Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 3 (2023)

Optimal Sizing and Placement of Energy Storage Systems in Hybrid Energy Environment

[1]Md Safdar Ali, [2]Abrar Ahmad, [3]Ibraheem, [4]Ward Ul Hijaz Paul, [5]Anwar Shahzad Siddiqui, [6]Sheeraz Kirmani

[1] [2] [3] [4] [5] [6]Department of Electrical Engineering, Jamia Millia Islamia, New Delhi

Abstract: The study suggests a method for setting up a photovoltaic (PV) system's hybrid energy storage system (HESS), which consists of batteries and supercapacitors, to have the best possible capacity. The objective is to reduce overall expenses, including investment and running costs, while minimizing variability in PV production and maximizing system performance.

The optimization model has two layers. In order to reduce the overall PV-HESS system cost, the higher layer chooses the battery and supercapacitor capacity and power ratings. Using deep reinforcement learning, the lower layer optimizes the PV-HESS system's performance over the course of a year.

The investment expenses for the battery and supercapacitor are taken into account in the top layer, together with the annual running costs determined by the bottom layer model. By regulating the HESS charging and discharging and lowering PV curtailment and fluctuation penalties, the lower layer seeks to reduce operational costs. Both layers' limitations and objective functions are presented.

The lower layer operation optimization problem is proposed to be solved via the deep deterministic policy gradient (DDPG) algorithm. The inputs include the PV output, load demand, electricity price, and the HESS state of charge. The control actions are the battery/supercapacitor power outputs.

In Shandong, China, a 1 MW PV system is being researched. The ideal HESS capacity arrangement, according to the results, reduces the overall cost as compared to no storage by 7.7%. To smooth out variations and move PV generation to times of high prices, the HESS works in concert with the battery and supercapacitor. It is demonstrated that the DDPG algorithm efficiently optimizes system performance.

In order to configure battery and supercapacitor capacities for a PV-HESS system while taking operating and investment costs into account, the study presents an optimisation technique. PV variability is managed by a reinforcement learning algorithm and a two-layer model to keep costs down.

Keywords: Photovoltaic systems, Energy storage, Hybrid storage systems, Battery energy storage, Supercapacitors, Capacity optimization, Cost minimization, Power fluctuation smoothing.

1. Introduction

Photovoltaic (PV) generation is becoming more widespread globally, however its variability due to weather conditions can affect power quality and reliability [1]. Energy storage systems (ESS) can smooth PV output fluctuations and shift generation to match demand, promoting self-consumption [2]. Determining optimal ESS sizing and technology selection is crucial for cost-effective PV-ESS systems [3].

Single ESS has limitations. Batteries have low power density while supercapacitors have low energy density [4-8]. Hybrid ESS (HESS) combining both can utilize their complementary characteristics [9-14]. Proper HESS configuration and coordination is needed to stabilize PV fluctuation and optimize operation [15].

Existing works have drawbacks. Frequency domain methods overly simplify allocation [10-14]. Direct optimization lacks minute-level resolution [15]. Reinforcement learning has a high computational burden. There is a need for an integrated strategy considering investment and operating costs, PV smoothing, and optimized scheduling.

This paper proposes a two-layer optimization strategy to configure battery and supercapacitor capacities for a PV-HESS system. The upper layer minimizes total cost while the lower layer uses deep reinforcement learning to optimize operation and obtain realistic operating costs. The approach smooths PV variability while optimizing the PV-HESS system. The introduction establishes the needs for optimal HESS sizing/technology selection for PV systems. A new strategy is proposed utilizing a two-layer model and reinforcement learning to consider costs and PV fluctuation suppression. The approach will be demonstrated in a PV system case study.

2. The hybrid energy storage system for photovoltaics

The hybrid energy storage system (HESS), photovoltaic generation, and utility grid connection make up the analyzed system configuration [16,17]. The HESS combines a supercapacitor for high power density with a battery for long-term storage. The PV output initially satisfies the load requirement. Based on power price signals and HESS state of charge, the HESS or utility grid fills any gap [18-20]. Overage PV generation above the load is used to power the HESS.

