Computer Science, Engineering and Technology
Vol: 2(1), March 2024
REST Publisher; ISSN: 2583-9179 (Online)
Website: https://restpublisher.com/journals/cset/
DOI: https://doi.org/10.46632/cset/2/1/8

Long-Term Power System Modeling and Optimization with Energy Storage Integration

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Abstract: *Energy Storage System (ESS) integration is essential to improving the sustainability, dependability, and effectiveness of contemporary power systems. The goal of this study is to create an extensive structure for the long-term modelling and optimisation of power systems that are connected with ESS. The study tackles important issues such controlling varying demand, preserving system stability, and managing transitory Renewable Energy (RE) production. Key parameters, including storage capacity, charge/discharge cycles, and operational constraints, are incorporated into the framework to assess the technical and economic impacts of ESS integration. Advanced optimization techniques are applied to identify optimal strategies for minimizing operational costs, maximizing RE utilization, and improving overall system performance. The results underline the potential of optimized ESS to enhance energy efficiency, reduce costs, and support the transition to sustainable and resilient power systems, ensuring long-term reliability and environmental benefits.*

Keywords: *Long-Term Power System Modelling, energy storage systems, renewable energy sources.*

1. INTRODUCTION

The global shift away from energy derived from fossil fuels supplies and towards Renewable Energy Sources (RESs) is essential to lowering carbon emissions and enhancing energy security. However, the erratic and sporadic characteristics of RE sources may result in issues with voltage and frequency stability, low power quality, and decreased system reliability. Energy Storage Systems (ESSs) are thought to be one of the most effective and realistic ways to deal with these issues. They provide efficient means of compensating for RES intermittency and optimising the use of energy to attain equilibrium between supply as well as demand for energy [1,2]. One type of ESS may not be able to fulfil the diverse energy service requirements of contemporary RE -integrated power systems due to its limited capacity, energy density, adaptability, and life cycles [1]. In order to give system operators more capacity, efficiency, and flexibility, a Hybrid Energy Storage System (HESS) combines the advantageous aspects of many energy storage systems. High-Power Storage (HPS) and High Energy Storage (HES) systems often make up HESSs; the HPS manages maximum and transient power, while the HES meets long-term energy demands [1].A combination of ESS technologies with different capacities, endurances, and speed of response is required to guarantee the stability of the power system. These technologies can provide vital related services for the network, such as Network Support and Control Ancillary Services (NSCAS) and Frequency Control Ancillary Services (FCAS) [3]. The output of RES is heavily affected by weather conditions. As RES proportions grow, the risk of supply-demand mismatches across different time scales emerges in power systems, driven by the uncertainty of RES output. In particular, RES output fluctuations may transform the net load curve into a “canyon curve” in some regions, where seasonal disparities between RES production and load result in imbalances of supply and demand during certain seasons [4]. The uncertainty associated with RES poses significant challenges to maintaining supply-demand equilibrium in power systems. Within this framework, energy storage technology is recognized as both a crucial innovation and an essential tool to address supply-demand balancing challenges over varying time scales in systems with high-RES integration. Nonetheless, a single type of energy storage resource alone cannot adequately manage supply-demand balance across multiple time scales [5]. To maintain a dynamic equilibrium between demand and supply over time and to manage the unpredictability of RES output, integrating diverse forms of energy storage is crucial. Of the many energy storage solutions, the agility and swift responsiveness of battery storage make it a vital component of power systems. Furthermore, hydrogen storage is seen as a pivotal innovation for achieving significant decarbonization and ensuring prolonged energy storage, particularly for seasonal energy demands. Progress in both hydrogen and battery storage systems will be instrumental in addressing climate objectives [6]. According to forecasts from the IEA, the global capacity of energy storage, encompassing systems like battery and hydrogen storage, should expand to around 1000 Giga Watts (GW) by 2030 to meet the energy transition requirements and environmental targets of nations. Thus, investigating collaborative strategies for planning Multi-Type Energy Storage Systems (MESS) to enhance the efficient deployment of various storage technologies holds immense importance. An independent power network, called a microgrid, integrates components like RES, energy ES, and manageable loads, operating either in island mode or connected to the main grid [7]. Supporting decarbonization, enhancing reliability, and reducing transmission infrastructure costs are key benefits of microgrids, although the irregular nature of RES introduces challenges in balancing short-term supply and demand. Furthermore, extreme weather patterns and seasonal changes in RES output [8] emphasize the critical role of managing energy resources in microgrids over the long term.

