behavior, and utilization. To manage the demand rising from EV charging, one of the solutions is the modelling of the EV load as well as the modelling of its uncertainty. This modelling enables the system operators to predict the amount of load increment to manage the impact of EV charging, estimate charging patterns and charging demand, update grid infrastructure, and optimize grid operation. There is significant research ongoing on the optimization of different parameters related to EV's, which includes EV charging models and optimal scheduling algorithms for efficient and smart electric vehicle charging. In [71], a model for optimal scheduling of EVs in office buildings during the demand response period is proposed. The model incorporated uncertainties of EV charging loads through Monte-Carlo simulation. The proposed method achieves several benefits, such as reduced non-guarantee rates for arrival and charging, lower operating costs, and low load variance.

A new data-driven approach [72] for optimization of charging and discharging capacities of the electric vehicle by involving uncertainties through predictor combining Wavelet Transform (WT), Deep Deterministic Policy Gradient (DDPG), and Quantile Regression (QR). The uncertainty involved is utilized for forecasting the uncertainty of energy consumption. The proposed approach and optimized model using 300 EV data based on Chinese city results in more accurate, efficient, and probabilistic forecasting compared to other conventional techniques. A two-stage stochastic energy scheduling model [73] is proposed, optimizing the day-ahead decisions and minimizing the real-time operations in a microgrid. The model considers renewable resources, baseload demands, and the uncertainty of EV demand. It includes various other EV parameters like Battery bank, non-linear charging/discharging, and efficiency oscillations. The model can be utilized to reduce operating costs associated with microgrids. A deep-learning-based convolution neural network (CNN) approach [74] is proposed for forecasting EV charging load at different charging stations based on the traffic flow and unpredictable charging behavior. Arrival rates of EVs are calculated using historical data. A novel probabilistic queuing model is employed to convert the traffic flow into charging loads, considering charging station service limitations and the behavior of the driver. The models help grid operators determine the number of dispatchable EVs in advance, reducing cost and mitigating risk. A concept of charging traffic flow (CTF) [75] is employed to explain the charging start time and other properties of EV charging. The proposed concept enables flexible simulation, parameter identification, and understanding of stochastic and deterministic scenarios. Ant Colony Optimization (ACO) is used for parameter identifications. The proposed concept represents a novel approach to studying the charging load profile for EV's.

The paper [76] focuses on the forecasting and modelling of the EV charging load behavior in various regions of the distributed network. The model considers various parameters, including the type of EV, charging equipment and other random parameters like user behavior and physiological factors. An EV economic dispatch model [77] is proposed for optimal scheduling for vehicle-to-grid (V2G) applications. The proposed model helps in the effective utilization of EV charging and discharging resources, the model is anticipated for aggregators to manage the service of EVs in a particular region. A bidirectional power flow strategy [78] is proposed for the optimization of a community-based microgrid considering PV, ESS, and EVs as alternative power sources. The proposed power flow and control strategy is based on EV availability, transformer loading and prices. A Markov model is used to predict EV availability and utilizes Mixed Integer Linear Programming (MILP) optimization for optimal charging and discharging scheduling. The proposed strategy helps in reducing operational costs with increased EV availability through incentives.

In the context of EV's, it is assumed that all types of EV's are connected to the power grid through either AC/DC converters or charging ports. Since the battery is the main source of power for EVs, the load of the EV battery is modelled based on its dependency on the grid voltage. The amount of additional active and reactive power required by the EV battery at a particular location is represented as a proportion of the total real power demand at that location shown in equation (1)-(2). This allows for accounting for the impact of EVs on the grid in terms of their power demand characteristics, which may vary depending on the voltage of the grid [79], [80].

$$P^0_{ev(n)} = \lambda_{ev} \times P^0_{L(n)} \tag{1}$$

$$Q^0_{ev(n)} = P^0_{ev(n)} \times \tan(\varphi_{n(c)}) \tag{2}$$

where $P^0_{ev(n)}$& $Q^0_{ev(n)}$ are the additional active and reactive power required due to penetration of EV load at bus n, λev is the scaling factor of the representing the penetration of the EV load, and $\tan(\varphi_{n(c)})$ is the power factor angle between the AC/DC converter. The total active and reactive power after the integration of EV load is represented in equation (3)-(4) [81].

$$P^t_{d(n)} = P^0_{L(n)} \times \left(\frac{V^t_{(n)}}{V^0_{(n)}}\right)^{\alpha} + \left\{P^0_{ev(n)} \times \frac{V^t_{(n)}}{V^0_{(n)}}\right\}^{\alpha_{ev}} \tag{3}$$

In equations (1, 3 & 4), $P^0_{L(n)}$ & $Q^0_{L(n)}$ refers to the nominal active and reactive power at bus n before the integration of EV load, $V^0_{(n)}$&$V^t_{(n)}$ are the nominal voltage magnitude of bus n at nominal and specified time, α & β are the exponents of active and reactive power, αev & βev are the exponents of the EV's active and reactive power load respectively. Now the uncertainty of the EV load can be modelled, it is associated with three variables namely, daily arrival time (time of parking), initial State of Charge (SoC) of the battery when the EV has arrived at the parking lot, and required travel distance, the three variables can be expresses as shown in equation (5-7) respectively [70], [87].

$$Q^t_{d(n)} = Q^0_{L(n)} \times \left(\frac{V^t_{(n)}}{V^0_{(n)}}\right)^{\beta} + Q^0_{ev(n)} \times \left(\frac{V^t_{(n)}}{V^0_{(n)}}\right)^{\beta_{ev}} \tag{4}$$

$$PDF_T(T) = \frac{1}{\sigma_T\sqrt{2\pi}} exp\left[\frac{-(T-\mu_T)^2}{2(\sigma_T)}\right] \tag{5}$$

$$PDF_{SOC}(SoC) = \frac{1}{\sigma_{SOC}\sqrt{2\pi}} exp\left[\frac{-(SoC-\mu_{SoC})^2}{2(\sigma_{SoC})}\right] \tag{6}$$

$$PDF_d(d) = \frac{1}{\sigma_d\sqrt{2\pi}} exp\left[\frac{-(\ln(d)-\mu_d)^2}{2(\sigma_d)}\right] \tag{7}$$

where, PDF_T is the Probability Distribution Function (PDF) of daily arrival time, σ_T is standard deviation of the daily arrival time, μ_T is mean of the daily arrival time, PDF_{SoC} is PDF of the initial battery SoC, σ_{SoC} is standard deviation of the initial SoC and μ_{SoC} is the mean value. PDF_d is the PDF of the travelling distance, μ_d and σ_d is the mean and standard deviation of the travelling distance.

B. PHOTOVOLTAIC (PV) MODELING

During the transition from fossil fuel-based generation to RE resource-based generation, especially solar energy, has played a major role in meeting the growing energy demand and simultaneously reducing greenhouse gas emissions. Solar offers an abundant source of energy, but due to its intermittent nature, it poses some challenges to the grid's reliability and stability and indirectly to its adoption. BESS has emerged as a promising solution to overcome these challenges by providing a means to store excessive solar energy and release it when required, making the energy supply more reliable and continuous. To ensure that this energy supply remains reliable, solar modeling becomes a necessity. Integration of the battery storage devices into the distribution grid will open the opportunity to not only store excessive energy but also improve the grid's frequency and voltage levels by providing ancillary services like frequency support, voltage support, and load balancing. PV modelling enables better prediction of solar energy generation and variation.

Eventually, helping the grid operators identify effective dispatch of the energy stored in the battery during low periods of solar generation. Moreover, solar modelling helps in the assessment of the battery's state of charge and capacity to absorb the excessive energy of the sun, therefore enhancing the overall efficiency of the services provided by the battery storage devices.

In recent years, there has been a lot of research done related to solar energy in terms of its uncertainty modelling, integration with energy storage devices, its grid integration and control algorithms. A profitable dispatch strategy [88] is introduced for an owner operating a PV plant along with battery storage devices. The strategy requires information about electricity prices and day-advance predictions of solar energy. This strategy concludes that the best strategy is to decide the power delivery by the battery storage based on the current electricity prices, regardless of the power generated by the PV plant. It also determines that if the owner aims to deliver only a certain amount of power, then profits will not be as high as they could be. A dedicated control strategy [89] for the maximization of revenue of a PV-BESS system in the daily market is proposed by determining the optimal parameters of the energy storage device. The strategy includes bidirectional energy flow with the grid to increase the system's profit. The strategy is based on complete data of PV generation, and a 10-year analysis is showcased. The results show a significant increase in the energy storage rate of return and achieving around 15% during the high PV penetration profiles. A techno-economic analysis [90] is performed to determine the optimal capacity of a battery

TABLE 4. Distribution functions used for PV modelling.

Distribution Function	Distribution Equation
Beta Distribution [82]	$$PDF_T(T) = \begin{cases} \frac{\gamma(\alpha+\beta)}{\gamma(\alpha)+\gamma(\beta)} \times G_s^{\alpha-1} \times (1-G_s)^{\beta-1}, & If\ 0 \le G_s \le 1, 0 \le \alpha,\beta \\ 0, & Otherwise \end{cases} \quad (8)$$ α & β are the beta functions, and can be calculated as: $$\beta = (1-\mu_s) \times \left(\frac{\mu_s \times (1+\mu_s)}{\sigma_s^2}\right) - 1 \quad (9)$$ $$\alpha = (1-\mu_s) \times \left(\frac{\mu_s \times \beta}{(1-\mu_s)}\right) - 1 \quad (10)$$
Lognormal Distribution[83]	$$PDF_s(G_s) = \frac{1}{G_s \sigma_s \sqrt{2\pi}} exp\left[-\frac{(\ln(G_s)-\mu)^2}{2\sigma_s^2}\right] \quad G_s > 0 \quad (11)$$ Where G_s represents the solar irradiance, μ is the mean value, and σ_s is standard deviation.
Weibull Distribution[84]	$$f(x;\lambda,k) = \frac{k}{\lambda}(\frac{x}{\lambda})^{k-1} e^{-(\frac{x}{\lambda})^k} \quad (12)$$ Where x is the solar irradiance values, λ is the average solar irradiance at specific location, and k represents the skewness and shape based on the local conditions.
Gamma Distribution[85]	$$f_G(x;\alpha,\beta) = \frac{1}{\beta^\alpha \gamma(\alpha)} . x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (13)$$ Where x is solar irradiation, and α & β are the shape and scale parameters respectively.
Inverse-Gamma Distribution[86]	$$f_{IG}(x,\lambda,\mu) = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left(-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right) \quad (14)$$ x is the solar irradiance, while μ & λ are the shape and scale parameters.

energy storage device combined with a PV array for maximum self-consumption for a desired household load. Data for the year 2021 regarding the energy consumption ambient temperature and irradiance is utilized for simulations. It is observed that the integration of PV with battery storage would increase the net present cost. It takes a certain amount of time to make a profit by using the stored energy. The time frame depends upon various factors like policies, cost, and electricity prices. Based on the RE resources, a city is proposed in the paper [91] to be considered a new city. This city is powered by different renewable resources like solar and wind. Battery storage devices are utilized to store excessive energy. It is observed that the energy generated costs around 7.5 cents per unit, whereas if the heat and pressure are increased, it results in a decrement of around 1 cent per unit of electricity. It is estimated that the implementation of solar panels and windmills would decrease the price of electricity by 3 to 4 cents. For uncertainty modelling, different PDF have been utilized, which include Weibull distribution, lognormal distribution, Gamma distribution, and inverse Gaussian distribution function. Table 4 shows the different PDF functions & their equations (8-14) used for solar modelling. The Weibull distribution can be applied if the data is skewed, consists of high valleys, wide variation, and development of realistic models. However, if other PDFs are considered, they are considered if the data is symmetrical or if the data consists of multiple peaks and modes.

C. WIND MODELING

Due to the unpredictable nature of the wind speed, it becomes difficult to estimate the total power generation from the wind turbines. There are various probability distribution functions to model its uncertainty, but the wind speed behavior is very similar to the Weibull distribution function [83], [92]. The modelling of wind speed distribution through Weibull distribution function is expressed in equation (15).

$$PDF_v(V) = \left(\frac{\beta}{\alpha}\right)\left(\frac{V}{\alpha}\right)^{\beta-1} exp\left[-\left(\frac{V}{\alpha}\right)^{\beta}\right]$$
$$0 \le V \le \infty \quad (15)$$

where $PDF_v(V)$ is the probability density of the wind speed, while α & β represents the scale and shape parameter of the PDF of Weibull function. Besides the Weibull function, the Rayleigh function can also be applied for modelling wind variation. In Rayleigh probability distribution function, V is the wind speed variation, Rayleigh is a special type of Weibull function where $\beta = 2$. Equation (16) shows the modelling of

Rayleigh PDF.

$$PDF_v(V) = \left(\frac{2V}{\alpha^2}\right) exp\left[-\left(\frac{V^2}{\alpha^2}\right)\right] \tag{16}$$

The output power generated from the wind turbine can be expressed as shown in equation (17).

$$P_w(V) = \begin{cases} 0 & \text{for } V < V_i \text{ and } V > V_0 \\ P_r\left(\frac{V-V_i}{V_r-V_i}\right) & \text{for } (V_i \leq V \leq V_r) \\ P_r & \text{for } (V_r \leq V \leq V_0) \end{cases} \tag{17}$$

Here P_r is the rated output power of the wind turbine. V_i, V_r, and V_0 are the Cut in, rated and out wind speed of the turbine. The shape (β) and scale parameter (α) of the Weibull distribution function can be calculated as in the equation (18).

$$\beta = \left(\frac{\sigma_{std}}{v_{mean}}\right)^{-1.806}; \quad c = \frac{v_{mean}}{\Gamma(1+(1/k))} \tag{18}$$

D. BATTERY MODELING

In recent times, there has been a great push towards the acceptance of green energy. Therefore, there is an expectancy of a large penetration of renewables and EVs in the power sector. With these large penetrations, various challenges come forward, such as the increasing demand and dynamic loading conditions, resulting in the degradation of the power quality at the distribution level, establishing the need for ancillary support. The integration of BESSs can address these challenges; these devices can be integrated at different locations, can be charged based on excessive renewable energy generation or at low peak times and can discharge power at peak load time. The BESS integration eventually decreases the pressure on the generation side, enhancing power quality.

Before integrating the BESS, it is necessary to model it to understand its accurate performance under various operating conditions and ensure that it meets the specific requirements of the grid operators. Modelling also helps in understanding the parameters that can be optimized to increase the efficiency of the BESS. BESS modelling involves technical parameter considerations like the charging and discharging cycle, SoC of the BESS, and voltage & current ratings. However, certain parameters, including battery capacity, power ratings, and cost, can be optimized to meet the power delivery demands for the ancillary services. This section discusses the modelling of BESS for various applications for ancillary services. Table 5 shows the different battery models used for other applications coming under the ancillary service.