The HESS aims to smooth rapid PV fluctuations and shift energy supply across time to increase self-consumption and reduce grid purchases. The battery provides longer duration storage while the supercapacitor handles short timescale variability. Their coordination enhances system performance [21,22]. The PV-HESS system architecture utilizes PV as the primary generation source along with a coordinated battery-supercapacitor HESS to manage PV intermittency. The HESS smooths fluctuations and optimizes operation to improve economics and reliability. Appropriately sizing the HESS capacities is key to realizing these benefits [23-25].

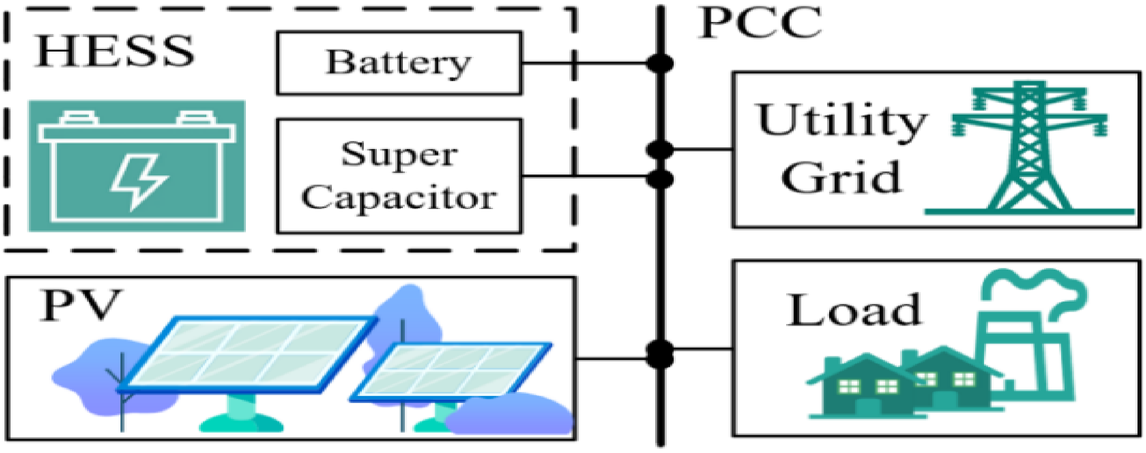

Fig 1: PV-HESS's structure.

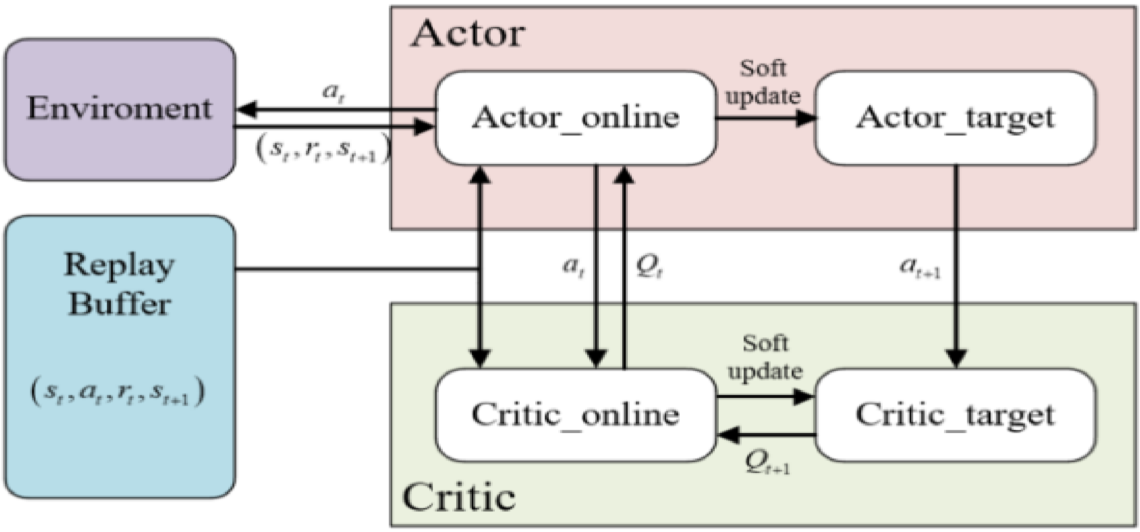

Fig 2: DDPG's structure.