2. LITERATURE REVIEW

Numerous studies have explored ESS planning methodologies. For battery storage planning, RES uncertainties are taken into account, and a robust optimization framework is utilized to refine the battery storage configuration on the RES side. Following the equal-area principle, battery capacity is optimized to enhance the efficient utilization of RES. Zhu et al., have presents a distributionally robust optimization model is developed to configure battery storage, factoring in RES uncertainties and focusing on increasing the flexibility of power systems [9]. Tang et al., have proposed a robust optimization often produces overly cautious results, leading to poor economic performance of the planning strategy [10]. To address this, stochastic optimization methods must be employed to improve the economic efficiency of planning while incorporating the effects of RES uncertainties. Fu et al., have conducted significant research has examined hydrogen storage planning. The author introduces an optimization framework for hydrogen energy storage [11]. Luo et al., have introduced a planning framework for hydrogen energy storage that accounts for its physical attributes [12]. Li et al., have stated that hydrogen storage systems are simulated through modelling in Simulink [13]. Xiong et al., have presented a hydrogen storage framework alongside an optimization model for electricity–heat–hydrogen operations. Expanding on these works, various studies have explored collaborative methods for planning Multi-Energy Storage Systems (MESS) [14]. Using seasonal-trend decomposition via LOESS (STL) techniques, Lu et al., have examined the capacities of battery and hydrogen storage systems [15]. Du et al., have incorporated a hydrogen storage framework into a co-planning model for power grids, facilitating integrated planning for battery and hydrogen storage [16]. Jiang et al., have outlined a hybrid hydrogen–battery storage approach for microgrids, modeling operational constraints and structuring the plan as a scenario-based two-stage framework [17]. Wu et al., have designed a joint optimization framework for a carbon-neutral microgrid, integrating hydrogen and battery storage, and formulates it using convex relaxation methods [18]. Wang et al., have created a methodology for developing multi-energy storage facilities, optimizing placement and capacity for batteries and thermal storage within regionally integrated energy systems to mitigate mismatches between renewable output and user demand [19]. Likewise, Gao et al., have proposed an optimization framework for MESS planning that evaluates power response traits of different storage media in integrated systems, optimizing both storage types and capacity [20]. According to Guerra et al., various LDES technologies, either for sale or in the process of being developed (such as lithium-ion batteries, hydrogen storage, energy from compressed air storage, pumped hydro, and flow batteries), feature distinct system configurations, cost models, and technical parameters. For instance, certain technologies, like compressed air storage and hydrogen storage, allow for decoupling charging and discharging power capacities, offering valuable flexibility from both operational and investment perspectives. However, some technologies may face restrictions in cycling capability, caused by mechanical aging or chemical degradation of electrochemical systems, potentially limiting the flexibility they can provide to power systems. Additionally, storage systems may operate in a storage-to-storage charging mode, where one device charges another, occasionally lowering the total cost of power systems. Therefore, modeling frameworks for storage technologies should accommodate various characteristics, including cycling limitations, lifespan, the decoupling of charging and discharging capacities, and inter-storage operations, such as multiscale technology evaluations [21]. Wang et al., have introduced a HESS, comprising SC and VRFB, to enhance voltage stability and smooth power output in a large-scale Hybrid Wind/PV Farm (HWPF) within a multi-machine power network. A control strategy based on probability has been employed to manage power sharing in the HESS. Small-signal stability analysis has been conducted using eigenvalue computations and root-locus plots, Including and excluding the HESS. Furthermore, time-domain models that are both dynamic and transient have been performed, accounting for abrupt changes in wind and PV outputs, to evaluate large-signal stability [22].

3. RESEARCH METHODOLOGY

To develop a framework for long-term power system modelling with ESS integration, this research begins by gathering data on RE patterns, energy demand fluctuations, and ESS parameters such as storage capacity, charge/discharge efficiency, and operational constraints. A mathematical model is formulated to capture the dynamic interactions between RES, ESS, and the grid, incorporating variability and operational challenges. Advanced optimization techniques, including linear and heuristic methods, are employed to design strategies that minimize operational costs, maximize RE utilization, and ensure system reliability. Various scenarios are simulated to evaluate the impacts of ESS under different renewable penetration levels and storage capacities. Sensitivity analyses are conducted to assess how key parameters influence technical and economic outcomes. The framework is validated through comparative analysis with established benchmarks to ensure robustness and practical applicability.

This structured approach aims to enhance energy efficiency, support the integration of renewable resources, and promote the development of sustainable, resilient power systems.

