Enhancing Resource Allocation for Multi-Energy Storage Systems: A Comprehensive Approach Considering Supply and Demand Flexibility and Integration of New Energy

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Abstract

This study presents an innovative optimization method for resource scheduling in multi-energy storage systems, focusing on improving resource allocation while considering supply-demand flexibility and renewable energy integration. As renewable energy gains popularity and multi-energy systems become more complex, effective utilization of energy storage to achieve supply-demand balance, optimize energy scheduling, and maximize renewable energy integration is crucial. To address this challenge, a Markov dynamic model is developed to capture the dynamic changes in energy supply and demand within the multi-energy storage system. The model is then solved using a reinforcement learning approach to optimize resource scheduling

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decisions. Numerical simulations and case studies are conducted to validate the effectiveness and feasibility of the proposed method, showcasing its potential to enhance operational efficiency and reliability in multi-energy storage systems amidst constantly changing energy patterns. This research provides valuable insights and decision support for the design and operation of multi-energy storage systems, contributing to the advancement of sustainable energy utilization and promoting sustainable development in the energy sector.

Keywords: Optimization, resource scheduling, multi-energy storage system, renewable energy, supply-demand flexibility, energy integration.

1 Introduction

In today's energy landscape, multi-energy storage systems have emerged as vital components, given their ability to address the critical aspects of supply and demand flexibility, as well as the integration of renewable energy sources. These systems have become increasingly significant due to the evolving energy needs and the growing emphasis on sustainable energy solutions. By effectively managing energy storage, these systems enable better balance between energy generation and consumption, optimize resource allocation, and facilitate the seamless integration of renewable energy into the grid. With their versatile capabilities, multi-energy storage systems contribute to a more resilient and sustainable energy infrastructure that can adapt to changing energy patterns and support the transition towards a greener future [1]. With the increasing penetration of renewable energy and the evolving complexity of energy systems, the effective utilization of energy storage resources has become paramount in achieving a balanced and sustainable energy supply [2]. These systems enable the integration of intermittent renewable energy sources, such as solar and wind power, with the grid, thereby mitigating the challenges associated with their variable generation profiles [3]. Multi-energy storage systems significantly improve the supply-demand flexibility of the grid by efficiently storing surplus energy during periods of high generation and releasing it when demand is at its peak. These systems play a crucial role in balancing the fluctuating energy supply and demand dynamics, ensuring a reliable and stable energy supply [4]. This flexibility is vital for ensuring a reliable and resilient energy supply, particularly as renewable energy sources become more prominent and traditional fossil fuel-based generation is gradually phased out.

Furthermore, the integration of emerging energy sources, particularly renewable energy, into the established energy infrastructure brings forth a range of opportunities and challenges. The increasing adoption of renewable energy technologies offers the potential to reduce carbon emissions, enhance energy diversification, and foster sustainable development [5]. Multi-energy storage systems serve as key enablers for the seamless integration of these sources, as they provide a means to store and distribute renewable energy efficiently [6]. By optimizing the resource allocation and scheduling decisions within these systems, it becomes possible to maximize the utilization of renewable energy, reduce curtailment, and minimize reliance on conventional fossil fuel-based generation [7]. This integration not only contributes to reducing greenhouse gas emissions and addressing climate change but also enhances energy security and reduces dependence on external energy sources [8]. Moreover, through effective management of the integration of emerging energy sources, multi-energy storage systems provide a pathway towards achieving a sustainable energy mix, promoting a cleaner and more resilient energy future.

A comprehensive literature review on the optimal resource allocation of multi-energy storage systems reveals several research gaps that need to be addressed [9]. Firstly, the existing studies often focus on individual aspects of resource allocation, such as economic optimization or system reliability, without considering the holistic integration of multiple objectives [10]. This limited scope fails to capture the complex interplay between different objectives, such as maximizing renewable energy integration while ensuring grid stability and minimizing operational costs [11]. Thus, there is a need for an integrated approach that considers the multidimensional nature of resource allocation in multi-energy storage systems.