3. Proposed HESS two-layer capacity configuration approach

HESS capacities while reducing total cost, a two-layer optimisation model is created. The battery and supercapacitor power/energy capabilities are determined by the top layer. It reduces the total annual operating costs and HESS investment costs offered by the bottom layer approach. Capacity is restricted within reasonable limitations by constraint [26,27].

The lower layer optimizes the PV-HESS operation over a year using deep reinforcement learning (DDPG). It minimizes operating cost by controlling HESS charging/discharging, reducing PV curtailment and fluctuation penalties. The PV output, load, electricity price, and HESS state of charge are inputs. The battery/supercapacitor power outputs are the control actions [28,29].

The upper layer obtains realistic operating costs from the lower layer to make informed capacity investment decisions. The lower layer optimizes operation based on the capacities set by the upper layer. The integrated strategy configures optimal HESS sizing while smoothing PV variability and coordinating devices.

The two-layer approach determines cost-optimal HESS capacities and power ratings considering investment costs, operating costs, and operational constraints. Deep reinforcement learning is used to optimize system operation and provide accurate data to the sizing layer.

3.1. The upper layer

The upper layer optimization minimizes the total cost (Ctotal) of the PV-HESS system including investment and operating costs:

$$\min C_{total} = C_{invest} + C_{op}$$

where Cop is the annual operating cost from the lower layer model and Cinvest is the investment cost:

$$C_{invest} = C_{cons,ba} + C_{cons,sc}$$

The battery investment cost (Ccons,ba) is calculated as:

$$C_{cons,ba} = (c1baPinv + c2baSinv)(1 + r)nba - (1 + r)-nba$$

where c1ba and c2ba are the battery power and capacity cost coefficients, Pba and Sba are the optimized capacities, r is the discount rate, and nba is the battery lifetime.

Similar equations are used to calculate the supercapacitor investment cost (Ccons,sc) based on its cost parameters and decision variables.

Capacity constraints limit the battery and supercapacitor sizes:

$$S_{ba,min} \leq S_{ba} \leq S_{ba,max}$$

$$S_{sc,min} \leq S_{sc} \leq S_{sc,max}$$

The higher layer optimization reduces the PV-HESS system's overall cost, including startup and ongoing expenses. The battery and supercapacitor capacities serve as the decision-making factors.

The annual operational cost from the bottom layer model and the HESS investment cost makes up the overall cost goal function. The purchase cost coefficients and lifetime characteristics are used to compute the investment cost from the configured power and energy capabilities of the battery and supercapacitor.

Based on practical system limits, constraints set minimum and maximum limits on the battery and supercapacitor capacities.

The top layer offers capacity optimization to reduce PV-HESS lifecycle costs. The lowest layer operational optimisation determines the operating costs. The higher layer's capacity acts as inputs for the lower layer. The cost-optimal capacities for the PV-HESS battery and supercapacitor are determined by the top layer optimization taking into account the operating and procurement costs discovered through reinforcement learning. Capacity restrictions guarantee that only workable solutions are available.

3.2 The lower layer

The primary purpose

The lower layer optimization seeks to reduce the PV-HESS system's yearly operating expense. The battery and supercapacitor charging and discharging controls are the decision variables.

The operating cost objective function comprises:

- PV-HESS operation cost
- Electricity purchase cost from the grid
- Penalty costs for PV power curtailment and fluctuations

The lowest layer lowers total operating costs, minimizes PV curtailment, and smooths PV variations by carefully managing the HESS charging and discharging.

The model's inputs include the PV output, load demand, electricity price, and HESS state of charge. The control outputs are the set-points for the supercapacitor and battery power.

The bottom layer optimisation seeks to reduce the PV-HESS system's annual operational cost (Cop):

$$\min Cop = Cop\_pv\_hess + Cbuy + Cpenalty$$

where:

Cop_pv_hess = PV-HESS operation cost

Cbuy = Electricity purchase cost from the grid

Cpenalty = Penalty costs for PV curtailment and fluctuations

The decision variables are the HESS battery and supercapacitor charging/discharging control signals. By optimizing these controls, the lower layer minimizes the overall operating cost.