A simple model of BESS involves different parameters like voltage, current, SoC, and active and reactive power, which are very crucial for BESS, especially for their integration in the transmission or distribution grid. A basic model of a BESS is shown in the equations (19)-(20).

$$E^{BESS}(t+1) = E^{BESS}(t) + \Delta t.P_t^{BESS,ch}(t).\eta^{ch}.\eta^{inv} \tag{19}$$

$$E^{BESS}(t+1) = E^{BESS}(t) - \Delta t.P_t^{BESS,dis}(t)/(\eta^{dis}.\eta^{inv}) \tag{20}$$

where $E^{BESS}(t)$ is the amount of energy stored in the battery pack at time (t) i.e., it means the State of Charge (SoC), $E^{BESS}(t+1)$ is the amount of energy storage at time + 1, $P_t^{BESS,ch}$ is the power absorbed during charging, $P_t^{BESS,dis}$ is the power discharged from the battery, Δt is the time duration under which the charging and discharging process takes place, ηch is the charging efficiency of the battery, η_{dis} is the discharging efficiency of the battery, and η_{inv} is the efficiency of the inverter. BESSs have a linear behavior for SoC, and is dependent over the voltage of the battery [113], [114]. The ideal SoC range is considered between 0.2 & 1. Equation (21) shows how the SoC of the battery can be calculated.

$$SOC = \frac{U_{DC} - U_{min} + IZ_i}{U_{max} - U_{min}} \tag{21}$$

$U_{DC} \rightarrow$ DC voltage of the converter
$U_{AC} \rightarrow$ AC voltage of the converter
$U_{min} \rightarrow$ minimum voltage of the full BESS cells
$U_{max} \rightarrow$ maximum voltage of the full BESS cells
$I \rightarrow$ Current in BESS
$Z_i \rightarrow$ Internal resistance of BESS cells

As shown in the above equations, the BESS is modelled more towards the DC voltage dependency. However, it becomes necessary to convert the DC voltage over the AC to provide the target ancillary services, which is achieved through a PWM converter. To avoid saturation and harmonics problems, the BESS model should satisfy the following equation (22).

$$U_{DC} \geq \frac{2\sqrt{2}}{\sqrt{3}} U_{AC} \tag{22}$$

IV. METHODS FOR OPTIMAL COST, SIZING AND PLACEMENT OF BESS

The optimal cost, sizing, and placement of BESS play a crucial role in maximizing the economic and technical aspects of BESS integration. Involving various factors like investment cost, maintenance cost, operation cost, and environmental benefits will ensure that the BESS placement is economically feasible and technically possible. In [115] a cost-effective analysis method is introduced, where the annual cost is estimated based on reactive power capacity of the compensators and batteries utilized to minimize the voltage rise from PV. The annual cost involves the cost per unit of the compensator and battery. Minimum cost is calculated by optimizing charging threshold of the battery storage. [116] proposes a multi objective model minimizing the operation cost and active power losses. The operation costs include active power generation from grid and reactive power from DERs. The model involves a Demand Response Program (DRP) adding flexibility to reduce the peak demand, eventually helping in lowering the cost. A CES cost model is proposed in [117] where cost

TABLE 5. Battery modelling parameters & charging/ discharging strategies.

Year	Battery Modeling Parameters	Charging/Discharging Strategy	Strategy Description
2024 [93]	SoC, thermoelectric coupling, degradation	Frequency regulation under thermoelectric degradation	Battery charging occurs during excess renewable generation or favorable conditions for grid support. Discharging happens during grid frequency deviations to provide frequency regulation, typically through bidirectional pulse currents, which is done to keep thermal temperature of cells within the battery maintained.
2024 [94]	Hydrogen storage, energy consumption, electrolysis efficiency	Direct utilization and storage for hydrogen management	Battery charging happens during high renewable generation, storing energy via hydrogen compression. Discharging occurs to meet hydrogen demand, directly utilizing stored hydrogen for energy needs.
2024 [95]	Battery capacity, charge/discharge rates, hybrid system dynamics	Hybrid energy storage system control	Battery charging takes place when there is excess renewable energy (solar/wind). Discharging occurs to meet demand peaks, balancing power and improving system stability through rapid response capabilities of supercapacitors.
2024 [96]	Reliability indicators, energy storage capacities, resource availability	Reliability-based optimization	Battery charging occurs when renewable sources exceed demand; batteries store excess energy. Discharging occurs during low renewable generation or peak load to maintain supply and reliability.
2023 [97]	Power limits, SoC, internal resistance	Energy arbitrage, frequency regulation, reserve power	Battery charging happens during periods of low electricity prices or high renewable generation. Discharging provides ancillary services like peak shaving, frequency regulation, and reserve power during high demand.
2023 [98]	Equivalent circuit models, SOC, Depth of Discharge (DoD), degradation mechanisms	Energy arbitrage, frequency regulation, voltage support	Battery charging occurs during surplus renewable generation or low demand. Discharging supports grid stability, including voltage and frequency regulation, during high demand or low renewable periods.
2023 [99]	SoC, climate data, vehicle occupancy	Recurrent Neural Network-LSTM and fuzzy logic for load prediction	Battery charging happens when renewable resources (solar/wind) are in surplus. Discharging serves EV load demands, optimizing grid and renewable use based on forecasted load profiles.
2023 [100]	SoC, Open Circuit Voltage, internal resistance, 0th order ECM	Co-optimizes real and reactive power	Charging occurs during off-peak or high renewable generation. Discharging supports peak shaving, power factor improvement, and cost-saving measures in distribution systems.
2023 [101]	SoC, load profiles, renewable integration	Modified metaheuristic technique for optimization	Battery charging occurs during high renewable generation. Discharging meets EV load demand and maintains grid stability through optimized energy distribution.
2023 [102]	Battery capacity, SOC, electrolysis efficiency	Hybrid optimization framework	Charges batteries during high renewable generation (solar/wind) to store surplus energy. Discharges during low generation periods to meet demand and maintain grid reliability.
2021 [103]	SoC limits, internal resistance, power ratings	Peak-shaving, regulation market	Battery gets charged during low-cost market periods and excess renewable generation. Discharges for frequency regulation, peak shaving, and grid services.
2020 [104]	SoC, charge/discharge efficiencies, power limits	Optimizes dispatch in markets, peak shaving	Battery charges during low electricity prices or high renewable generation. Discharges for peak shaving, frequency regulation, and to support EV charging stations.
2020 [105]	DoD, cycle numbers, environmental impacts	Optimizes whole-life cycle, balancing services	Initially charges for frequency regulation. After significant degradation, charges and discharges for energy arbitrage and load shifting.
2019 [106]	SoC, DoD, efficiency	Real-time coordinated control	Battery charges when PV generation exceeds consumption, focusing on peak periods to prevent overvoltage and discharges to support voltage control during high fluctuations.
2019 [107]	Battery size, intelligent control algorithms, load profiles	Intelligent generation control algorithms	Battery charging happens during high wind power generation to stabilize output. Discharges to balance and smooth grid output, maintaining monotonic cycles to prolong battery life.
2016 [108]	SoC, DoD, charge/discharge rates	Monotonic charging/discharging strategy	Battery gets charged when renewable output exceeds demand or for pre-compensation of predicted imbalances. Discharges to correct minute-to-minute power imbalance between generation and demand.
2015 [109]	SoC, DoD, charge cycles	Rain-flow cycle counting algorithm	Charges when PV generation exceeds local consumption, prioritizing peak generation hours. Discharges to prevent overvoltage and support grid stability.
2014 [110]	SoC, DoD, charge/discharge efficiencies	Decentralized control for voltage support	Charges based on grid demand, time-of-use tariffs, and renewable generation availability. Discharges to provide grid support, such as vehicle-to-grid (V2G) services, during peak demand.
2014 [111]	EV penetration, charging time, charging characteristics, driving patterns	Managed charging, smart grid integration, vehicle-to-grid (V2G)	Charges EVs based on grid demand, renewable energy availability, and time-of-use pricing. Discharges for grid support using vehicle-to-grid (V2G) operations during peak demand or when grid stabilization is needed.
2012 [112]	Battery capacity, SoC, voltage limits	Agent-based control for optimal dispatch	Charging occurs when grid conditions allow for energy storage replenishment, ensuring readiness for grid support. Discharging takes place to restore load during faults, provide voltage support, and maintain islanded operation stability.

TABLE 6. Literature review of different modelling techniques and optimization of parameters associated with BESS.

Author	Objective Function	Type of Battery	Distributed Energy Resource (DER)	Test System	Grid Services				
					Voltage Support	Frequency Support	Load Shifting	Reactive Power Support	Black Start
H. Kang et al. 2024[121]	self-efficiency rate, peak load of residential building	×	PV	×	×	×	×	×	×
P. Wongdet et al. 2023[122]	Net present value of the Battery	Lead Acid	PV & Wind	×	×	×	×	×	×
W. A. Oraibi et al. 2023[124]	Annualized costs, investment cost of Stationary BESS (SBESS), Power Electronic Vehicle Parking Lots (PEV-PLs), and maintenance cost of SBESS, RES, and PEV-PLs.	×	PV & Wind	IEEE 33 Bus system	×	✓ Active Power	×	×	×
T. Costa et al. 2023[125]	Capacity Selection, time, maximum depth of discharge (DOD_{max}), losses	Lead Carbon and lithium-ion	PV	230/500 KV substation in Alagoas, Brazil	×	✓	×	×	×
K. Balu et al. 2023[126]	power losses, cost of energy losses, and total voltage deviation.	×	×	IEEE 33 & 136 bus system	✓	✓ Active Power Support	×	×	×
B. Yildiz et al. 2023[127]	×	×	PV	×	×	×	×	×	×
X. Liu et al. 2023[128]	Carbon Emission and Charging cost in a day.	Lithium-ion	Photovoltaic Energy Storage System (PESS)	×	×	×	×	×	×
A. A. Abou El-Ela et al. 2022[129]	Cost of Energy Not Supplied (CENS), Life Cycle Cost (LCC) of PV and battery Storage Unit, Cost of energy loss, total emission cost, and corrected Cost to Failure (CTF) ratio.	Lithium-ion	PV	IEEE 30 & 69 bus system	×	×	×	×	×
T. Gu et al. 2022[130]	Optimal charging-discharging, capacity selection, power losses, and voltage fluctuation.	×	PV & Wind	IEEE 33 bus system	✓	×	×	×	×
V. B. Pamshetti et al. 2022[131]	total economic cost, includes investment cost, operating cost of battery energy storage system and soft open point, energy purchased cost, and carbon emission cost.	×	PV	IEEE 33 bus system	✓	✓ Active Power Support	×	✓	×
A. Ghaffari et al. 2022[132]	cost of ESS, power losses, flicker emissions and voltage deviation	Lead Acid	PV & Wind	IEEE 33 bus system	✓	×	×	✓	×
H. A. Taha et al. 2022[92]	Economic index voltage stability factor and minimization of power losses.	×	Solar & Wind	IEEE 33 bus system	✓	✓ Active Power Support	×	×	×
D.A. Kez et al. 2022[133]	×	×	Inverter-based resources (PV and Wind)	39 bus system	×	✓	×	×	×
H. Yin et al. 2021[134]	System fluctuation and annual operational cost.	×	Wind	IEEE 34 bus system	✓	✓	×	✓	×

TABLE 6. ***(Continued.)*** **Literature review of different modelling techniques and optimization of parameters associated with BESS.**

O. Zarenia et al. 2021[135]	System losses	×	×	IEEE 33 bus system	×	×	×	×	×
P. Rajesh et al. 2021[136]	Reduction of Unbalanced Distributed Network (UDN) power loss and elimination of the voltage deviation.	×	Solar & Wind	IEEE 33 bus system	✓	✓ Active Power Support	×	×	×
V. Janamala et al. 2021[137]	Power loss and voltage deviation	×	PV	IEEE 33 bus system	✓	×	×	×	Standalone
B. Khaki 2021[138]	Cost of wind turbine and cost of BESS, considering BESS's system cost, power conversion costs and cost of balance of plant.	Lead Acid & Li-ion	Wind	33 bus system	×	×	×	✓	×
B. Wang et al. 2021[139]	Power imbalance by optimizing the battery energy storage system allocation and operation including uncertainty.	×	PV	IEEE 34 & 123 bus system	×	✓ Active Power Support	×	×	×
B. Ahmadi et al. 2021[140]	Voltage profile improvement and annual operation and maintenance cost of Distributed Generation (DG) and BESSs.	×	Wind & PV	33 & 69 bus system	✓	×	×	×	×
B. Mukhopadhyay et al. 2020[141]	Power loss and deviation of node voltages in network considering PV, BESS, and DG.	NaS	PV-DG	69 bus system	✓	✓ Active Power	×	×	×
P. Lata et al. 2020 [142]	Cost of energy not supplied, life cycle cost including operational investment cost, and cost related to the power loss.	×	×	30 bus radial system & IEEE 69 bus system	✓	×	×	×	×
S. Sharma et al. 2020[143]	Power loss and grid demand cost considering wind scenario, grid electricity prices, responsive nonresponsive load, power generation by wind, and charging and discharging of BESS.	×	Wind	33 & 108 Indian Distributed Network	✓	×	×	×	×
P. Prabawa et al. 2020[144]	Maximise the objective function depending upon the restored load in time horizon and time interval according to load.	×	×	IEEE 33 bus system	✓	×	×	×	×
Y. Zheng et al. 2020[145]	The objective function involves minimization of investment cost, operating cost, maintenance cost and residual value. The objective function also considers the planning scenario.	Lead Acid battery	×	IEEE 15 & 69 bus system	✓	✓ Active Power Support	×	×	×
P. Singh et al. 2020[146]	The objective function involves the minimization of annual energy loss, node voltage deviation, demand deviation index, and daily charging discharging energy mismatch index.	×	Wind	33 bus system	✓	✓ Active Power Support	×	×	×
L. A. Wong et al. 2020[147]	The objective function considered involves minimization of total power loss in a Distributed Network depending upon the current of the branch, resistance of the branch, and total number of branches.	×	PV	×	×	✓	×	×	×