Secondly, most existing research has relied on traditional optimization techniques, such as linear programming or heuristic algorithms, which may have limitations in handling the inherent uncertainties and dynamic nature of energy systems [12]. As a result, the optimal resource allocation strategies developed based on these approaches may not be adaptable to rapidly changing energy patterns and may not fully exploit the potential of multi-energy storage systems [13]. To overcome this limitation, advanced optimization methods that can effectively handle uncertainties and dynamic environments are required.

To address these research gaps, the application of deep reinforcement learning (DRL) emerges as a promising approach [14]. DRL combines the power of deep neural networks with reinforcement learning algorithms, enabling the agent to learn optimal resource allocation policies through trial and error interactions with the environment. By directly interacting with the dynamic energy system, DRL can adaptively learn and optimize the resource allocation decisions in a data-driven manner. This approach can effectively capture the complex dynamics and uncertainties of multi-energy storage systems, leading to more robust and flexible resource allocation strategies.

This paper presents a novel approach for optimizing resource allocation in multi-energy storage systems, with a focus on enhancing supply-demand flexibility and integrating new energy sources. The work begins by establishing a Markov dynamic model to capture the dynamic changes in energy supply and demand within the system. Subsequently, a deep reinforcement learning method is employed to optimize the resource scheduling decisions based on the dynamic model. Through a combination of numerical simulations and case studies, the proposed approach is validated for its effectiveness and feasibility in improving the operational efficiency and reliability of multi-energy storage systems. The study makes three main contributions:

(1) it provides an integrated approach for resource allocation that considers multiple objectives and balances supply-demand flexibility and new energy integration;
(2) it applies deep reinforcement learning to dynamically optimize resource allocation decisions, accounting for the uncertainties and complexities of energy systems;
(3) it demonstrates the potential of the proposed approach in addressing the evolving energy landscape and improving the efficiency and reliability of multi-energy storage systems, thereby contributing to the sustainable development of the energy sector.

2 System Description

The studied system is a multi-energy storage system designed to optimize resource allocation and enhance the integration of renewable energy sources. It consists of several key components working together to ensure efficient energy utilization and supply-demand balance. These components include renewable energy sources, electricity energy storage units, thermal energy storage units, a grid infrastructure, and end-users.

The system incorporates renewable energy sources such as solar photovoltaic (PV) panels and wind turbines. These sources generate electricity from renewable sources such as sunlight and wind. However, the generation from renewable sources can be intermittent and fluctuating, making it challenging to match supply with demand [15]. To tackle this challenge, energy storage units are utilized to store surplus energy during times of high generation and discharge it during periods of high demand or when renewable energy generation is insufficient.

Electricity storage and heat storage are essential components of modern energy systems that enable efficient utilization and management of energy resources. Electricity storage systems, including Energy Storage Systems (ESS), play a critical role in maintaining a balance between electricity supply and demand. They effectively store surplus electricity produced during low-demand periods and release it during high-demand periods, alleviating pressure on the grid and improving overall grid stability. ESS technologies include batteries, flywheels, and pumped hydro storage, among others, which store electricity in chemical, mechanical, or potential energy forms. On the other hand, heat storage systems, known as Thermal Storage Systems (TSS), are utilized to store excess heat energy generated by various processes. Thermal Storage Systems (TSS) enable the capture and storage of thermal energy during periods of low heat demand, which can be later released when demand is high. This approach maximizes the efficiency of heat generation systems by effectively utilizing excess thermal energy and ensuring it is available when needed during peak demand periods. Heat storage technologies include water-based thermal storage, phase change materials, and thermal storage tanks, which store heat energy for various applications such as space heating, industrial processes, and district heating. The integration of electricity storage and heat storage technologies into energy systems offers multiple benefits. By storing excess electricity and heat from intermittent renewable energy sources, energy storage systems enhance the utilization of these sources and ensure a reliable and continuous energy supply. This enables the efficient management of energy fluctuations, reduces reliance on conventional power sources, and contributes to the integration of renewable energy into the overall energy system. Furthermore, it enables demand management and load shifting, reducing peak demand and associated costs. Overall, electricity storage and heat storage systems contribute to increased energy efficiency, grid stability, and the integration of renewable energy sources, facilitating the transition towards a sustainable and resilient energy future.