4. TYPES OF ES

A thorough assessment of ES technology' technical and financial features. An outline of the mechanical systems (such as compressed air ES [CAES], pump storage hydropower [PSH], and flywheel ES [FES]); electrical systems (such as supercapacitors and superconducting magnetic ES [SMES]); electrochemical systems (such as lithium-ion, lead-acid, and flow batteries); and hydrogen ES. The overview concluded that when PSH and CAES systems are used on a wide scale, they provide low-cost ES capacity with high-power ratings and extended discharge periods. However, FES systems have relatively smaller capacity for storage despite providing remarkable power. There is continuing work being done on hydrogen ES, specifically using clathrate hydrates and carbon nanotubes. Flow batteries provide the benefit of decoupled ES and power capacities in the case of electrochemical ES, making it easy to modify both. Flow batteries have seen major technological advancements, and commercialisation is about to follow. Although there is still a major problem with the battery life of lithium-ion batteries, which is mostly caused by cell deterioration and the mining procedures for metals like cobalt and lithium, the expense of lithium-ion is fast declining. Fig. 1 illustrates the relationship among low-carbon power production sources, conversion of energy techniques, and the subsequent potential GIES technologies, demonstrating the critical role that energy transition performs in ES. A heat engine can be used to transform thermal power into kinetic energy, once chemical energy has been transformed into thermal energy by combustion or other reactions. A generator that produces electricity then transforms this kinetic energy. Additionally, a thermoelectric generator can be used to convert heat energy into electrical power. However, these generators are still too costly for high-power applications because to their mere 8% efficiency.

5. PROPOSED LOAD MODELS

In both short-term and some long-term research, the daily load curve is frequently used. The daily load curve can frequently be approximated using multiple sequential load segments in order to strike a compromise between computational difficulty and solution accuracy. The terms "peak," "mean," and "off-peak" have been used to describe the LDC curve in a number of earlier studies that looked into the long-term functioning of power systems. However, this estimation is insufficient and does not correctly reflect the features of ESSs because of the "double peak" aspect of the daily load curve, which is observed in electrical networks (Fig. 1). Consequently, the simplest approximation's model ought to have a minimum of five load segments. The two shoulder sections, the two lower parts at the start and finish of the daily load curve, and the two highest points are all well represented by these five segments. Fig. 1 provides an illustration of this approach. The most straightforward estimate that can accurately depict the charging and discharging behaviour of an ESS with a daily cycle is the approximated curve in Figure 1. In the future, additional load segments can be added to the five-piece fundamental framework to increase the approximation. A seven-piece approximation might be made, for instance, by inserting two extra segments among the initial and subsequent pieces as well as the fourth and fifth pieces. This procedure can also be applied to models with load segments that are hourly or even shorter. The algorithm for daily load approximation shown in figure 2.

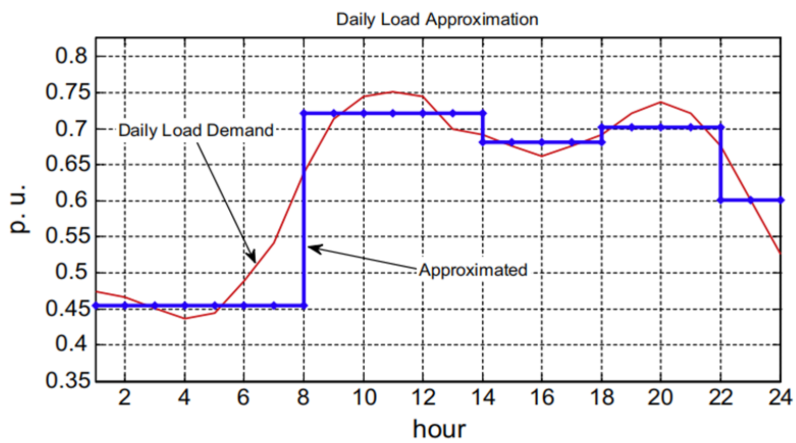

FIGURE 1. Suggested model for estimating the daily load curve.

LDES refers to systems capable of storing energy for extended periods, often used to balance renewable energy (RE) production and demand. The mathematical modelling of LDES depends on the specific technology (e.g., batteries, pumped hydro, thermal storage). Below is a generalised formulation of energy storage dynamics.