incorporates consumer cost and return on investment ensuring there is low installation and maintenance cost along with higher profitability than DERs, the model helps to reduce the consumer cost by 28% and lowers the line losses. A cost model involving capital, maintenance, and net present cost of BESS and PV is presented in [118] is minimized by determining the optimal size and location of the BESS. In [119] an advance battery aging cost model is proposed based on Arrhenius law, to measure the battery aging more accurately. The model involves cyclic aging cost with operation cost, resulting in an increase in battery life and 27% more profitability. A cost model including the degradation and cyclic aging is present in [120] which is optimized to reduce the degradation cost. The model is developed for hybrid-battery systems integrated with PV. Reduction in degradation costs results in leveraging energy arbitrage and managing operational cost with benefits. To achieve effective usage of BESS for various ancillary services like frequency support, active and reactive power support, and black start, it is necessary to employ effective methods for determining the optimal cost, placement, and sizing of the BESS. In [121] introduces an RL-based model for optimizing BESS scheduling at the building level, emphasizing self-sufficiency and economic benefits. However, it only partially addresses broader challenges like hybrid BESS integration and dynamic grid impacts, which are essential for a more resilient and efficient energy system. The study [122] optimizes BESS capacity and cost in standalone microgrids, focusing on battery lifetime and economic efficiency. However, it overlooks key aspects like voltage and frequency regulation, provision of ancillary services, and hybrid BESS integration, which are vital for ensuring grid stability and broader system reliability. In [123] study on providing a reliable electricity in rural areas through PV-BESS configuration is conducted. The research specifically focusses on performance of systems control mechanism providing frequency and voltage support using MPPT control. The study suggests that usage of PV-BESS configuration results in efficient management of load demand in rural areas. The study [148] focusses on improving the energy efficiency of inverter drive refrigerators with PV battery in residential areas. The study finds out the optimal system configurations to reduce energy consumption. Comparing inverter and non-inverter-based refrigerators in AC and DC environment. The study observes that a daily 300 Wh energy could be saved in inverted driven refrigerators in DC environment. In [149] viability of battery systems with PV for residential purposes. The study explores the technical and operational viability to mitigate grid stress and enhance residential energy consumption. The study suggests that integration of energy storage devices will reduce the unviability of PV installations, furthermore it would reduce the battery cost enabling increased energy tariff opening profitability for both grid and consumers. For a PV and battery system to be installed in residential would increase the need of intelligent switching between the devices for efficient operations. A similar study is conducted in [150], a battery power system is proposed that can change between AC and PV power targeting efficient and reliable power for residential appliances. This switching strategy boosts the efficiency of appliances by 99% compared to traditional switching. For standalone PVs an assessment study [151] of different types of battery storage technologies is conducted, checking the economic viability, technical properties and environmental impact of batteries throughout their life cycle. The assessment suggest batteries installed with standalone PV would contribute to 68% of total emissions in a 1.5 kW PV panel, the study suggests to consider batteries with higher charging discharging cycles for suitable renewable applications. The paper [124] focuses on optimal planning of SBESS and PEV-PLs enhancing in high renewable penetration scenario, however, it lacks in offering advance energy management strategy to provide voltage and reactive power regulation between BESS and EVs. The paper [125] proposed a method for optimal placement and sizing of Hybrid BESS in AC microgrid ensuring continuous power supply. The paper does not thoroughly explore advance operational strategies of BESS such as adaptive SoC management, which is critical for optimizing BESS performance. In [126] strategy for optimal placement and sizing of EV charging station with distributed generation and BESS is proposed. The paper lacks coordinated control strategies between BESS and EV load, also BESS is not explored to provide dynamic response for grid services. Paper [127] analyzes the curtailment of PV and BESS in low voltage network, the approach requires more examination of spatial distribution between BESS and PV and its impact on the grid. Factors such as feeder length, location of BESS, and load distribution, can significantly affect the voltage levels. In [128] impact analysis of PV and ESS adoption on public transport through a simulation-based approach, it mainly focusses on the optimal bus scheduling neglecting the perspective of ESS utilization for frequency voltage, regulation, eventually resulting in degrading grid stability, and ineffective use of energy in public transport. In paper [129] a robust optimization approach for BESS and PV integration in distribution systems is proposed. Maximizing the battery life and minimizing costs, however it overlooks the BESS operation strategy which could have further given more optimized values. In [130] NSGA-II is employed for optimal placement and sizing of BESS in distributed network. The objectives are to reduce losses, but it lacks coordination between the BESS and distributed resources reducing line losses, also maximize usage of renewable energy and enhance grid stability. The paper [131] proposes a two-stage coordinated optimization framework for placement of BESS and Soft Open Point (SOP) in high PV penetrated distributed network, involving demand response, and conservation voltage reduction. The study does not fully explore synergetic benefits of BESS and SOPs working together. BESS can offer dynamic discharge capabilities; SOPs could provide power flow between feeders and offer reactive power support. The paper [132] discusses optimal placement and sizing of ESS, WT, and PV in dis-

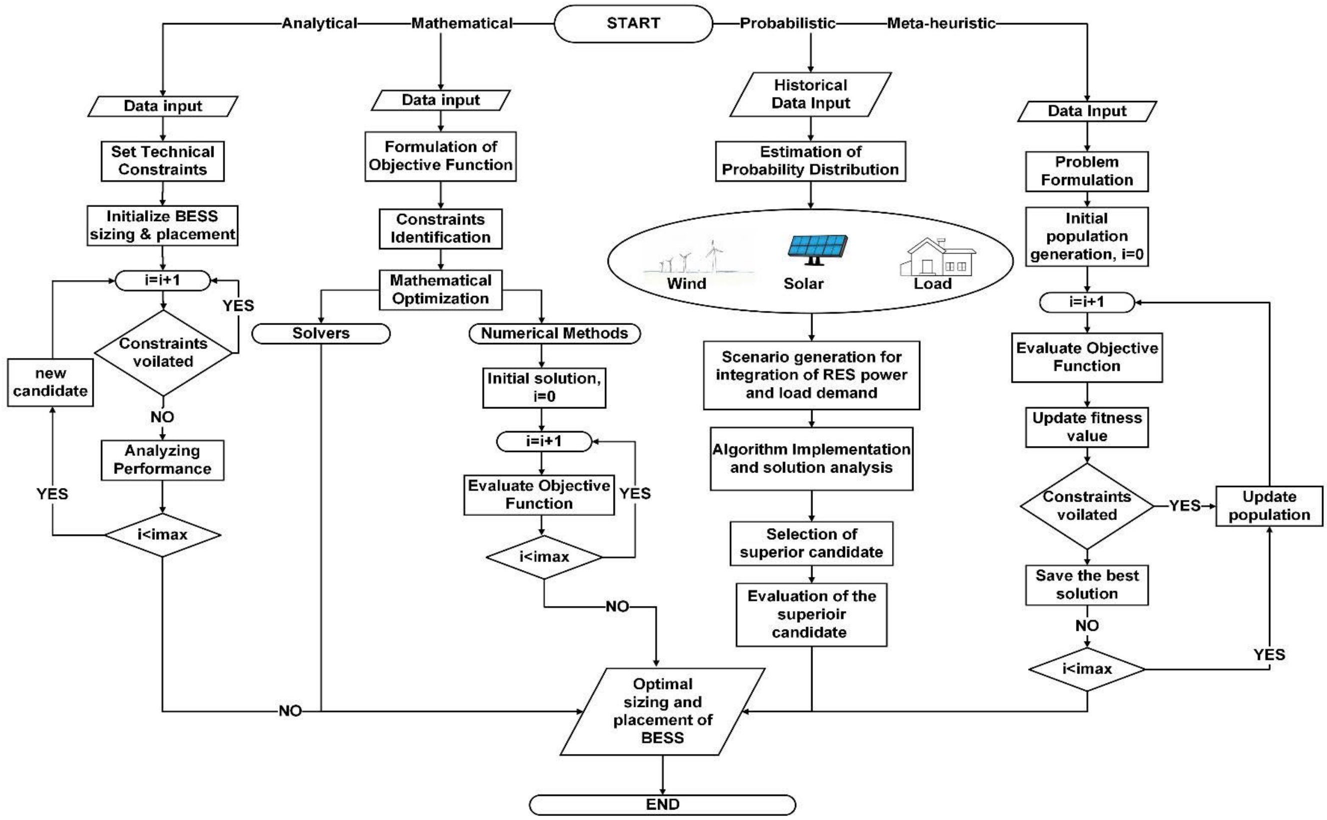

FIGURE 3. Flowchart of analytical, mathematical, probabilistic, and metaheuristic methods.

tributed network, while focusing on mitigating the flicker emissions. The strategy treats ESS and DGs separately rather than capitalizing their combined potential for more effective voltage and power flow control. In [92] a multi-objective model for optimal placement and management of WTs & PV, BESS, and capacitor banks in distributed network, incorporating demand response and RE curtailment is presented. The study does not involve dynamic voltage and frequency regulation using BESS and DGs. It would allow more effective management of voltage fluctuation especially under high penetration of renewables. The paper [133] performs allocation analysis of fast frequency response in power system with high non-synchronous penetration levels, focusing on placement of grid-forming converters for frequency stabilization. A multi-objective approach involving factors like voltage, power loss, economic cost with frequency stabilization would have offered a more holistic framework for frequency regulation. A two-step method [134] using Power Sensitivity Analysis (PSA) and multi-objective optimization for determining optimal placement and size of ESS considering transient response in wind power is proposed in the study. The study lacks in considering ESS with other technologies such demand response, DGs, or EV. Involvement of these would leverage synergies between them enhancing grid performance. A two-stage game-based approach [135] for energy storage pricing in radial network is proposed in the study. Focusses on loss reduction and motivate energy storage users via dynamic pricing. The pricing is based on a predefined scenario missing real-time adaptive control mechanism. Involving grid changing parameters such as load fluctuation, renewable generation variability increasing the model flexibility. In paper [136] integration of BESS with wind turbine in an unbalanced radial distribution network using an optimization technique is proposed in this study. Capacity and location of BESS is determined using optimization. However, the study lacks in considering BESS to provide grid support during low period of wind generation or high demand. In paper [137] optimal allocation of Interline-PV and BESS in an islanded electrical distributed network is determined using optimization technique considering EV penetration. The study emphasizes power losses and voltage profile improvement; however, it does not fully explore dynamic voltage and frequency regulation capabilities of BESS focusing more on static control. The paper [138] presents optimization framework for placement and sizing of BESS and wind turbine in distribution network. The framework aims to reduce both active and reactive power loss along with cost. The study focusses on economic optimization, considering a constant load profile, considering load forecasting and demand response would achieve more better placement and sizing, matching supply and demand chain. The paper [139] focuses on improving hosting capacity by optimal allocation of BESS. The study emphasizes mitigating voltage rise and power unbalance through static allocation of BESS, missing dynamic behavior of BESS. Utilization of BESS in isolation resulting in under capitalization coordinated control with PV enhance renewable utilization. While paper [140] focusses on multi-objective optimization approach to improve voltage profile by placement and sizing of DERs and BESS. The study considers components somewhat isolated from each other rather than considering dynamic interaction providing robustness against major grid changes. The paper [141] focusses on placement and sizing of BESS and PV-DG by static and dynamic reconfiguration of distributed network. However, the optimization models lack in considering the variability and uncertainty in load forecasting. Stochastic modelling approach would have better handled uncertainties in load and renewable generation. The paper [142] focusses on optimal placement and sizing of ESS to reduce cost related to energy not supplied and power loss but does not explore role of ESS in providing ancillary services, implementing these would have maximize benefit of ESS integration. The paper [143] employs a static optimization approach to minimize power loss and power demand cost through optimal coordination of DGs and BESS. The framework does not provide detailed scenario analysis for uncertainties in load growth and renewable penetration. Such analysis is important to check the effectiveness of proposed algorithms. A Multi Agent System [144] is proposed for service restoration focusing on network reconfiguration and dispatching static & mobile ESS. The framework does not involve any dynamic control strategy for ESS to manage grid stability, specifically under conditions of fluctuating loads and renewable generation. The paper [145] focusses on static optimization for placement of BESS in radial network to control voltage regulation and energy cost. The study does not consider any DERs, therefore lacking in proper coordination of BESS to balance the supply and demand chain more effectively. The study [146] focusses on optimal placement of BESS by minimizing the energy and power loss by providing voltage and active power regulation. However, study does not address role of BESS in providing frequency support which are crucial for system having renewable penetration. While paper [147] focusses on optimization of BESS placement and sizing considering duck curve phenomena to reduce system losses. The study focusses on duck curve by optimizing BESS but lacks in coordinating it with any demand side management strategy such as load shifting, and energy efficient measures. In summary, many studies have explored BESS performance using different techniques that can be broadly grouped into five main categories; analytical method, mathematical method, probabilistic method, meta-heuristic method, and artificial neural network method. The overall approach of all these methods is shown in Fig. 3. For optimization of these parameters, different objective functions are either single-objective or multi-objective-based. Table 6 presents the overall review of different papers describing the objective function taken, the type of battery, the RE resources considered, and the type of ancillary service the battery is providing.

A. ANALYTICAL METHOD

Analytical techniques are commonly employed to optimize the cost, size, and placement of BESS. These methods typically utilize mathematical approaches that involve algebraic functions to determine the optimal solution. Commonly, these techniques entail utilizing functions that can be directly derived and executed for iterative or repetitive computations until an optimal resolution is attained. While performing iterative computations, it is possible to manipulate variables such as power and energy capacity within a predetermined time frame to derive solutions based on one or more criteria.

B. MATHEMATICAL METHOD

These methods involve both analytical and numerical approaches for finding the optimal solution of BESS. It obtains the optimal solution by creating an approximate model, where the objective function is estimated by an iterative process that is carried out until the optimal solution is attained. These methods include linear programming, non-linear programming, mixed-integer programming, or convex optimization. Compared to other solvers like General Algebraic Modelling Systems (GAMS) and CPLEX, mathematical optimizations provide better efficiency and accuracy. For large-scale and long-term BESS applications, mathematical optimizations provide inaccuracy. A mixed integer nonlinear programming is used to create a mathematical model that optimizes the cost associated with the energy hubs, considering resilience constraints and the role of energy storage devices in the system [152]. A mixed integer linear programming model is developed for the development of a behavioral home energy management structure, and the model is a solver using a CPLEX solver in a GAMS environment [153].

C. PROBABILISTIC METHOD

The probabilistic method for identifying BESS location considers the uncertainties involved in various parameters like load profile, RE generation pattern, and market prices. This method is categorized into two parts: (i) Chance-constrained method and (ii) Stochastic optimization method. They usually depend upon the PDFs of models exhibiting uncertainty. Multiple PDFs are used; however, some PDFs are used specifically for a specific application. For example, for wind output generation, Weibull distribution is usually used, Beta functions are used for solar power output, and normal distribution functions are used for load demand. For optimal sizing and placement of BESS, both chance-constrained and stochastic optimization methods can be implemented, depending upon the objective function and its constraints.

The chance-constrained method primarily focuses on fulfilling the objective function by satisfying predefined constraints. It aims to balance the system's performance and risk, ensuring that the system operates within permissible limits and uncertain conditions. At the same time, the stochastic optimization method tackles the problem of uncertainties associated with them by considering the PDF of the variables. It enhances the system's performance by capturing the varying nature of the uncertain variables. A probabilistic capacity planning methodology for plug-in electric vehicles is presented with an on-site energy storage device. A Markov-modulated poison process is used for modelling the system. It considers various parameters like the number of vehicles present at the charging lot along with the energy storage charge level as the system's state, and the paper explores the relationship between the energy storage size, customer statistics, and grid power [154]. A probabilistic method based on Clayton Copula is used to determine the optimal location of the BESS, considering the wind power uncertainty and inter-farm correlation. A multi-objective optimization problem is proposed considering the entire wind power joint distribution to minimize the overall system cost, carbon emissions, and power losses [155].

D. METAHEURISTIC METHOD

Metaheuristic algorithms are optimization techniques inspired either by a natural process or metaphor. These techniques are flexible, model-free, and more robust against the local optimal solutions. They are designed so that it becomes efficient to explore the search space and find the near-optimal solution, especially in complex and computationally challenging functions that traditional methods may not be able to perform. These algorithms do not guarantee optimal solutions but focus on the iterative process based on defined instructions. Compared to other techniques like analytical and mathematical, these algorithms may not perform too efficiently when there is a set of constraints defined which are complicated.

E. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network (ANN) is a powerful tool that can be used for BESS placement optimization. It is used for modelling complex networks, classification, approximation, and recognition. ANNs are trained based on historical data and can learn complex patterns and the relationships within the data. ANN is commonly used to optimize the BESS placement by creating multiple scenarios and for predicting the optimal configuration based on the trained data set and objectives.

Finally, several gaps in the existing BESS literature have been found that hold back optimization of performance and integration with the grid. Many of them lack effective integration of real-time grid conditions and dynamic market participation strategies—critical for meeting maximum utility from BESS in a fluctuating grid environment. Besides, the present design lacks multi-ancillary service co-optimization, which should optimally enhance BESS economic and operational benefits such as energy arbitrage, frequency regulation, and voltage support. This necessitates the development of more advanced control algorithms in that respect to provide multiple ancillary services effectively in the presence of real-time grid fluctuations. It is further essential to take into consideration a broader scope in relation to ancillary services since most studies nowadays focus on very specific services, leaving the potential development of BESS aside. The effective strategies of market participation are also underrepresented, thus hindering economic and operational optimization of BESS within varied energy markets. The missing element is the development of such adaptive charging and discharging strategies that take grid power and frequency variations in real-time, important for better efficiency and longevity of BESS. Filling these gaps will result in more effective use of BESS to enhance grid stability, flexibility, and overall economic efficiency.

TABLE 7. Case studies of cascading effects due to false data injection.

Case	Overview	Incident	Impact
Stuxnet Attack (2010)	A cyberattack on Iran's nuclear facilities, specifically targeting SCADA systems of uranium centrifuges.	Stuxnet altered operational data, causing centrifuges to operate at unsafe speeds, leading to physical destruction.	Highlighted the potential for false data injection to cause cascading failures in critical infrastructure.
Black Energy Malware Attack (2015)	Targeted Ukrainian power companies, manipulating data and disrupting industrial control systems.	Caused power outages affecting approximately 230,000 people.	Demonstrated how false data injection can lead to significant grid instability and outages.
Night Dragon (2011)	Series of cyberattacks on global energy companies, focusing on stealing data and manipulating control systems.	Injected false data into control systems, aiming to disrupt operations.	Highlighted the risk of cyber-espionage leading to operational failures and potential cascading effects.
Ukrainian Power Grid Cyberattack (2015)	Hackers took control of SCADA systems of three Ukrainian distribution companies.	Injected false data, causing widespread outages.	Showed how cyber threats could initiate cascading failures in the power grid.
Maroochy Water Services Cyberattack (2000)	Attack on Australian sewage system by a former employee manipulating SCADA systems.	False data injection caused environmental damage.	Illustrated how false data injection in critical infrastructure could lead to severe operational failures.

The electrical transmission and distribution power network is a complex and interdependent system that requires continuous monitoring and precise control to ensure reliable and sufficient power supply. The power grid stability and security are facing ever greater challenges as renewable energy resource connections increase and network management technologies advance. FDI attack is a significant threat to grid stability. These cyber-attacks manipulate the data that the grid operators receive into making decisions and actions that may eventually destabilize the grid. When grid operators act upon manipulated data, it can lead to wrong load forecasting, mismatched supply and demand, and a dispatch error in generation. These issues can quickly escalate to the tripping of power lines, shutdowns of power plants, and widespread outages, eventually resulting in a cascading failure, as shown in Fig. 4. Once the false data is injected into the distribution grid, due to the tripping of relays and circuit breaker, the distribution towers connected in series get disconnected from each other and therefore result in an overall blackout of the system. Table 7 illustrates several notable cases where the False Data Injection led to the cascading failure in power systems.

V. ROLE OF BESS IN MITIGATING CASCADING EFFECTS AND FALSE DATA INJECTION IN POWER GRIDS

Cascading effects are caused by the failure of a power system component to support the failure of other power components, propagating significant and wide-area power outages. The integrated feature of the power grid operates in such a way that a disturbance in one area will have serious wide-area effects on other parts of the grid. Table 8 provides the incidents of cascading failures due to component failure in the power system. In [156], a brief study of the cascading effect in cyber-physical power systems is explored. They have investigated the independence of different clusters during cascading failure and have analyzed the robustness of the system under various attack scenarios. An event-triggered hybrid system model [157] is proposed to describe the cascading failure in power grids. The model involves various physical responses such as frequency regulation, relay protection, and dispatching action. Another study [158] investigates how false data injection affects the decision-making and the control process in the communication network and simulates a cascading failure due to a cyber-attack. Based on the study, a novel model is proposed for improving the monitoring and controlling of cyber networks along with the power flow characteristics of the network. To analyze the impact of false data injection at the transmission level, a bi-level mixed integer linear programming (BMILP) is developed to analyze the false data injection in multiple transmission lines [159]. A detection framework is also proposed based on the recursive weighted least-square (WLS) state estimation, providing effective detection of FDI. A data-driven methodology [160] is also developed to analyze the risk involved in the cascading failure of the network. A physics-based model is used to generate the training data set for the training of Feed-Forward Neural Networks (FNN) and Graph Neural Networks (GNN). The GNN model achieved an accuracy of around 96%, whereas FNN achieved around 85%. A methodology for identification and assessment of cascading failure by establishing four indexes based on grid topologies [168]. The indexes are developed to create a cascading failure searching index game model for determining the weights of each index. A cooperative immune quantum particle swarm optimization is also proposed to solve the model and achieve optimal Nash equilibrium solutions. Another model is known as Power-loss failure, Out-of-control failure, and Data-blocking failure for analysis of the cascading failure due to cyber-attacks in cyber-physical power systems [169]. They introduced fragmentation and compatibility into the model, influencing the cyber-physical power system. They concluded that the involvement of these parameters improves the system's resilience. Based on the literature survey, it can be concluded that there are several models for the analysis, prediction, and detection of possible cyber-attacks in cyber-physical power systems resulting in cascading failure. However, strategies for the reduction of cascading have not been explored in the above literature. A reduction in cascading can increase the resiliency of the system overall.

BESS is one of the key solutions in mitigating cascading effects, especially those caused by FDI attacks. BESS can be an immediate power backup and a frequency and voltage stabilizer. In this way, it can support load balancing and black start operations. BESS integration within the power grid system will hence give operators the ability to increase grid resilience under a cyber threat and a more reliable power supply.

VI. PROPOSED FRAMEWORK

This section presents a framework that draws upon various techniques documented in the literature to address placement, sizing, resilience, and cyber security concerns. As evidenced by the Table 6, the process of optimizing BESS involves determining the most favorable dimensions, locations, and capabilities. The optimization of size and placement has been a topic of interest in literature, with a variety of approaches being employed. These approaches include analytical, mathematical, probabilistic, metaheuristic, and artificial neural networks, as outlined in Section IV. The proposed framework entails a series of steps aimed at achieving optimal size placement, cost-effectiveness, and longevity of BESS. The framework under consideration enhances the network's resilience holistically by furnishing backup to the crucial regions that are impacted by the cascading effect triggered by a cyber assailant via FDI.

Fig. 5 illustrates a proposed framework for achieving increased network resiliency in the event of renewable intermittent or cyber-attacks. This is accomplished through the optimal sizing and placement of BESS within a dynamic distribution grid. Input data for load modelling involves the collection of historical electricity consumptions at various times (e.g., hourly, daily, weekly) for different consumers (e.g., residential, commercial, and industrial), feeder ratings, and feeder length. For solar and EV data generation, various parameters like solar irradiance, solar panel characteristics, EV penetration data, EV charging profile, and EV battery characteristics are required. The modelling of distributed energy resources like solar can be done using physical,

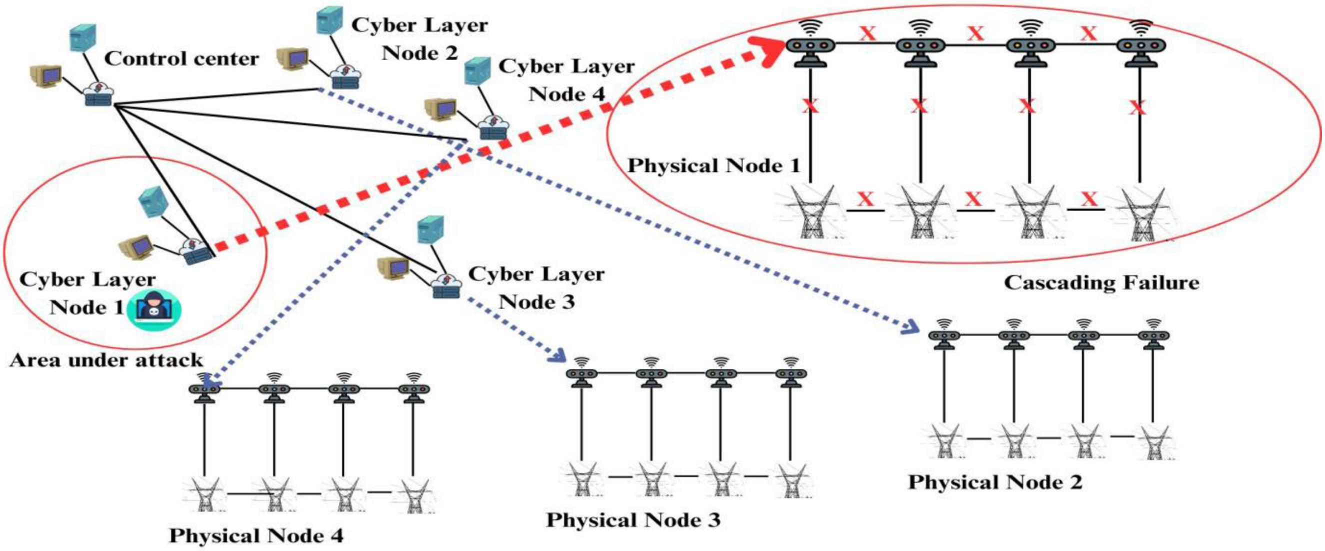

FIGURE 4. Cascading failure in electrical grid.

TABLE 8. Case studies of cascading effects due to component failures.

Case	Overview	Incident	Impact
Western U.S. Power Grid Failure of 1996	A heatwave led to the tripping of several transmission lines in the Western United States.	Failure spread across the interconnected grid, affecting 7.5 million customers.	The instability was exacerbated by high demand for air conditioning and inadequate reactive power.
Italy, 2003 [161]	Major blackout affecting around 60 million people.	Triggered by a fault originating in Switzerland, leading to a tree flashover and a 380 kV tie line trip.	Resulted in approximately 6.4 GW of unmet load, with power restored after several hours, highlighting inadequate coordination and real-time monitoring.
Northeast Blackout of 2003[162]	Major power outage affecting parts of the northeastern and midwestern United States and Ontario, Canada.	The initial cause was a software bug in the alarm system of an energy management system in Ohio. A series of high-voltage transmission lines went offline due to overgrown trees.	Within minutes, over 50 million people were left without power, demonstrating the rapid escalation of cascading failures.
European Blackout of 2006[163]	Planned disconnection of a transmission line over the Ems River in Germany.	Led to a cascading failure affecting over 15 million households across Europe.	The grid was unable to handle the sudden redistribution of power, leading to widespread outages in Germany, France, Italy, and Spain.
Brazilian Blackout of 2009	Cascading failure in Brazil left 60 million people without power.	Initial trigger was a lightning strike on a key transmission line, which led to the tripping of other lines and shutdown of multiple power plants.	The interconnected nature of the grid facilitated the rapid spread of the outage.
Indian Blackout of 2012[164]	The world's largest blackout, affecting around 620 million people.	Multiple transmission lines tripped due to excessive demand and a lack of reactive power support.	The grid's inability to maintain stability caused a cascading failure that spread across northern, eastern, and northeastern India.
Turkey, 2015[165]	Blackout lasting over 8 hours, affecting the entire Turkish power system.	Initiated by a major tie-line trip due to overload, causing separation of eastern and western regions.	Resulted in over frequency and under frequency conditions, highlighting the need for real-time monitoring and contingency preparedness.
United Kingdom, 2019[166]	Major power outage affecting over 1 million consumers, disrupting several interdependent services.	Triggered by a lightning strike causing vector shift protection, reducing power output and triggering load shedding.	Highlighted the impact on critical services like railways and hospitals, emphasizing the need for improved protection schemes.
Pakistan, 2021[167]	Nationwide blackout affecting the entire country.	Caused by an electrical fault in southern Pakistan, leading to cascading outages.	Restoration process took around 20-22 hours, with post-incident analysis citing operator experience and negligence as contributing factors.

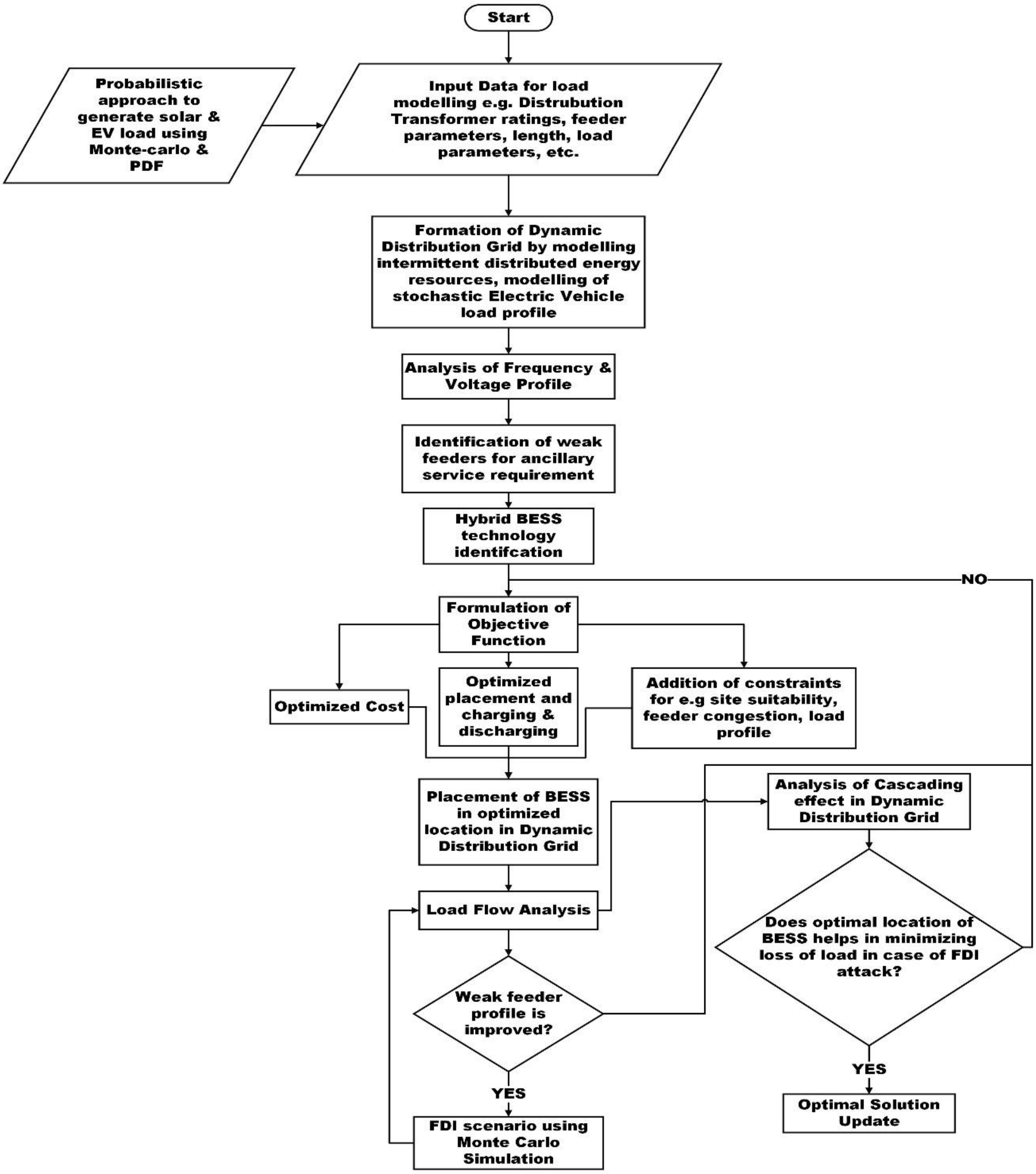

FIGURE 5. Framework flowchart.

statistical, and machine learning models. The uncertainty associated with solar resources can be achieved using Monte Carlo simulation or time series simulation. Similarly, the modelling of stochastic EV load can be done by analyzing the charging behavior, initial charging time, and charging duration. The stochastic nature of the EV load shows the randomness or uncertainty, which is modelled using probability distribution functions.