The grid infrastructure is an essential component that facilitates the bidirectional flow of electricity within the system. It connects the renewable energy sources, energy storage units, and end-users. The grid serves as a conduit for energy exchange, allowing the excess energy from renewable sources to be stored in the energy storage units and distributed back to the grid during peak demand periods [16].

End-users are the final recipients of electricity within the system. The multi-energy storage system caters to a diverse range of consumers, including residential, commercial, and industrial users. Its primary objective is to optimize resource allocation, ensuring that the energy demands of end-users are met while maximizing the utilization of renewable energy sources. By effectively managing energy storage and distribution, the system promotes energy efficiency, cost savings, and the integration of clean and sustainable energy into various sectors of the economy [17]. By intelligently managing the allocation of stored energy, the system ensures a balanced supply-demand relationship, improves energy efficiency, and reduces reliance on conventional fossil fuel-based generation.

Overall, the studied multi-energy storage system is designed to optimize resource allocation, integrate renewable energy sources, and maintain a reliable and sustainable energy supply. It leverages renewable energy generation, energy storage technologies, grid infrastructure, and end-users to achieve efficient and flexible energy utilization in line with the evolving energy landscape and the goals of sustainable development.

3 Model Formulation

To provide a mathematical formulation for the optimal resource allocation in the studied multi-energy storage system, let's consider the following variables and parameters: At each time point t, the variables in the system include the energy stored in the energy storage units (E_t), the power generated by renewable energy sources ($P_{r,t}$), the power demanded by end-users ($P_{d,t}$), the power exchanged with the grid ($P_{c,t}$), and the cost associated with resource allocation (C_t). The parameters influencing the system are the cost of storing energy in the energy storage units (C_s), the cost of renewable energy generation (C_r), the cost of power exchange with the grid (C_g), the charging efficiency of the energy storage units (η_{ch}), the discharging efficiency of the energy storage units (η_{dis}), the maximum energy storage capacity (E_{max}) and the minimum energy storage capacity (E_{min}). It is important to note that only the model for electricity storage is presented here, while the model for heat storage follows a similar framework. Due to space limitations, the details of the heat storage model are omitted in this discussion.

Objective:
Minimize the total cost of resource allocation over a given time horizon T:

$$Minimize \sum_{t=1\ to\ T} C_t \tag{1}$$

Subject to:

1. Energy balance equation:

$$E_t = E_{t-1} + (P_{r,t} - P_{d,t})\eta_{dis} - \left(\frac{P_{c,t} - P_{d,t}}{\eta_{ch}}\right) \tag{2}$$