Key inputs are the PV generation, load demand, electricity price, and HESS state of charge. The battery and supercapacitor power set-points are the optimized control outputs.

The lower layer reinforcement learning optimization determines optimal HESS operation to minimize the PV-HESS annual operating cost. This provides realistic cost data to the upper layer capacity optimization model.

(1) PV-HESS operation cost:

$$Cop\_pv\_hess = \Sigma[cpvPop(t) + cbaPba(t) + cscPsc(t)]\Delta t$$

where cpv, cba, csc are the PV, battery, and supercapacitor cost coefficients. Pop, Pba, Psc are the PV, battery, and supercapacitor power.

(2) Electricity purchase cost:

$$Cbuy = \Sigma[cbuy(t)Pbuy(t)]\Delta t$$

where cbuy is the time-varying electricity price and Pbuy is the purchased grid power.

(3) Penalty costs:

Cpenalty = {

$\omega 1[Pt(t) - \Delta Plim]\Delta t$, if $\Delta Pt > \Delta Plim$

$\omega 2[-Pbuy(t)]\Delta t$, if $Pbuy(t) < 0$

where ω1, ω2 are penalty coefficients. ΔPt is the power fluctuation and ΔPlim is the limit. Penalties apply for fluctuations exceeding the limit and PV curtailment ($Pbuy < 0$).

The lower layer operating cost comprises the HESS operation cost, electricity purchases, and penalties for excessive PV fluctuations and curtailment. Optimizing HESS coordination minimizes this cost.

(1) Power balance constraint:

$$Ppv(t) + Pba(t) + Psc(t) + Pbuy(t) = Pload(t)$$

where Pload is the load demand.

(2) Battery constraints:

$Pba,min \le Pba(t) \le Pba,max$

$Pba(t) - Pba(t-1) \le Dba$

$Eba(t) = Eba(t-1) + Pba(t)\Delta t$

$Eba,min \le Eba(t) \le Eba,max$

$Eba(0) = Eba,ini,\ Eba(T) = Eba,end$

where Pba,max and Dba are the power and ramp limits, and Eba,min/max the energy limits.

(3) Supercapacitor constraints:

$$Psc,min \le Psc(t) \le Psc,max$$

$$Esc(t) = Esc(t-1) + Psc(t)\Delta t$$

$$Esc,min \le Esc(t) \le Esc,max$$

$$Esc(0) = Esc,ini,\ Esc(T) = Esc,end$$

where Psc, max and Psc,min is the supercapacitor power limits, and Esc,min/max the energy limits. Esc,ini and Esc,end are the initial and end of cycle energy levels. The supercapacitor has constraints on power, energy, and ramping similar to the battery. The coordination of the battery and supercapacitor is optimized to minimize the PV-HESS operating cost.