A simulation is conducted on the distribution grid that is characterized by its dynamic nature and the presence of PV and EV's. The analysis focuses on the frequency and voltage profiles to comprehend the respective contributions of each parameter toward ensuring the grid's stability and dependable power provision. The dynamic distribution grid was subjected to a voltage and frequency analysis, which revealed the presence of weak feeders. These feeders were identified based on their voltage levels falling below the acceptable limits, high voltage drops, and high-frequency deviations beyond the acceptable range. Subsequently, the requisite assistance is identified. Through the integration of voltage and frequency analysis with load and DERs, the identification of weak feeders and the determination of requisite ancillary services is achieved. Various battery technologies suitable for providing ancillary services are recognized based on their technical characteristics, such as energy density, response time, and charging and discharging cycles. The establishment of objectives can be attained through the contemplation of diverse parameters, such as SoC, charging and discharging cycles, cost, placement, and life cycle. Nevertheless, the formulation of the objective functions is performed separately. The efficacy of these objective functions is constrained by various parameters such as the length of the feeder, power of the feeder, voltage of the feeder, SoC limits, and suitability of the site. BESS are situated at the most suitable positions as determined by employing optimization methodologies. Upon the allocation of the BESS, a load flow analysis is conducted to evaluate the extent to which the BESS enhances the power quality of the dynamic distributed grid. A Monte Carlo simulation is utilized to examine the support provided by BESS by generating a simulated scenario of false data injection in the dynamic distribution grid, which leads to a cascading effect. The purpose of this analysis is to evaluate the effectiveness of BESS support. This study examines the resilience of the network and investigates how BESS located at optimal locations can aid in the recovery of cascading affected areas. If the impacted regions are more extensive, the objective function is reformulated to enhance resiliency and diminish the cascade affected area. The procedure is continued until the impacted chain reaction region is determined to be of minimal size. The proposed framework is expected to address power quality concerns and enhance the adaptability of the dynamic system to unforeseen electric vehicle loads and cyber security risks.

However the proposed framework depends on several parameters like data dependency, optimization algorithms used for the optimization and stochastic modelling of the grid. If the data is not accurate the optimization results will be not reliable.

VII. EV PENETRATION ESTIMATION USING PROPOSED FRAMEWORK

Based on the proposed framework, the EV load penetration for the Uttarakhand region in India is estimated using PDFs and socio-economic parameters like income, population density, grid availability and altitude. The study aims to aid grid operators in managing and predicting power demand increment from increased EV charging. Firstly, data collection from different districts in the Uttarakhand region is conducted. Population density, average income, grid availability, and altitude are considered the parameters of input. Lastly, the total EV registered in different districts is the output variable. After data collection, regression analysis is done to identify the weight relation of these parameters concerning the EV numbers. The weights of these parameters are shown in Table 9.

After the weights calculation of the socio-economic parameters, several supervised machine learning algorithms are utilized, including Random Forest (RF), Support Vector Machine (SVM), Decision Trees, ANN, and K- nearest neighbor (KNN) to estimate total EV numbers across 10,000 different points in Uttarakhand region. After the EV penetration estimation across various locations, the study conducted the impact on the grid by modelling the load curve based on the type 1 charger with a 3.5kW rating every day in February. During this study, the charging time was segmented into two peak periods (5 am to 9 am & 6 to 10 pm), representing that the domestic charging will peak during these periods to assess the load fluctuations. Based on this statement, an average EV power demand curve for the day in February is estimated and shown in Fig. 6.

Now, further work involves the integration of this EV power demand curve into the distribution grid, analyzing its impact on voltage profile, frequency profile and line losses, and identifying the optimal locations for placing BESS and improving the power quality.

TABLE 9. Parameter weights.

Weightage	Value	Weightage	Value
Population density	1.67	Altitude	-0.0832
Income	0.0074	Grid Availability	8.097

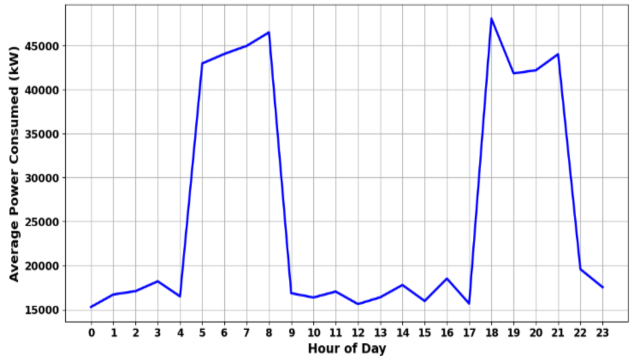

FIGURE 6. EV load curve [170].

VIII. CONCLUSION

Battery Energy Storage Systems (BESS) use in distributed networks has demonstrated tremendous potential for improving grid stability, providing vital ancillary services, and facilitating the integration of renewable energy sources and electric vehicles (EVs). BESS can increase the overall power supply reliability by managing voltage and frequency deviations. This review paper gives insights into the advancement, challenges and strategies for placement of BESS, focusing on economic and technical feasibility. The following conclusions can be drawn:

- BESS has shown great capability in stabilizing the grid by offering ancillary services, including frequency, voltage, and active and reactive power support. By its rapid charging and discharging operations, BESS limits the fluctuations introduced by renewables and EVs in the distribution network.

- It is identified that significant advancements have been achieved in optimizing the BESS sitting, sizing and cost. However, most of the techniques rely on static optimization, missing the flexibility to adapt to real-time grid conditions and sudden changes in demand and generation. This issue urges for a more dynamic optimization technique, hybrid optimization techniques having the advantages of existing analytical, mathematical, probabilistic, artificial neural network and meta-heuristic methods providing the scalability and reliability for large-scale BESS applications. The BESS can dynamically charge and discharge them based on the grid conditions, offering superiority in complex operational scenarios.
- Integration of BESS in modern distributed networks possesses certain challenges involving uncertainties in electricity demand, variable renewable output, EV charging demand, and varying market prices. St stochastic and probabilistic techniques are employed to address these uncertainties. It is important to involve BESS and renewables parameters in the economic models for better adaptability of BESS.
- Digitalization of the grid network and the increasing reliance on smart devices and control mechanisms lead to grid network exposure towards cyber threats, especially false data injection (FDI) attacks. These threats can disrupt the grid, resulting in cascading failures. To address these concerns, a strategic framework for BESS is proposed. The strategic framework focuses on improving the power quality, support, and paid restoration capacity against cyber-attacks. The framework ensures the secure operation of BESS within the highly digitalized grid network.

In the future, integrating the BESS in the power system will not be applicable to providing the ancillary services. Still, it will also provide a transaction market where the grid and the user will use this technology for their benefit. Advanced machine learning (ML) and artificial intelligence (AI) will enhance the BESS operation with advanced predictive technologies based on the previous data. Hybrid optimization algorithms that blend other optimization benefits with real-time data and predictive modelling will improve the scalability of the BESS for long-duration applications. These hybrid models will allow dynamic operations of the BESS, resulting in minimizing cost and maximizing performance, along with stable grid operations. Moreover, digitalization in the grid network needs proper measures to avoid cyber threats resulting in cascading failure. Strategies involving the node theory with BESS placement and sizing will help further to reduce these possibilities by determining the optimal locations, avoiding the maximum area disrupted.

REFERENCES

[1] S. Balasubramanian and P. Balachandra, ''Indian electricity system transition and its challenges: A review,'' *J. Asian Energy Stud.*, vol. 6, no. 1, pp. 1–24, Jan. 2022, doi: 10.24112/jaes.060001.

[2] *Energy Storage System (ESS) Road Map for India 2019–2032*, India Energy Storage Alliance (IESA), India, 2019.

[3] M. Debanjan and K. Karuna, ''An overview of renewable energy scenario in India and its impact on grid inertia and frequency response,'' *Renew. Sustain. Energy Rev.*, vol. 168, Oct. 2022, Art. no. 112842, doi: 10.1016/j.rser.2022.112842.

[4] K. Prakash, M. Ali, M. N. I. Siddique, A. A. Chand, N. M. Kumar, D. Dong, and H. R. Pota, ''A review of battery energy storage systems for ancillary services in distribution grids: Current status, challenges and future directions,'' *Frontiers Energy Res.*, vol. 10, Sep. 2022, Art. no. 971704, doi: 10.3389/fenrg.2022.971704.

[5] S. Saha, M. I. Saleem, and T. K. Roy, ''Impact of high penetration of renewable energy sources on grid frequency behaviour,'' *Int. J. Electr. Power Energy Syst.*, vol. 145, Feb. 2023, Art. no. 108701, doi: 10.1016/j.ijepes.2022.108701.

[6] L. R. Visser, E. M. B. Schuurmans, T. A. AlSkaif, H. A. Fidder, A. M. van Voorden, and W. G. J. H. M. van Sark, ''Regulation strategies for mitigating voltage fluctuations induced by photovoltaic solar systems in an urban low voltage grid,'' *Int. J. Electr. Power Energy Syst.*, vol. 137, May 2022, Art. no. 107695, doi: 10.1016/j.ijepes.2021.107695.

[7] A. Navon, R. Nitskansky, E. Lipman, J. Belikov, N. Gal, A. Orda, and Y. Levron, ''Energy storage for mitigating grid congestion caused by electric vehicles: A techno-economic analysis using a computationally efficient graph-based methodology,'' *J. Energy Storage*, vol. 58, Feb. 2023, Art. no. 106324, doi: 10.1016/j.est.2022.106324.

[8] H. Zhao, Q. Wu, S. Hu, H. Xu, and C. N. Rasmussen, ''Review of energy storage system for wind power integration support,'' *Appl. Energy*, vol. 137, pp. 545–553, Jan. 2015, doi: 10.1016/j.apenergy.2014.04.103.

[9] A. Alzahrani, H. Alharthi, and M. Khalid, ''Minimization of power losses through optimal battery placement in a distributed network with high penetration of photovoltaics,'' *Energies*, vol. 13, no. 1, p. 140, Dec. 2019, doi: 10.3390/en13010140.

[10] P. H. A. Barra, W. C. de Carvalho, T. S. Menezes, R. A. S. Fernandes, and D. V. Coury, ''A review on wind power smoothing using high-power energy storage systems,'' *Renew. Sustain. Energy Rev.*, vol. 137, Mar. 2021, Art. no. 110455, doi: 10.1016/j.rser.2020.110455.

[11] M. Y. Worku, ''Recent advances in energy storage systems for renewable source grid integration: A comprehensive review,'' *Sustainability*, vol. 14, no. 10, p. 5985, May 2022, doi: 10.3390/su14105985.

[12] Y. Yang, S. Bremner, C. Menictas, and M. Kay, ''Battery energy storage system size determination in renewable energy systems: A review,'' *Renew. Sustain. Energy Rev.*, vol. 91, pp. 109–125, Aug. 2018, doi: 10.1016/j.rser.2018.03.047.

[13] M. Yekini Suberu, M. Wazir Mustafa, and N. Bashir, ''Energy storage systems for renewable energy power sector integration and mitigation of intermittency,'' *Renew. Sustain. Energy Rev.*, vol. 35, pp. 499–514, Jul. 2014, doi: 10.1016/j.rser.2014.04.009.

[14] Z. Hameed, S. Hashemi, H. H. Ipsen, and C. Træholt, ''A business-oriented approach for battery energy storage placement in power systems,'' *Appl. Energy*, vol. 298, Sep. 2021, Art. no. 117186, doi: 10.1016/j.apenergy.2021.117186.

[15] S. Zhang, Y. Li, E. Du, C. Fan, Z. Wu, Y. Yao, L. Liu, and N. Zhang, ''A review and outlook on cloud energy storage: An aggregated and shared utilizing method of energy storage system,'' *Renew. Sustain. Energy Rev.*, vol. 185, Oct. 2023, Art. no. 113606, doi: 10.1016/j.rser.2023.113606.

[16] K. Xu, Y. Niu, and Z. Zhang, ''Cloud-based frequency control for multiarea power systems: Privacy preserving via homomorphic encryption,'' *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 54, no. 8, pp. 5172–5184, Aug. 2024, doi: 10.1109/TSMC.2024.3393865.

[17] V. K. Saini, A. Seervi, R. Kumar, M. A. Mahmud, and A. S. Al-Sumaiti, ''Cloud energy storage based embedded battery technology architecture for residential users cost minimization,'' *IEEE Access*, vol. 10, pp. 43685–43702, 2022, doi: 10.1109/ACCESS.2022.3168599.

[18] H. Ebrahimi, A. Yazdaninejadi, and S. Golshannavaz, ''Transient stability enhancement in multiple-microgrid networks by cloud energy storage system alongside considering protection system limitations,'' *IET Gener., Transmiss. Distrib.*, vol. 17, no. 8, pp. 1816–1826, Apr. 2023, doi: 10.1049/gtd2.12539.

[19] K. Wang, J. Wu, X. Zheng, J. Li, W. Yang, and A. V. Vasilakos, ''Cloud-edge orchestrated power dispatching for smart grid with distributed energy resources,'' *IEEE Trans. Cloud Comput.*, vol. 11, no. 2, pp. 1194–1203, Apr./Jun. 2023, doi: 10.1109/TCC.2022.3185170.

[20] J. Liu, N. Zhang, C. Kang, D. S. Kirschen, and Q. Xia, ''Decision-making models for the participants in cloud energy storage,'' *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 5512–5521, Nov. 2018, doi: 10.1109/TSG.2017.2689239.

[21] L. Ruan, Y. Yan, S. Guo, F. Wen, and X. Qiu, ''Priority-based residential energy management with collaborative edge and cloud computing,'' *IEEE Trans. Ind. Informat.*, vol. 16, no. 3, pp. 1848–1857, Mar. 2020, doi: 10.1109/TII.2019.2933631.