1. Energy Storage Capacity: This represents the total energy the storage system can hold, calculated as the

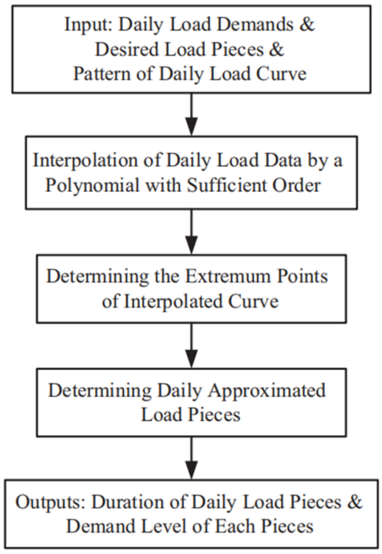

FIGURE 2. A daily load estimation algorithm

product of the power rating (P) and the maximum discharge duration (T). It defines the maximum potential energy capacity:

$$E_{\text{max}} = P \cdot T$$

where:

- E_{max}: Maximum energy capacity (in kWh or MWh)
- P: Power rating (in kW or MW)
- T: Maximum discharge duration at full power (in hours)

2. State of Charge (SOC): The state of charge at time t is given by:

$$SOC(t) = SOC(t-1) + \eta_c \cdot P_c(t) \cdot \Delta t - \frac{P_d(t) \cdot \Delta t}{\eta_d}$$

where:

- $SOC(t)$: Energy stored at time t (in kWh or MWh)
- $P_c(t)$: Charging power at time t (in kW or MW)
- $P_d(t)$: Discharging power at time t (in kW or MW)
- η_c, η_d: Charging and discharging efficiencies ($0 < \eta \leq 1$)
- Δt: Time step (in hours)

3. Energy Constraints: To ensure safe operation within system limits, the state of charge must satisfy:

$$0 < SOC(t) \leq E_{\text{max}}$$

4. Round-Trip Efficiency: The round-trip efficiency represents the overall efficiency of a full charge-discharge cycle:

$$\eta_{\text{rt}} = \eta_c \cdot \eta_d$$

5. Power Balance Equation: The power balance reflects the net power interaction with the grid:

$$P_{\text{net}}(t) = P_{\text{in}}(t) - P_{\text{out}}(t)$$

where:

- $P_{\text{net}}(t)$: Net power supplied to the grid
- $P_{\text{in}}(t)$: Power input to the system (charging)
- $P_{\text{out}}(t)$: Power output from the system (discharging)

6. Losses: Losses due to inefficiencies in charging and discharging are given by:

$$L(t) = (1 - \eta_c) \cdot P_c(t) + (1 - \eta_d) \cdot P_d(t)$$

7. Economic Cost of Storage: The total economic cost of the storage system over its lifetime can be expressed as:

$$C_{\text{total}} = C_{\text{cap}} + C_{\text{op}} + C_{\text{cycle}}$$

where:

- $C_{\text{cap}} = C_{\text{unit}} \cdot E_{\text{max}}$: Capital cost (based on installed capacity)
- C_{op}: Fixed operational costs (e.g., maintenance)
- C_{cycle}: Variable cost per charge-discharge cycle

8. Storage Duration: The effective discharge duration at time t is calculated as:

$$T_{\text{discharge}} = \frac{SOC(t)}{P_d}$$

This indicates how long the system can continue discharging at its rated power.

6. POTENTIAL BENEFITS PROVIDED

System-Wide Benefits of Long-Duration Energy Storage: Power systems can benefit from long-duration energy storage in many ways, including permitting shifting time of energy supply through price arbitrage, reducing initial operations and shutdown costs for generators, improving generator efficiency, providing additional amenities, controlling transmission congestion, providing firm ability, delaying expenditures in transmission or distribution networks, and promoting resilience. In order to achieve these results,this will dissect each component of system-wide benefits in this part and highlight the unique benefits that long-duration energy storage technologies provide.

Energy Arbitrage: Energy storage, which can function both as a generator and a load, enables energy arbitrage by storing energy during periods of low pricing (when there is surplus production) and discharging during high-price periods (when demand is high). The results of energy arbitrage are evident in various ways, such as absorbing surplus energy from Variable Renewable Energy (VRE) sources, shifting demand from peak to off-peak periods, and exploiting fluctuations in energy prices.

Improvements in Generator Efficiency: Energy storage enhances the efficiency of gas generators by modifying their operating setpoints. Traditional natural gas combustion-turbine (NGCT) and natural gas combined-cycle (NGCC) generators exhibit a rapid decline in efficiency under partial load conditions. By adjusting the part-load operating points, energy storage helps reduce overall fuel consumption and, as a result, the fuel costs across the entire system.