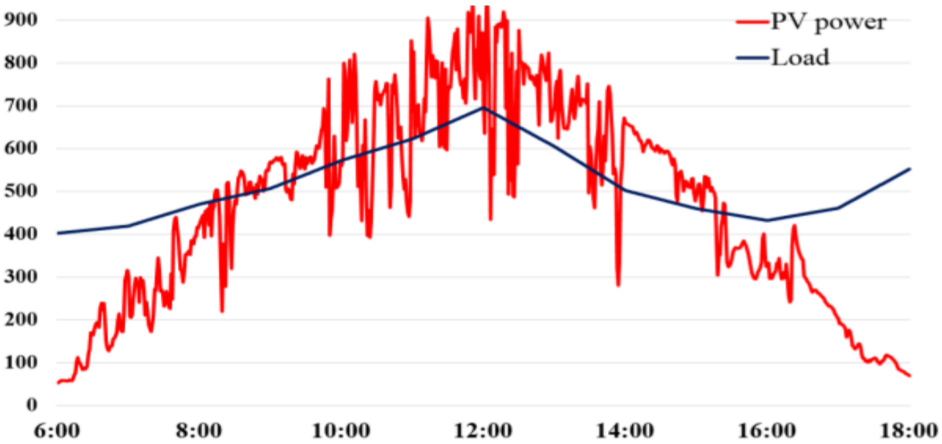

Fig 3: PV power and load at 6:00-18:00

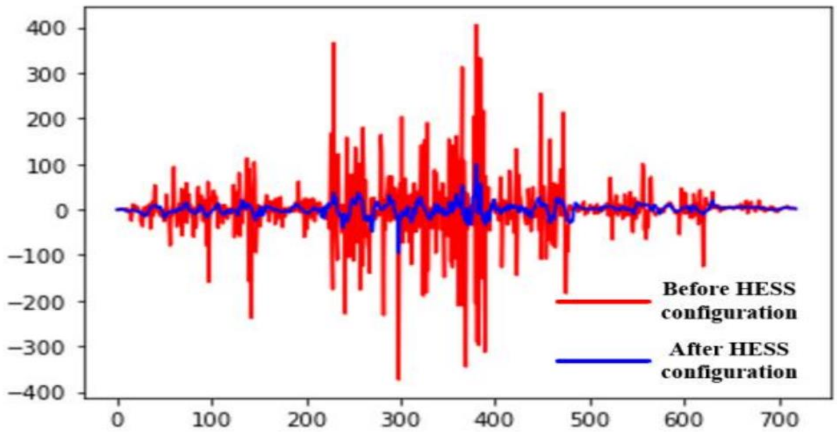

Fig 4: The power fluctuation in PCC

3.3 Deep deterministic policy gradient-based solution algorithm

Conventional optimisation techniques are unable to effectively solve the suggested two-layer model due to the minute-level time resolution required to optimize the supercapacitor performance.

Instead, Deep Deterministic Policy Gradient (DDPG), a deep reinforcement learning technique, is used. Complex problems with several variables and constraints can be optimized using DDPG.

The inputs to the DDPG algorithm, which represents the environmental condition, are the PV power, load demand, electricity price, and HESS state of charge. The outputs dictating the control actions are the set-points for the battery and supercapacitor power.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 3 (2023)

To be compatible with the reinforcement learning method, the goal of minimizing operational costs is changed to maximizing a reward function. The algorithm discovers the most cost-effective control strategy for the HESS.

The suggested model can be solved effectively in a challenging, high-resolution simulation environment thanks to DDPG. This offers a sizable benefit over conventional optimisation methods.

The two-layer HESS capacity setup and operating strategy can be optimized using deep reinforcement learning via the DDPG algorithm, offering a practical solution.

4. Case study

4.1 Setting parameters

The suggested approach is used as a case study for a 1MW PV demonstration project in Shandong Province, China.

As illustrated in Figure 3, the PV output power from 6:00 to 18:00 with a one-minute resolution is employed. The daily scheduling cycle for PV-HESS is from 6:00 to 18:00.

As inputs to the DDPG algorithm, the PV generation, load demand, and electricity price data for these hours are retrieved throughout a complete year.

Tables 1 and 2 contain important parameter settings such the HESS cost and performance coefficients. These correspond to reasonable values for the supercapacitor and battery systems.

An existing 1MW PV plant's detailed PV, load, and price statistics are used in the case study. Based on actual systems, the parameters for the battery and supercapacitor models have been established. This offers a realistic illustration of the ideal HESS sizing strategy.