[22] A. Yazdaninejadi and H. Ebrahimi, ''A new protection algorithm for tackling the impact of fault-resistance and cloud energy storage on coordination of recloser-fuse protection,'' *IET Gener., Transmiss. Distrib.*, vol. 17, no. 8, pp. 1827–1835, Apr. 2023, doi: 10.1049/gtd2.12691.

[23] M. Weiss, P. Dekker, A. Moro, H. Scholz, and M. K. Patel, ''On the electrification of road transportation—A review of the environmental, economic, and social performance of electric two-wheelers,'' *Transp. Res. D, Transp. Environ.*, vol. 41, pp. 348–366, Dec. 2015, doi: 10.1016/j.trd.2015.09.007.

[24] M. Muratori, P. Jadun, B. Bush, D. Bielen, L. Vimmerstedt, J. Gonder, C. Gearhart, and D. Arent, ''Future integrated mobility-energy systems: A modeling perspective,'' *Renew. Sustain. Energy Rev.*, vol. 119, Mar. 2020, Art. no. 109541, doi: 10.1016/j.rser.2019.109541.

[25] B. Şengül and H. Mostofi, ''Impacts of E-micromobility on the sustainability of urban transportation—A systematic review,'' *Appl. Sci.*, vol. 11, no. 13, p. 5851, Jun. 2021, doi: 10.3390/app11135851.

[26] T. Massier, D. Recalde, R. Sellmair, M. Gallet, and T. Hamacher, ''Electrification of road transport in Singapore and its integration into the power system,'' *Energy Technol.*, vol. 6, no. 1, pp. 21–32, Jan. 2018, doi: 10.1002/ente.201700652.

[27] S. Sachan, S. Deb, and S. N. Singh, ''Different charging infrastructures along with smart charging strategies for electric vehicles,'' *Sustain. Cities Soc.*, vol. 60, Sep. 2020, Art. no. 102238, doi: 10.1016/j.scs.2020.102238.

[28] A. Hirsch, Y. Parag, and J. Guerrero, ''Microgrids: A review of technologies, key drivers, and outstanding issues,'' *Renew. Sustain. Energy Rev.*, vol. 90, pp. 402–411, Jul. 2018, doi: 10.1016/j.rser.2018.03.040.

[29] T. Adefarati and R. C. Bansal, ''Reliability, economic and environmental analysis of a microgrid system in the presence of renewable energy resources,'' *Appl. Energy*, vol. 236, pp. 1089–1114, Feb. 2019, doi: 10.1016/j.apenergy.2018.12.050.

[30] S. Aoufi, A. Derhab, and M. Guerroumi, ''Survey of false data injection in smart power grid: Attacks, countermeasures and challenges,'' *J. Inf. Secur. Appl.*, vol. 54, Oct. 2020, Art. no. 102518, doi: 10.1016/j.jisa.2020.102518.

[31] R. Deng, P. Zhuang, and H. Liang, ''CCPA: Coordinated cyber-physical attacks and countermeasures in smart grid,'' *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2420–2430, Sep. 2017, doi: 10.1109/TSG.2017.2702125.

[32] F. Zhai, T. Yang, B. Zhao, and H. Chen, ''Privacy-preserving outsourcing algorithms for multidimensional data encryption in smart grids,'' *Sensors*, vol. 22, no. 12, p. 4365, Jun. 2022, doi: 10.3390/s22124365.

[33] A. Hamlyn, H. Cheung, T. Mander, L. Wang, C. Yang, and R. Cheung, ''Computer network security management and authentication of smart grids operations,'' Presented at the IEEE Power Energy Soc. Gen. Meeting-Convers. Del. Electr. Energy 21st Century, Pittsburgh, PA, USA, Jul. 2008.

[34] X. Li, L. Wang, N. Yan, and R. Ma, ''Cooperative dispatch of distributed energy storage in distribution network with PV generation systems,'' *IEEE Trans. Appl. Supercond.*, vol. 31, no. 8, pp. 1–4, Nov. 2021, doi: 10.1109/TASC.2021.3117750.

[35] S. Koohi-Kamali, V. V. Tyagi, N. A. Rahim, N. L. Panwar, and H. Mokhlis, ''Emergence of energy storage technologies as the solution for reliable operation of smart power systems: A review,'' *Renew. Sustain. Energy Rev.*, vol. 25, pp. 135–165, Sep. 2013, doi: 10.1016/j.rser.2013.03.056.

[36] H. Ibrahim, A. Ilinca, and J. Perron, ''Energy storage systems—Characteristics and comparisons,'' *Renew. Sustain. Energy Rev.*, vol. 12, no. 5, pp. 1221–1250, Jun. 2008, doi: 10.1016/j.rser.2007.01.023.

[37] M. T. Ameen, Z. Ma, A. Smallbone, R. Norman, and A. P. Roskilly, ''Demonstration system of pumped heat energy storage (PHES) and its round-trip efficiency,'' *Appl. Energy*, vol. 333, Mar. 2023, Art. no. 120580, doi: 10.1016/j.apenergy.2022.120580.

[38] Q. Li, S. S. Choi, Y. Yuan, and D. L. Yao, ''On the determination of battery energy storage capacity and short-term power dispatch of a wind farm,'' *IEEE Trans. Sustain. Energy*, vol. 2, no. 2, pp. 148–158, Apr. 2011, doi: 10.1109/TSTE.2010.2095434.

[39] Z. A. Obaid, L. M. Cipcigan, M. T. Muhssin, and S. S. Sami, ''Control of a population of battery energy storage systems for frequency response,'' *Int. J. Electr. Power Energy Syst.*, vol. 115, Feb. 2020, Art. no. 105463, doi: 10.1016/j.ijepes.2019.105463.

[40] B. Chreim, M. Esseghir, and L. Merghem-Boulahia, ''Recent sizing, placement, and management techniques for individual and shared battery energy storage systems in residential areas: A review,'' *Energy Rep.*, vol. 11, pp. 250–260, Jun. 2024, doi: 10.1016/j.egyr.2023.11.053.

[41] D. A. Elalfy, E. Gouda, M. F. Kotb, V. Bureš, and B. E. Sedhom, ''Comprehensive review of energy storage systems technologies, objectives, challenges, and future trends,'' *Energy Strategy Rev.*, vol. 54, Jul. 2024, Art. no. 101482, doi: 10.1016/j.esr.2024.101482.

[42] P. Yu, J. Zhu, J. Liang, H. Chen, and X. Xiong, ''Construction method of ancillary emergency backup service based on battery energy storage system,'' *Int. J. Electr. Power Energy Syst.*, vol. 147, May 2023, Art. no. 108881, doi: 10.1016/j.ijepes.2022.108881.

[43] H. Zhu, H. Li, G. Liu, Y. Ge, J. Shi, H. Li, and N. Zhang, ''Energy storage in high variable renewable energy penetration power systems: Technologies and applications,'' *CSEE J. Power Energy Syst.*, vol. 9, no. 6, pp. 2099–2108, 2023, doi: 10.17775/CSEEJPES.2020.00090.

[44] S. Sahoo and P. Timmann, ''Energy storage technologies for modern power systems: A detailed analysis of functionalities, potentials, and impacts,'' *IEEE Access*, vol. 11, pp. 49689–49729, 2023, doi: 10.1109/ACCESS.2023.3274504.

[45] M. K. Khan, M. Raza, M. Shahbaz, U. Farooq, and M. U. Akram, ''Recent advancement in energy storage technologies and their applications,'' *J. Energy Storage*, vol. 92, Jul. 2024, Art. no. 112112, doi: 10.1016/j.est.2024.112112.

[46] B. Yang, J. Wang, Y. Chen, D. Li, C. Zeng, Y. Chen, Z. Guo, H. Shu, X. Zhang, T. Yu, and L. Sun, ''Optimal sizing and placement of energy storage system in power grids: A state-of-the-art one-stop handbook,'' *J. Energy Storage*, vol. 32, Dec. 2020, Art. no. 101814, doi: 10.1016/j.est.2020.101814.

[47] M. A. Hannan, S. B. Wali, P. J. Ker, M. S. A. Rahman, M. Mansor, V. K. Ramachandaramurthy, K. M. Muttaqi, T. M. I. Mahlia, and Z. Y. Dong, ''Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues,'' *J. Energy Storage*, vol. 42, Oct. 2021, Art. no. 103023, doi: 10.1016/j.est.2021.103023.

[48] A. A. Kebede, T. Kalogiannis, J. Van Mierlo, and M. Berecibar, ''A comprehensive review of stationary energy storage devices for large scale renewable energy sources grid integration,'' *Renew. Sustain. Energy Rev.*, vol. 159, May 2022, Art. no. 112213, doi: 10.1016/j.rser.2022.112213.

[49] S. Doraswamy, N. Dama, S. M. Kurivella, B. Goalla, and V. R. Veeredhi, ''Study on temperature dependency of lignosulfonate's electrical conductivity for lead-acid energy storage,'' *Mater. Today, Proc.*, pp. 1–6, Mar. 2023, doi: 10.1016/j.matpr.2023.03.177.

[50] A. Arabkoohsar, ''Classification of energy storage systems,'' in *Mechanical Energy Storage Technologies*. Cambridge, MA, USA: Academic, 2021, pp. 1–12.

[51] F. Torabi and P. Ahmadi, ''Battery technologies,'' in *Simulation of Battery Systems*. Cambridge, MA, USA: Academic, 2020, pp. 1–54.

[52] M. Patel, K. Mishra, R. Banerjee, J. Chaudhari, D. K. Kanchan, and D. Kumar, ''Fundamentals, recent developments and prospects of lithium and non-lithium electrochemical rechargeable battery systems,'' *J. Energy Chem.*, vol. 81, pp. 221–259, Jun. 2023, doi: 10.1016/j.jechem.2023.02.023.

[53] P. Breeze, ''Power system energy storage technologies,'' in *Power Generation Technologies*. Cambridge, MA, USA: Academic, 2019, pp. 219–249.

[54] N. Gupta, N. Kaur, S. K. Jain, and K. S. Joshal, ''Smart grid power system,'' in *Advances in Smart Grid Power System*. Cambridge, MA, USA: Academic, 2021, pp. 47–71.