Reduction in Startup and Shutdown Costs: Reducing startup and shutdown costs is achieved by decreasing the need to start or shut down a generator. The process of starting up or shutting down an entire plant, particularly for gas, coal, and nuclear facilities, incurs significant costs. Approximately $30,000 for NGCC generators, more than $12,000. for coal units, $2,000 for NGCT generators, and roughly $100,000 for nuclear power plants are the mean startup costs for all deployed units in the 2050 WI network.

Ancillary Services: Black start, regulation, supplemental reserves, voltage support, spinning and non-spinning reserves, frequency responsiveness, and load following or scaling help for RE are just a few of the additional services that energy storage can provide. Furthermore, to provide ancillary services, fossil fuel or nuclear generators typically must reduce their load points, leaving extra capacity unutilized. The efficiency of these generators tends to drop sharply under part-load conditions, which leads to direct fuel costs for part-load operation and an opportunity cost for otherwise possible energy generation. In contrast, energy storage can offer these services at lower marginal costs, presenting an opportunity to decrease system costs.

Congestion Management: Insufficient transmission capacity prevents the least-cost energy from being transmitted, which can lead to transmission congestion and, occasionally, extremely high congestion charges. Installing energy storage in the right places can help reduce the requirement for peak transmission capacity by acting as a less expensive local resource and allowing charging to occur at non-congested times. By doing this, substantial congestion costs may be avoided. Long-duration energy storage can also help relieve congestion by supplying energy needed via counter-flow when installed at electrically busy upstream buses.

7. RESULT AND DISCUSSION

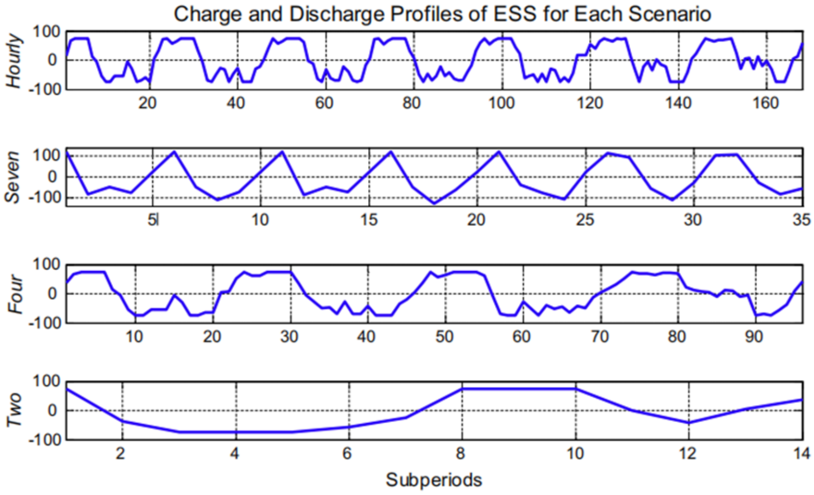

FIGURE 3. Charge and discharge patterns of ESSs across different scenarios

Figure 3 presents the charge and discharge profiles of an ESS for four scenarios: Hourly, Seven, Four, and Two, plotted over Subperiods. The Hourly profile is highly dynamic, with frequent and sharp fluctuations between charging and discharging over 160 subperiods. The Seven scenario shows smoother periodic cycles with reduced variability over 35 subperiods. The Four profile demonstrates moderate fluctuations, with smaller peaks and troughs across 90 subperiods. In contrast, the Two scenario is the smoothest, featuring a gradual single cycle of discharge and charge over 14 subperiods. As the scenarios progress from Hourly to Two, the profiles transition from short-term dynamic adjustments to longer and steadier operational cycles. This reflects different ESS strategies, possibly aligned with varying system demands, grid conditions, or energy scheduling requirements.

8. CONCLUSION

This research presents a comprehensive framework for optimizing ESS integrated into power grids, emphasizing the role of LDES in balancing RE fluctuations and enhancing system reliability. The optimization model developed identifies strategies for minimizing operational costs while maximizing RE utilization. Through detailed simulations, the research demonstrates that ESS can provide substantial system-wide benefits, including energy arbitrage, improved generator efficiency, and reduced startup/shutdown costs. The integration of ESS also supports ancillary services, congestion management, and resilience during peak demand periods, encouraging the development of a more robust and sustainable energy system. Furthermore, The study emphasises the importance of technology for hydrogen storage and batteries in achieving long-term decarbonization and meeting global climate goals. This framework is essential for guiding future investments in energy storage infrastructure, ensuring the continued transition towards RES. The findings contribute valuable insights into the optimization of power systems with integrated ESS, laying the groundwork for future advancements in energy management.

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