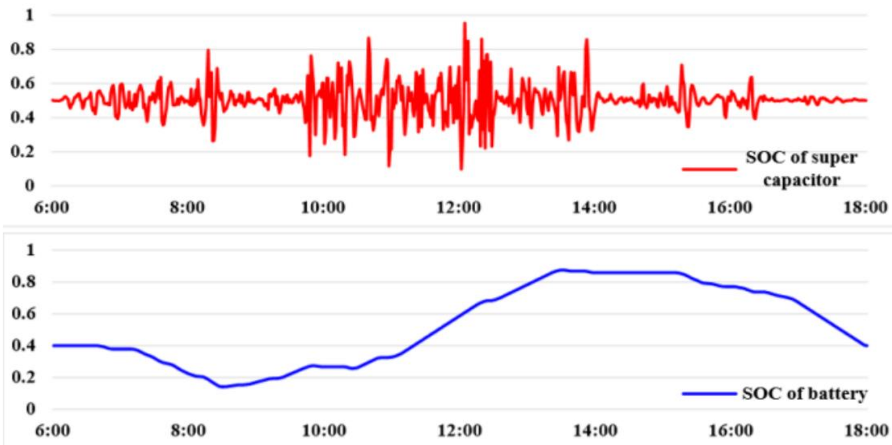

Fig 5: The SOC of HESS

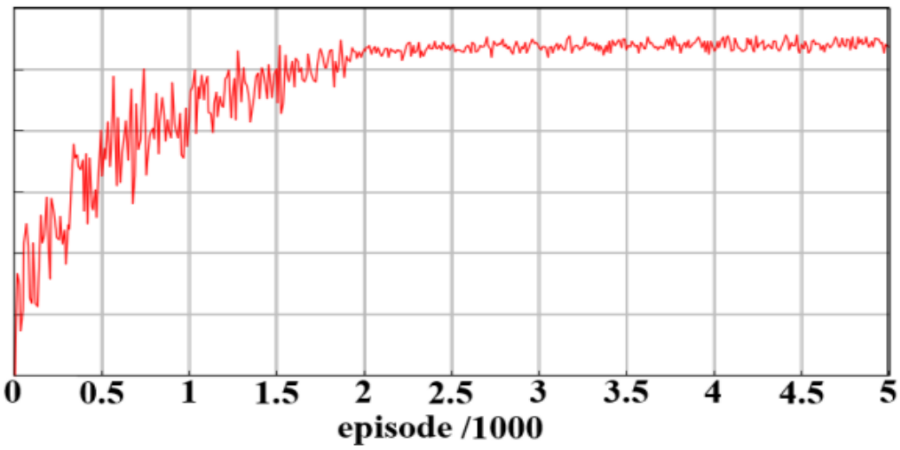

Fig 6: The reward of DDPG

Table 1: Modified HESS parameters

ESS Type	Purchase Cost Coefficients (CNY/kW)	Operating Cost (CNY/kWh)	Lifetime (years)	SOC Limits
Battery	4000	0.04	15	[0.2, 0.9]
Supercapacitor	1200	0.015	10	[0.05, 0.8]

Table 2: Modified Time of Use Tariff

Time Period	Electricity Price (CNY/kWh)
6:00-8:00	0.45
8:00-12:00	1.15
12:00-17:00	0.85
17:00-18:00	1.4

Table 3 presents the capacity optimization results for the PV system case study, comparing four configurations: no storage, battery only, supercapacitor only, and the proposed HESS (battery + supercapacitor).

Table 3: HESS Capacity Optimization Results

Configuration	Battery (kW/kWh)	Supercapacitor (kW/kWh)	Investment Cost (kCNY)	Operating Cost (kCNY)	Total Cost (kCNY)
No storage	0	0	0	645.85	645.85
Battery only	102.24/320.08	0	143.32	478.72	622.04
Supercapacitor only	0	309.27/17.11	53.54	556.51	610.05
Proposed HESS	80.29/289.65	261.67/12.04	167.76	428.23	595.99

The suggested HESS, which combines a supercapacitor and battery, has the lowest overall cost. Despite having a greater upfront cost, HESS effectively lowers operational and penalty expenses, which leads to a 7.7% lower overall cost as compared to the scenario where there is no storage.In the suggested HESS technique, the table shows the cost-minimal sizes for the battery and supercapacitor as well as the optimized capacities for the various combinations. Figure 4 compares the power fluctuation at the PCC before and after the optimized HESS was installed. The fact that fluctuations are greatly minimized shows how well the HESS works to smooth out PV variability. In order to withstand high frequency variations with significant instantaneous amplitudes, the supercapacitor rapidly charges and discharges. Additionally, the battery helps to reduce swings at lower frequencies. Figure 5 shows how the supercapacitor frequently switches between the charging and discharging states. The battery has fewer state changes, which lengthens its lifespan and lowers expenses. The reward function from the DDPG algorithm throughout training iterations is shown in Figure 6. The incentive starts out modestly but rises as more training samples are collected. The reward stabilizes after 2000 iterations, indicating that the algorithm has reached an optimized solution. The proposed technique may successfully size and operate the PV-HESS system according to the results of the analysis of the power fluctuations, HESS operation, and DDPG reward function. The strategy maximizes economics while minimizing volatility.