[55] S. C. Johnson, F. Todd Davidson, J. D. Rhodes, J. L. Coleman, S. M. Bragg-Sitton, E. J. Dufek, and M. E. Webber, ''Selecting favorable energy storage technologies for nuclear power,'' in *Storage and Hybridization of Nuclear Energy*. Cambridge, MA, USA: Academic, 2019, pp. 119–175.
[56] Z. Abdin and K. R. Khalilpour, ''Single and polystorage technologies for renewable-based hybrid energy systems,'' in *Polygeneration With Polystorage for Chemical and Energy Hubs*. Cambridge, MA, USA: Academic, 2019, pp. 77–131.
[57] E. N. Kumi, ''Energy storage technologies,'' in *Pumped Hydro Energy Storage for Hybrid Systems*. Cambridge, MA, USA: Academic, 2023, pp. 1–21.
[58] I. Dincer and D. Erdemir, ''Fundamentals and concepts,'' in *Heat Storage Systems for Buildings*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 1–35.
[59] A. El-Kharouf and M. F. Kaya, ''Fuel-cell (hydrogen) electric hybrid vehicles,'' in *Alternative Fuels and Advanced Vehicle Technologies for Improved Environmental Performance*. Sawston, U.K.: Woodhead Publishing, 2022, pp. 681–710.
[60] A. Aktaş and Y. Kirçiçek, ''Solar hybrid systems and energy storage systems,'' in *Solar Hybrid Systems*. Cambridge, MA, USA: Academic, 2021, pp. 87–125.
[61] J. M. González-González, Á. P. Parrilla, and J. A. Aguado, ''Chemical energy storage technologies,'' in *Encyclopedia of Electrical and Electronic Power Engineering*. Amsterdam, The Netherlands: Elsevier, 2023, pp. 426–439.
[62] Y. Sawle and M. Thirunavukkarasu, ''Techno-economic comparative assessment of an off-grid hybrid renewable energy system for electrification of remote area,'' in *Design, Analysis, and Applications of Renewable Energy Systems*. Cambridge, MA, USA: Academic, 2021, pp. 199–247.
[63] F.-B. Wu, B. Yang, and J.-L. Ye, ''Technologies of energy storage systems,'' in *Grid-scale Energy Storage Systems and Applications*. Cambridge, MA, USA: Academic, 2019, pp. 17–56.
[64] A. M. Vassallo, ''Applications of batteries for grid-scale energy storage,'' in *Advances in Batteries for Medium and Large-Scale Energy Storage*. Sawston, U.K.: Woodhead Publishing, 2015, pp. 587–607.
[65] S. B. Wali, M. A. Hannan, P. J. Ker, S. A. Rahman, K. N. Le, R. A. Begum, S. K. Tiong, and T. M. I. Mahlia, ''Grid-connected lithium-ion battery energy storage system towards sustainable energy: A patent landscape analysis and technology updates,'' *J. Energy Storage*, vol. 77, Jan. 2024, Art. no. 109986, doi: 10.1016/j.est.2023.109986.
[66] Y. Yuan and X. Yuan, ''The advances and opportunities of developing solid-state battery technology: Based on the patent information relation matrix,'' *Energy*, vol. 296, Jun. 2024, Art. no. 131178, doi: 10.1016/j.energy.2024.131178.
[67] A. Alkhalidi, M. K. Khawaja, and S. M. Ismail, ''Solid-state batteries, their future in the energy storage and electric vehicles market,'' *Sci. Talks*, vol. 11, Sep. 2024, Art. no. 100382, doi: 10.1016/j.sctalk.2024.100382.
[68] N. G. Chatzigeorgiou, S. Theocharides, G. Makrides, and G. E. Georghiou, ''A review on battery energy storage systems: Applications, developments, and research trends of hybrid installations in the end-user sector,'' *J. Energy Storage*, vol. 86, May 2024, Art. no. 111192, doi: 10.1016/j.est.2024.111192.
[69] J. D. Alvarez Guerrero, B. Bhattarai, R. Shrestha, T. L. Acker, and R. Castro, ''Integrating electric vehicles into power system operation production cost models,'' *World Electric Vehicle J.*, vol. 12, no. 4, p. 263, Dec. 2021, doi: 10.3390/wevj12040263.
[70] K. Qian, C. Zhou, M. Allan, and Y. Yuan, ''Modeling of load demand due to EV battery charging in distribution systems,'' *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011, doi: 10.1109/TPWRS.2010.2057456.
[71] Y. Ding, Y. Zhu, Q. Wang, Z. Tian, R. Yan, Z. Yan, and X. Xia, ''A comprehensive scheduling model for electric vehicles in office buildings considering the uncertainty of charging load,'' *Int. J. Electr. Power Energy Syst.*, vol. 151, Sep. 2023, Art. no. 109154, doi: 10.1016/j.ijepes.2023.109154.
[72] X. Cheng, R. Zhang, and S. Bu, ''A data-driven approach for collaborative optimization of large-scale electric vehicles considering energy consumption uncertainty,'' *Electric Power Syst. Res.*, vol. 221, Aug. 2023, Art. no. 109461, doi: 10.1016/j.epsr.2023.109461.
[73] P. Diaz-Cachinero, J. I. Muñoz-Hernandez, and J. Contreras, ''A microgrid model with EV demand uncertainty and detailed operation of storage systems,'' *IEEE Trans. Ind. Appl.*, vol. 58, no. 2, pp. 2497–2511, Mar. 2022, doi: 10.1109/TIA.2021.3135801.
[74] X. Zhang, K. W. Chan, H. Li, H. Wang, J. Qiu, and G. Wang, ''Deep-learning-based probabilistic forecasting of electric vehicle charging load with a novel queuing model,'' *IEEE Trans. Cybern.*, vol. 51, no. 6, pp. 3157–3170, Jun. 2021, doi: 10.1109/TCYB.2020.2975134.
[75] S. Yang, M. Wu, X. Yao, and J. Jiang, ''Load modeling and identification based on ant colony algorithms for EV charging stations,'' *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 1997–2003, Jul. 2015, doi: 10.1109/TPWRS.2014.2352263.
[76] M. M. H. Mostafa, Z. Jiang, H. Zou, and S. Manickam, ''Modeling of electric vehicle charging load in different areas of distribution network,'' in *Proc. E3S Web Conf.*, vol. 261, 2021, p. 01007, doi: 10.1051/e3sconf/202126101007.
[77] S. Guo, Z. Qiu, C. Xiao, H. Liao, Y. Huang, T. Lei, D. Wu, and Q. Jiang, ''A multi-level vehicle-to-grid optimal scheduling approach with EV economic dispatching model,'' *Energy Rep.*, vol. 7, pp. 22–37, Nov. 2021, doi: 10.1016/j.egyr.2021.10.058.
[78] E. Srilakshmi and S. P. Singh, ''Energy regulation of EV using MILP for optimal operation of incentive based prosumer microgrid with uncertainty modelling,'' *Int. J. Electr. Power Energy Syst.*, vol. 134, Jan. 2022, Art. no. 107353, doi: 10.1016/j.ijepes.2021.107353.
[79] N. Mehboob, M. Restrepo, C. A. Cañizares, C. Rosenberg, and M. Kazerani, ''Smart operation of electric vehicles with four-quadrant chargers considering uncertainties,'' *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2999–3009, May 2019, doi: 10.1109/TSG.2018.2816404.
[80] B. Wang, D. Zhao, P. Dehghanian, Y. Tian, and T. Hong, ''Aggregated electric vehicle load modeling in large-scale electric power systems,'' *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 5796–5810, Sep. 2020, doi: 10.1109/TIA.2020.2988019.
[81] N. Pompern, S. Premrudeepreechacharn, A. Siritaratiwat, and S. Khunkitti, ''Optimal placement and capacity of battery energy storage system in distribution networks integrated with PV and EVs using metaheuristic algorithms,'' *IEEE Access*, vol. 11, pp. 68379–68394, 2023, doi: 10.1109/ACCESS.2023.3291590.
[82] Y. Lv, L. Guan, Z. Tang, and Q. Zhao, ''A probability model of PV for the middle-term to long-term power system analysis and its application,'' *Energy Proc.*, vol. 103, pp. 28–33, Dec. 2016, doi: 10.1016/j.egypro.2016.11.244.
[83] M. Ebeed and S. H. E. A. Aleem, ''Overview of uncertainties in modern power systems: Uncertainty models and methods,'' in *Uncertainties in Modern Power Systems*. Cambridge, MA, USA: Academic, 2021, pp. 1–34.
[84] O. M. Kam, S. Noël, H. Ramenah, P. Kasser, and C. Tanougast, ''Comparative Weibull distribution methods for reliable global solar irradiance assessment in France areas,'' *Renew. Energy*, vol. 165, pp. 194–210, Mar. 2021, doi: 10.1016/j.renene.2020.10.151.
[85] S.-H. Park and J.-H. Kim, ''Application of gamma process model to estimate the lifetime of photovoltaic modules,'' *Sol. Energy*, vol. 147, pp. 390–398, May 2017, doi: 10.1016/j.solener.2017.03.061.
[86] A. K. Khamees, A. Y. Abdelaziz, M. R. Eskaros, M. A. Attia, and A. O. Badr, ''The mixture of probability distribution functions for wind and photovoltaic power systems using a metaheuristic method,'' *Processes*, vol. 10, no. 11, p. 2446, Nov. 2022, doi: 10.3390/pr10112446.
[87] A. Ali, D. Raisz, K. Mahmoud, and M. Lehtonen, ''Optimal placement and sizing of uncertain PVs considering stochastic nature of PEVs,'' *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1647–1656, Jul. 2020, doi: 10.1109/TSTE.2019.2935349.
[88] R. A. Campos, G. L. Martins, and R. Rüther, ''Assessing the influence of solar forecast accuracy on the revenue optimization of photovoltaic + battery power plants in day-ahead energy markets,'' *J. Energy Storage*, vol. 48, Apr. 2022, Art. no. 104093, doi: 10.1016/j.est.2022.104093.
[89] D. Borkowski, P. Oramus, and M. Brzezinka, ''Battery energy storage system for grid-connected photovoltaic farm—Energy management strategy and sizing optimization algorithm,'' *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108201, doi: 10.1016/j.est.2023.108201.
[90] Q. Hassan, M. K. Abbas, V. S. Tabar, S. Tohidi, M. Al-Hitmi, M. Jaszczur, A. Z. Sameen, and H. M. Salman, ''Collective self-consumption of solar photovoltaic and batteries for a micro-grid energy system,'' *Results Eng.*, vol. 17, Mar. 2023, Art. no. 100925, doi: 10.1016/j.rineng.2023.100925.
[91] A. Boretti, ''Integration of solar thermal and photovoltaic, wind, and battery energy storage through AI in NEOM city,'' *Energy AI*, vol. 3, Mar. 2021, Art. no. 100038, doi: 10.1016/j.egyai.2020.100038.

[92] H. A. Taha, M. H. Alham, and H. K. M. Youssef, "Multi-objective optimization for optimal allocation and coordination of wind and solar DGs, BESSs and capacitors in presence of demand response," *IEEE Access*, vol. 10, pp. 16225–16241, 2022, doi: 10.1109/ACCESS.2022.3149135.

[93] Y. Qin, X. Chen, Z. Xu, J. Du, H. Wang, Q. Zhang, and M. Ouyang, "Lithium ion batteries participating in frequency regulation for power grid under the thermoelectric coupling degradation mechanisms," *eTransportation*, vol. 19, Jan. 2024, Art. no. 100290, doi: 10.1016/j.etran.2023.100290.

[94] Y. Zhou, Y. Wang, and M. Yang, "Optimal integration of renewable energy in refinery hydrogen management systems: Energy storage and direct utilization," *Energy Convers. Manage.*, vol. 304, Mar. 2024, Art. no. 118223, doi: 10.1016/j.enconman.2024.118223.

[95] A. Fatih Guven, A. Y. Abdelaziz, M. M. Samy, and S. Barakat, "Optimizing energy dynamics: A comprehensive analysis of hybrid energy storage systems integrating battery banks and supercapacitors," *Energy Convers. Manage.*, vol. 312, Jul. 2024, Art. no. 118560, doi: 10.1016/j.enconman.2024.118560.

[96] C. Gusain, U. Nangia, and M. M. Tripathi, "Optimal sizing of standalone hybrid renewable energy system based on reliability indicator: A case study," *Energy Convers. Manage.*, vol. 310, Jun. 2024, Art. no. 118490, doi: 10.1016/j.enconman.2024.118490.

[97] C. Opathella, A. Elkasrawy, A. A. Mohamed, and B. Venkatesh, "Optimal scheduling of merchant-owned energy storage systems with multiple ancillary services," *IEEE Open Access J. Power Energy*, vol. 7, pp. 31–40, 2020, doi: 10.1109/OAJPE.2019.2952811.

[98] F. Calero, C. A. Cañizares, K. Bhattacharya, C. Anierobi, I. Calero, M. F. Z. de Souza, M. Farrokhabadi, N. S. Guzman, W. Mendieta, D. Peralta, B. V. Solanki, N. Padmanabhan, and W. Violante, "A review of modeling and applications of energy storage systems in power grids," *Proc. IEEE*, vol. 111, no. 7, pp. 806–831, Jul. 2023, doi: 10.1109/JPROC.2022.3158607.

[99] S. Hasan, M. Zeyad, S. M. M. Ahmed, D. M. Mahmud, M. S. T. Anubhove, and E. Hossain, "Techno-economic feasibility analysis of an electric vehicle charging station for an international airport in chattogram, Bangladesh," *Energy Convers. Manage.*, vol. 293, Oct. 2023, Art. no. 117501, doi: 10.1016/j.enconman.2023.117501.

[100] H. Shin and R. Baldick, "Optimal battery energy storage control for multi-service provision using a semidefinite programming-based battery model," *IEEE Trans. Sustain. Energy*, vol. 14, no. 4, pp. 2192–2204, Oct. 2023, doi: 10.1109/TSTE.2023.3263236.

[101] M. Bilal, F. Ahmad, and M. Rizwan, "Techno-economic assessment of grid and renewable powered electric vehicle charging stations in india using a modified metaheuristic technique," *Energy Convers. Manage.*, vol. 284, May 2023, Art. no. 116995, doi: 10.1016/j.enconman.2023.116995.

[102] Z. Medghalchi and O. Taylan, "A novel hybrid optimization framework for sizing renewable energy systems integrated with energy storage systems with solar photovoltaics, wind, battery and electrolyzer-fuel cell," *Energy Convers. Manage.*, vol. 294, Oct. 2023, Art. no. 117594, doi: 10.1016/j.enconman.2023.117594.

[103] N. B. Arias, J. C. López, S. Hashemi, J. F. Franco, and M. J. Rider, "Multi-objective sizing of battery energy storage systems for stackable grid applications," *IEEE Trans. Smart Grid*, vol. 12, no. 3, pp. 2708–2721, May 2021, doi: 10.1109/TSG.2020.3042186.

[104] L. Argiolas, M. Stecca, L. M. Ramirez-Elizondo, T. B. Soeiro, and P. Bauer, "Optimal battery energy storage dispatch in energy and frequency regulation markets while peak shaving an EV fast charging station," *IEEE Open Access J. Power Energy*, vol. 9, pp. 374–385, 2022, doi: 10.1109/OAJPE.2022.3198553.

[105] Y. Zhang, Y. Xu, H. Yang, Z. Y. Dong, and R. Zhang, "Optimal whole-life-cycle planning of battery energy storage for multi-functional services in power systems," *IEEE Trans. Sustain. Energy*, vol. 11, no. 4, pp. 2077–2086, Oct. 2020, doi: 10.1109/TSTE.2019.2942066.

[106] J. Krata and T. K. Saha, "Real-time coordinated voltage support with battery energy storage in a distribution grid equipped with medium-scale PV generation," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3486–3497, May 2019, doi: 10.1109/TSG.2018.2828991.

[107] T. S. Mahmoud, B. S. Ahmed, and M. Y. Hassan, "The role of intelligent generation control algorithms in optimizing battery energy storage systems size in microgrids: A case study from western Australia," *Energy Convers. Manage.*, vol. 196, pp. 1335–1352, Sep. 2019, doi: 10.1016/j.enconman.2019.06.045.

[108] A. V. Savkin, M. Khalid, and V. G. Agelidis, "A constrained monotonic charging/discharging strategy for optimal capacity of battery energy storage supporting wind farms," *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 1224–1231, Jul. 2016, doi: 10.1109/TSTE.2016.2528222.

[109] X. Ke, N. Lu, and C. Jin, "Control and size energy storage systems for managing energy imbalance of variable generation resources," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 70–78, Jan. 2015, doi: 10.1109/TSTE.2014.2355829.

[110] F. Marra, G. Yang, C. Træholt, J. Østergaard, and E. Larsen, "A decentralized storage strategy for residential feeders with photovoltaics," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 974–981, Mar. 2014, doi: 10.1109/TSG.2013.2281175.

[111] A. M. A. Haidar, K. M. Muttaqi, and D. Sutanto, "Technical challenges for electric power industries due to grid-integrated electric vehicles in low voltage distributions: A review," *Energy Convers. Manage.*, vol. 86, pp. 689–700, Oct. 2014, doi: 10.1016/j.enconman.2014.06.025.

[112] C. P. Nguyen and A. J. Flueck, "Agent based restoration with distributed energy storage support in smart grids," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 1029–1038, Jun. 2012, doi: 10.1109/TSG.2012.2186833.

[113] A. Valencia, R. A. Hincapie, and R. A. Gallego, "Optimal location, selection, and operation of battery energy storage systems and renewable distributed generation in medium–low voltage distribution networks," *J. Energy Storage*, vol. 34, Feb. 2021, Art. no. 102158, doi: 10.1016/j.est.2020.102158.

[114] M. Kilic and A. F. Altun, "Dynamic modelling and multi-objective optimization of off-grid hybrid energy systems by using battery or hydrogen storage for different climates," *Int. J. Hydrogen Energy*, vol. 48, no. 60, pp. 22834–22854, Jul. 2023, doi: 10.1016/j.ijhydene.2022.12.103.

[115] M. Takagi, K. Fukushima, N. Tagashira, K. Okada, and H. Asano, "Cost-effectiveness analysis method for voltage stabilization in case of combining storage battery and reactive power compensator," *J. Energy Storage*, vol. 93, Jul. 2024, Art. no. 112065, doi: 10.1016/j.est.2024.112065.

[116] G. Gangil, S. K. Goyal, and A. Saraswat, "A multi-objective techno-economic operation of distribution network considering reactive power support from renewable energy and battery storage system," *J. Energy Storage*, vol. 102, Nov. 2024, Art. no. 114116, doi: 10.1016/j.est.2024.114116.

[117] R. Hemmati, S. Mahdavi, and M. A. Jirdehi, "A novel and cost-effective model for cloud energy storage based on a dual storage setup in active distribution grid with resilience consideration," *J. Cleaner Prod.*, vol. 471, Sep. 2024, Art. no. 143432, doi: 10.1016/j.jclepro.2024.143432.

[118] S. Ray, K. Kasturi, S. Patnaik, and M. R. Nayak, "Battery energy storage with renewable energy sources integration in unbalanced distribution network considering time of use pricing," *Renew. Energy Focus*, vol. 51, Oct. 2024, Art. no. 100630, doi: 10.1016/j.ref.2024.100630.

[119] L. Zhang, Y. Yu, B. Li, X. Qian, S. Zhang, X. Wang, X. Zhang, and M. Chen, "Improved cycle aging cost model for battery energy storage systems considering more accurate battery life degradation," *IEEE Access*, vol. 10, pp. 297–307, 2022, doi: 10.1109/ACCESS.2021.3139075.

[120] M. Wicke and T. Bocklisch, "Hierarchical energy management of hybrid battery storage systems for PV capacity firming and spot market trading considering degradation costs," *IEEE Access*, vol. 12, pp. 52669–52686, 2024, doi: 10.1109/ACCESS.2024.3387748.

[121] H. Kang, S. Jung, H. Kim, J. Jeoung, and T. Hong, "Reinforcement learning-based optimal scheduling model of battery energy storage system at the building level," *Renew. Sustain. Energy Rev.*, vol. 190, Feb. 2024, Art. no. 114054, doi: 10.1016/j.rser.2023.114054.