5. Conclusion

The capacity configuration of a hybrid battery-supercapacitor energy storage system (HESS) for a photovoltaic (PV) installation is proposed in this research as an optimisation technique. The objective is to reduce overall costs while minimizing variations in PV production.

A two-layer model is created, the upper layer of which establishes the ideal HESS component sizes by reducing startup and ongoing expenses. Deep reinforcement learning is used in the lowest layer to enhance system performance and provide accurate cost information.

The battery and supercapacitor capacities are restricted to keep them within practical ranges. The minute-resolution model can be solved using the deep deterministic policy gradient approach.

A case study demonstrates the approach for a 1 MW PV system in China. Results show the optimized HESS decreases the total cost by 7.7% compared to no storage. The supercapacitor handles high frequency fluctuations while the battery participates in smoothing and shifting energy.

In conclusion, the proposed HESS capacity optimization strategy smoothly integrates PV generation using properly sized battery and supercapacitor storage. The approach reduces lifetime costs while managing PV variability. The model provides a valuable tool for designing cost-effective PV-HESS systems.

References

[1] Li B, Li X., Bai X., Li Z. (2018) Storage Capacity Allocation Strategy for Distribution Network with Distributed Photovoltaic Generators. Journal of Modern Power Systems and Clean Energy, 6: 1234-1243.

[2] Neto P., Saavedra O, Ribeiro L. (2018) A Dual-Battery Storage Bank Configuration for Isolated Microgrids Based on Renewable Sources. IEEE Transactions on Sustainable Energy, 9: 1618- 1626.

[3] Yang J., Jawad S., Liu J., et al. (2022) A Regulating Capacity Determination Method for Pumped Storage Hydropower to Restrain PV Generation Fluctuations. CSEE Journal of Power and Energy Systems, 8: 304-316.

[4] Sharma P., Sharma A. (2022) Review on Flywheel Energy Storage System in Microgrid. In: 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). pp. 699-702.

[5] Choi M., Kim S., Seo S. (2012) Energy Management Optimization in a Battery/Supercapacitor Hybrid Energy Storage System. IEEE Transactions on Smart Grid, 3: 463-472.

[6] Niladri, Chakraborty, Syamasree, et al. (2019) Hybrid SMES Based Reactive Power Dispatch by Cuckoo Search Algorithm. IEEE Transactions on Industry Applications, 55: 907-917.

[7] Xiong Y., Chen L., Zheng T., et al. (2021) Electricity-Heat-Hydrogen Modeling of Hydrogen Storage System Considering Off-Design Characteristics. IEEE Access, 9: 156768-156777.

[8] Cleary B., Duffy A., et al. (2015) Assessing the Economic Benefits of Compressed Air Energy Storage for Mitigating Wind Curtailment. IEEE Transactions on Sustainable Energy, 6: 1021- 1028. [9] Li J.,

[9] Gee A., Zhang M., Yuan W. (2015) Analysis of Battery Lifetime Extension in a SMESbattery Hybrid Energy Storage System Using a Novel Battery Lifetime Model. Energy, 86: 175-185.

[10] Yan C., Fan Y., Yao B. (2019) Strategy for Smoothing Photovoltaic Power Fluctuation of Hybrid Energy Storage System Using Self-adaptive Variational Mode Decomposition. High Voltage Technology, 45: 1898-1906. ICEECT-2022 Journal of Physics: Conference Series 2404 (2022) 012016 IOP Publishing doi:10.1088/1742-6596/2404/1/012016 8

[11] Li X., Wang J., Qiu Y., Hou Y., Zhou Q. (2022) Optimal Allocation of Hybrid Energy Storage Capacity Based on Variational Mode Decomposition. Acta Energiae Solaris Sinica, 43: 88-96.

[12] Han X., Chen F., et al. (2012) A Power Smoothing Control Strategy and Optimized Allocation of Battery Capacity Based on Hybrid Storage Energy Technology. Energies, 5: 1593-1612.

[13] Khosravi M., Afsharnia S., Farhangi S. (2021) Optimal Sizing and Technology Selection of Hybrid Energy Storage System with Novel Dispatching Power for Wind Power Integration. International Journal of Electrical Power & Energy Systems, 127: 106660.

[14] Wu Z., Jiang X., Ma H., Ma S. (2014) Wavelet Packet-fuzzy Control of Hybrid Energy Storage Systems for PV Power Smoothing. Proceedings of the CSEE, 34: 317-324.

[15] Yan N., Zhang B., et al. (2018) Hybrid Energy Storage Capacity Allocation Method for Active Distribution Network Considering Demand Side Response. IEEE Transactions on Applied Superconductivity, 28: 1-4

[16] Ahmad M, Ali D, Paul WUH, et al (2023) Management of Energy and Coordinated Control of PV/HESS in Islanded DC Microgrid. In: Smart Energy and Advancement in Power Technologies. Springer, Singapore, pp 325–339

[17] Akhtar I, Paul WUH, Kirmani S, Asim M (2021) Cost Analysis of 18 kW Solar Photovoltaic System for Smart Cities Growth in India. In: Lecture Notes in Electrical Engineering

[18] Paul WUH, Siddiqui AS, Kirmani S (2023a) Intelligent Load Management System Development with Renewable Energy for Demand Side Management. International Journal of Advanced Engineering and Management Research 08:140–153. https://doi.org/10.51505/ijaemr.2023.8213

[19] Paul WUH, Siddiqui AS, Kirmani S (2022a) Demand Side Management and Demand Response For Optimal Energy Usage: An Overview. Paripex Indian Journal of Research 151–152. https://doi.org/10.36106/paripex/0608823

[20] Paul WUH, Siddiqui AS, Kirmani S (2022b) Demand Side Management Strategies in Residential Load With Renewable Energy Integration: A Brief Overview. Paripex Indian Journal of Research 11:66–69. https://doi.org/10.36106/paripex/3007742

[21] Paul WUH, Siddiqui AS, Kirmani S (2023d) Optimal Rescheduling for Transmission Congestion Management using Intelligent Hybrid Optimization. In: Communications in Computer and Information Science. Springer Nature Switzerland AG

[22] Bashir MU, Paul WUH, Ahmad M, et al (2021) An Efficient Hybrid TLBO-PSO Approach for Congestion Management Employing Real Power Generation Rescheduling. Smart Grid and Renewable Energy 12:113–135. https://doi.org/10.4236/sgre.2021.128008

[23] Paul WUH, Siddiqui AS, Kirmani S (2023c) Optimal Positioning of Distributed Energy using Intelligent Hybrid Optimization. J Phys Conf Ser

[24] Ali D, Paul WUH, Ali MS, et al (2021) Optimal Placement of Distribution Generation Sources in Hybrid Generation Network. Smart Grid and Renewable Energy 12:65–80. https://doi.org/10.4236/sgre.2021.125005

[25] Ali MdS, Ahmad A, Paul WUH, et al (2023) Optimal Allocation of Wind-Based Distributed Generators in Power Distribution Systems Using Probabilistic Approach. In: Smart Energy and Advancement in Power Technologies. Springer Singapore, pp 385–396

[26] Paul WUH, Siddiqui AS, Kirmani S (2023b) Intelligent Load Management System Development with Renewable Energy for Demand Side Management. International Journal of Advanced Engineering and Management Research 8:. https://doi.org/10.51505/ijaemr.2022.8213

[27] Kirmani S, Paul WUH, Bhat MB, et al (2023) Optimal Allocation of V2G Stations in a Microgrid Environment: Demand Response. In: 2023 International Conference on Power, Instrumentation, Energy and Control (PIECON). IEEE, pp 1–6

[28] Siddiqui O, Paul WUH, Kirmani S, et al (2022) Voltage and Frequency Control in a Microgrid. Journal of Engineering Science and Technology Review 15:115–124. https://doi.org/10.25103/jestr.156.14

[29] Paul WUH, Kirmani S, Bhat MB, Nahvi SA (2020) Data Based Controller Design for PMDC Motor Setup using System Identification. Studies in Indian Place Names 40:11