[122] P. Wongdet, T. Boonraksa, P. Boonraksa, W. Pinthurat, B. Marungsri, and B. Hredzak, "Optimal capacity and cost analysis of battery energy storage system in standalone microgrid considering battery lifetime," *Batteries*, vol. 9, no. 2, p. 76, Jan. 2023, doi: 10.3390/batteries9020076.

[123] S. Chauhan and B. Singh, "Control of solar PV-integrated battery energy storage system for rural area application," *IET Renew. Power Gener.*, vol. 15, no. 5, pp. 1030–1045, Apr. 2021, doi: 10.1049/rpg2.12086.

[124] W. A. Oraibi, B. Mohammadi-Ivatloo, S. H. Hosseini, and M. Abapour, "A resilience-oriented optimal planning of energy storage systems in high renewable energy penetrated systems," *J. Energy Storage*, vol. 67, Sep. 2023, Art. no. 107500, doi: 10.1016/j.est.2023.107500.

[125] T. Costa, A. Arcanjo, A. Vasconcelos, W. Silva, C. Azevedo, A. Pereira, E. Jatobá, J. B. Filho, E. Barreto, M. G. Villalva, and M. Marinho, "Development of a method for sizing a hybrid battery energy storage system for application in AC microgrid," *Energies*, vol. 16, no. 3, p. 1175, Jan. 2023, doi: 10.3390/en16031175.

[126] K. Balu and V. Mukherjee, "Optimal allocation of electric vehicle charging stations and renewable distributed generation with battery energy storage in radial distribution system considering time sequence characteristics of generation and load demand," *J. Energy Storage*, vol. 59, Mar. 2023, Art. no. 106533, doi: 10.1016/j.est.2022.106533.

[127] B. Yildiz, N. Stringer, T. Klymenko, M. S. Samhan, G. Abramowitz, A. Bruce, I. MacGill, R. Egan, and A. B. Sproul, "Real-world data analysis of distributed PV and battery energy storage system curtailment in low voltage networks," *Renew. Sustain. Energy Rev.*, vol. 186, Oct. 2023, Art. no. 113696, doi: 10.1016/j.rser.2023.113696.

[128] X. Liu, X. C. Liu, C. Xie, and X. Ma, "Impacts of photovoltaic and energy storage system adoption on public transport: A simulation-based optimization approach," *Renew. Sustain. Energy Rev.*, vol. 181, Jul. 2023, Art. no. 113319, doi: 10.1016/j.rser.2023.113319.

[129] A. A. A. El-Ela, R. A. El-Sehiemy, A. M. Shaheen, W. A. Wahbi, and M. T. Mouwafi, "A multi-objective equilibrium optimization for optimal allocation of batteries in distribution systems with lifetime maximization," *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105795, doi: 10.1016/j.est.2022.105795.

[130] T. Gu, P. Wang, F. Liang, G. Xie, L. Guo, X.-P. Zhang, and F. Shi, "Placement and capacity selection of battery energy storage system in the distributed generation integrated distribution network based on improved NSGA-II optimization," *J. Energy Storage*, vol. 52, Aug. 2022, Art. no. 104716, doi: 10.1016/j.est.2022.104716.

[131] V. B. Pamshetti and S. P. Singh, "Coordinated allocation of BESS and SOP in high PV penetrated distribution network incorporating DR and CVR schemes," *IEEE Syst. J.*, vol. 16, no. 1, pp. 420–430, Mar. 2022, doi: 10.1109/JSYST.2020.3041013.

[132] A. Ghaffari, A. Askarzadeh, and R. Fadaeinedjad, "Optimal allocation of energy storage systems, wind turbines and photovoltaic systems in distribution network considering flicker mitigation," *Appl. Energy*, vol. 319, Aug. 2022, Art. no. 119253, doi: 10.1016/j.apenergy.2022.119253.

[133] D. A. Kez, A. M. Foley, and D. J. Morrow, "Analysis of fast frequency response allocations in power systems with high system non-synchronous penetrations," *IEEE Trans. Ind. Appl.*, vol. 58, no. 3, pp. 3087–3101, May 2022, doi: 10.1109/TIA.2022.3160997.

[134] H. Yin, H. Lan, D. C. Yu, Y.-Y. Hong, and R.-Y. Li, "An improved optimal allocation scheme of energy storage system in a distribution system based on transient stability," *J. Energy Storage*, vol. 34, Feb. 2021, Art. no. 101977, doi: 10.1016/j.est.2020.101977.

[135] O. Zarenia, M. J. Shabani, M. J. Salehpour, J. Zhang, and L. Wang, "A new two-stage game-based approach for energy storage pricing in radial distribution system considering uncertainty," *J. Energy Storage*, vol. 38, Jun. 2021, Art. no. 102510, doi: 10.1016/j.est.2021.102510.

[136] P. Rajesh, C. Naveen, A. K. Venkatesan, and F. H. Shajin, "An optimization technique for battery energy storage with wind turbine generator integration in unbalanced radial distribution network," *J. Energy Storage*, vol. 43, Nov. 2021, Art. no. 103160, doi: 10.1016/j.est.2021.103160.

[137] V. Janamala and D. S. Reddy, "Coyote optimization algorithm for optimal allocation of interline—Photovoltaic battery storage system in islanded electrical distribution network considering EV load penetration," *J. Energy Storage*, vol. 41, Sep. 2021, Art. no. 102981, doi: 10.1016/j.est.2021.102981.

[138] B. Khaki, "Joint sizing and placement of battery energy storage systems and wind turbines considering reactive power support of the system," *J. Energy Storage*, vol. 35, Mar. 2021, Art. no. 102264, doi: 10.1016/j.est.2021.102264.

[139] B. Wang, C. Zhang, Z. Y. Dong, and X. Li, "Improving hosting capacity of unbalanced distribution networks via robust allocation of battery energy storage systems," *IEEE Trans. Power Syst.*, vol. 36, no. 3, pp. 2174–2185, May 2021, doi: 10.1109/TPWRS.2020.3029532.

[140] B. Ahmadi, O. Ceylan, and A. Ozdemir, "A multi-objective optimization evaluation framework for integration of distributed energy resources," *J. Energy Storage*, vol. 41, Sep. 2021, Art. no. 103005, doi: 10.1016/j.est.2021.103005.

[141] B. Mukhopadhyay and D. Das, "Multi-objective dynamic and static reconfiguration with optimized allocation of PV-DG and battery energy storage system," *Renew. Sustain. Energy Rev.*, vol. 124, May 2020, Art. no. 109777, doi: 10.1016/j.rser.2020.109777.

[142] P. Lata and S. Vadhera, "Reliability improvement of radial distribution system by optimal placement and sizing of energy storage system using TLBO," *J. Energy Storage*, vol. 30, Aug. 2020, Art. no. 101492, doi: 10.1016/j.est.2020.101492.

[143] S. Sharma, K. R. Niazi, K. Verma, and T. Rawat, "Coordination of different DGs, BESS and demand response for multi-objective optimization of distribution network with special reference to Indian power sector," *Int. J. Electr. Power Energy Syst.*, vol. 121, Oct. 2020, Art. no. 106074, doi: 10.1016/j.ijepes.2020.106074.

[144] P. Prabawa and D.-H. Choi, "Multi-agent framework for service restoration in distribution systems with distributed generators and static/mobile energy storage systems," *IEEE Access*, vol. 8, pp. 51736–51752, 2020, doi: 10.1109/ACCESS.2020.2980544.

[145] Y. Zheng, Y. Song, A. Huang, and D. J. Hill, "Hierarchical optimal allocation of battery energy storage systems for multiple services in distribution systems," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1911–1921, Jul. 2020, doi: 10.1109/TSTE.2019.2946371.

[146] P. Singh, N. K. Meena, A. Slowik, and S. K. Bishnoi, "Modified African buffalo optimization for strategic integration of battery energy storage in distribution networks," *IEEE Access*, vol. 8, pp. 14289–14301, 2020, doi: 10.1109/ACCESS.2020.2966571.

[147] L. A. Wong, V. K. Ramachandaramurthy, S. L. Walker, and J. B. Ekanayake, "Optimal placement and sizing of battery energy storage system considering the duck curve phenomenon," *IEEE Access*, vol. 8, pp. 197236–197248, 2020, doi: 10.1109/ACCESS.2020.3034349.

[148] A. H. Sabry and P. J. Ker, "Improvement on energy consumption of a refrigerator within PV system including battery storage," *Energy Rep.*, vol. 7, pp. 430–438, Nov. 2021, doi: 10.1016/j.egyr.2021.01.011.

[149] V. Bagalini, B. Y. Zhao, R. Z. Wang, and U. Desideri, "Solar PV-battery-electric grid-based energy system for residential applications: System configuration and viability," *Research*, vol. 2019, pp. 1–17, Jan. 2019, doi: 10.34133/2019/3838603.

[150] A. H. Sabry, W. Z. Wan Hasan, Y. Alkubaisi, and M. Z. A. Ab-Kadir, "Battery backup power system for electrical appliances with two options of primary power sources," Presented at the IEEE 5th Int. Conf. Smart Instrum., Meas. Appl. (ICSIMA), Songkhla, Thailand, Nov. 2018.

[151] D. Akinyele, J. Belikov, and Y. Levron, "Battery storage technologies for electrical applications: Impact in stand-alone photovoltaic systems," *Energies*, vol. 10, no. 11, p. 1760, Nov. 2017, doi: 10.3390/en10111760.

[152] J. Khayatzadeh, S. Soleymani, S. B. Mozafari, and H. M. Shourkaei, "Optimizing the operation of energy storage embedded energy hub concerning the resilience index of critical load," *J. Energy Storage*, vol. 48, Apr. 2022, Art. no. 103999, doi: 10.1016/j.est.2022.103999.

[153] S. Dorahaki, M. Rashidinejad, S. F. Fatemi Ardestani, A. Abdollahi, and M. R. Salehizadeh, "A home energy management model considering energy storage and smart flexible appliances: A modified time-driven prospect theory approach," *J. Energy Storage*, vol. 48, Apr. 2022, Art. no. 104049, doi: 10.1016/j.est.2022.104049.

[154] I. S. Bayram, S. Galloway, and G. Burt, "A probabilistic capacity planning methodology for plug-in electric vehicle charging lots with on-site energy storage systems," *J. Energy Storage*, vol. 32, Dec. 2020, Art. no. 101730, doi: 10.1016/j.est.2020.101730.

[155] A. A. Ahmad, R. Sirjani, and S. Daneshvar, "New hybrid probabilistic optimisation algorithm for optimal allocation of energy storage systems considering correlated wind farms," *J. Energy Storage*, vol. 29, Jun. 2020, Art. no. 101335, doi: 10.1016/j.est.2020.101335.

[156] L. Chen, D. Yue, C. Dou, Z. Cheng, and J. Chen, "Robustness of cyber-physical power systems in cascading failure: Survival of interdependent clusters," *Int. J. Electr. Power Energy Syst.*, vol. 114, Jan. 2020, Art. no. 105374, doi: 10.1016/j.ijepes.2019.06.032.

[157] Y. Yang, Y. Zhou, J. Wu, Z. Xu, S. He, X. Guan, and T. Liu, "An event-triggered hybrid system model for cascading failure in power grid," *IEEE Trans. Autom. Sci. Eng.*, vol. 19, no. 3, pp. 1312–1325, Jul. 2022, doi: 10.1109/TASE.2022.3169069.

[158] J. Li, C. Sun, and Q. Su, "Analysis of cascading failures of power cyber-physical systems considering false data injection attacks," *Global Energy Interconnection*, vol. 4, no. 2, pp. 204–213, Apr. 2021, doi: 10.1016/j.gloei.2021.05.002.

[159] J. Khazaei and M. H. Amini, "Protection of large-scale smart grids against false data injection cyberattacks leading to blackouts," *Int. J. Crit. Infrastruct. Protection*, vol. 35, Dec. 2021, Art. no. 100457, doi: 10.1016/j.ijcip.2021.100457.

[160] A. Varbella, B. Gjorgiev, and G. Sansavini, "Geometric deep learning for online prediction of cascading failures in power grids," *Rel. Eng. Syst. Saf.*, vol. 237, Sep. 2023, Art. no. 109341, doi: 10.1016/j.ress.2023.109341.

[161] (Aug. 2004). *Final Report of the Investigation Committee on the September 3 Blackout in Italy*. [Online]. Available: http://ns2.rae.gr/old/cases/C13/italy/UCTE_rept.pdf

[162] G. Andersson, P. Donalek, R. Farmer, N. Hatziargyriou, I. Kamwa, P. Kundur, N. Martins, J. Paserba, P. Pourbeik, J. Sanchez-Gasca, R. Schulz, A. Stankovic, C. Taylor, and V. Vittal, "Causes of the 2003 major grid blackouts in north America and europe, and recommended means to improve system dynamic performance," *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1922–1928, Nov. 2005, doi: 10.1109/TPWRS.2005.857942.

[163] J. W. Bialek, "Why has it happened again? Comparison between the UCTE blackout in 2006 and the blackouts of 2003," in *Proc. IEEE Power Technol.*, Jul. 2007, pp. 51–56.

[164] V. Rampurkar, P. Pentayya, H. A. Mangalvedekar, and F. Kazi, "Cascading failure analysis for Indian power grid," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1951–1960, Jul. 2016, doi: 10.1109/TSG.2016.2530679.

[165] (Apr. 2016). *Project Group Turkey. Report on Blackout in Turkey on 31 March 2015*. [Online]. Available: https://docs.entsoe.eu/dataset/ops-report-turkey-blackout-march2015/resource/08fb8ed2-5b40-4b94-90b0-5682bcd618cb

[166] S. Wilde. (Aug. 9, 2019). *Power Outage Report*. [Online]. Available: https://www.ofgem.gov.uk/sites/default/files/docs/2020/01/9_august_2019_power_outage_report.pdf

[167] (Feb. 2021). *Inquiry Report Regarding Total Power System Collapse*. [Online]. Available: https://www.nepra.org.pk/Standards/2021/Inquiry%20Report%20regarding%20total%20power%20system%20collapse%20on%2009%20Jan%202021.PDF

[168] D. Zhu, W. Cheng, J. Duan, H. Wang, and J. Bai, "Identifying and assessing risk of cascading failure sequence in AC/DC hybrid power grid based on non-cooperative game theory," *Rel. Eng. Syst. Saf.*, vol. 237, Sep. 2023, Art. no. 109359, doi: 10.1016/j.ress.2023.109359.

[169] H. Liu, X. Chen, L. Huo, Y. Zhang, and C. Niu, "Impact of inter-network assortativity on robustness against cascading failures in cyber–physical power systems," *Rel. Eng. Syst. Saf.*, vol. 217, Jan. 2022, Art. no. 108068, doi: 10.1016/j.ress.2021.108068.

[170] A. Chhetri, D. K. Saini, M. Yadav, and N. Pal, "Performance analysis of machine learning algorithms for estimation of EV penetration," in *Microsystem Technologies*. Berlin, Germany: Springer 2024, doi: 10.1007/s00542-024-05804-x.

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