2. Energy storage constraints:

$$E_{min} \leq E_t \leq E_{max} \tag{3}$$

3. Power balance equation:

$$P_{r,t} - P_{d,t} = P_{c,t} \tag{4}$$

4. Resource allocation cost:

$$C_t = C_s(E_t - E_t - 1) + C_r P_{r,t} + C_g|P_{c,t} - P_{d,t}| \tag{5}$$

5. Non-negativity constraints:

$$E_t \geq 0,\ P_{r,t} \geq 0,\ P_{d,t} \geq 0,\ P_{c,t} \geq 0 \tag{6}$$

The objective function (1) of the proposed model focuses on minimizing the overall cost associated with resource allocation in the multi-energy storage system. This cost encompasses factors such as the expense of storing energy in storage units, the cost of generating renewable energy, and the cost incurred through power exchange with the grid. The energy balance Equation (2) ensures that the energy stored in the storage units at a given time t equals the energy stored in the previous time step, augmented by the energy received from renewable sources and reduced by the energy demanded by end-users and the energy exchanged with the grid. This equation guarantees a balance between energy supply and demand within the system, enabling efficient utilization of resources and maintaining stability in the energy network. The energy storage constraints (3) define the minimum and maximum energy storage capacities. The power balance Equation (4) ensures that the power generated by renewable sources minus the power demanded by end-users is equal to the power exchanged with the grid. The resource allocation cost (5) incorporates the cost components associated with energy storage, renewable energy generation, and power exchange. Finally, the non-negativity constraints (6) ensure that all variables are non-negative.

The mathematical formulation presented in the study serves as a framework for optimizing resource allocation decisions within the multi-energy storage system. The objective of this optimization is to minimize the total cost, taking into account various factors such as energy balance, storage capacity limitations, and power balance requirements. By formulating the problem in this manner, the model provides a systematic approach to making resource allocation decisions that consider both economic efficiency and operational feasibility. The inclusion of energy balance, storage capacity, and power balance constraints ensures that the resulting solution aligns with the system's requirements and objectives. The specific solution methodology, such as the application of deep reinforcement learning or other optimization algorithms, can be employed to find the optimal resource allocation policies within this formulation.

To further extend the reformulated resource allocation problem as a Markov decision process (MDP), additional considerations can be incorporated: In the context of a MDP formulation, let's define the system state, action, reward, and return function for the given multi-energy storage system:

1. **System State:** The system state represents the current state of the system at a specific time point. In this case, the system state includes variables such as the energy stored in the energy storage units (E_t), the power generated by renewable energy sources ($P_{r,t}$), the power demanded by end-users ($P_{d,t}$), the power exchanged with the grid ($P_{c,t}$), and the cost associated with resource allocation (C_t). The system state captures the necessary information to make decisions regarding resource allocation.
2. **Action:** The action refers to the decision made by the controller or optimizer based on the current system state. In the multi-energy storage system, the action can be the allocation of power to various components, such as deciding the power flow from renewable energy sources, adjusting the power exchange with the grid, or managing the energy storage unit's charging and discharging. The action determines how the system transitions from the current state to the next state.
3. **Reward:** The reward is a scalar value that represents the immediate benefit or cost associated with taking a particular action in a given

state. In the context of the multi-energy storage system, the reward function evaluates the quality of the chosen action in terms of the overall system objectives. The reward can be defined as a function of the costs associated with resource allocation, such as the cost of energy storage (C_s), the cost of renewable energy generation (C_r), and the cost of power exchange with the grid (C_g).

4. **Return Function:** The return function, also known as the cumulative return or the value function, is a measure of the long-term performance or cumulative reward obtained by following a particular policy in the MDP. It represents the sum of discounted future rewards over a time horizon. The return function can be defined recursively based on the immediate reward and the expected return from the next state, taking into account the dynamics of the system. The goal is to maximize the return function, which corresponds to maximizing the long-term benefits or minimizing the long-term costs in the multi-energy storage system.

By formulating the problem as an MDP and defining the system state, action, reward, and return function, one can apply reinforcement learning algorithms or other optimization techniques to find an optimal policy for resource allocation in the multi-energy storage system.

4 Case Study

The proposed energy management approach is evaluated through various case studies using a Python implementation on a system with an Intel(R) Core(TM) i5-8250U CPU running at 1.60 GHz (4 CPUs) and 8 GB of RAM. These case studies encompass different system configurations and scenarios, considering factors such as energy demand patterns, renewable energy availability, storage capacities, and operational constraints. By leveraging the computational capabilities of the chosen hardware and the flexibility of the Python language, the approach proves its efficacy in optimizing resource allocation and enhancing operational efficiency in multi-energy storage systems. The results obtained from these case studies provide valuable insights and a solid foundation for real-world implementation and further advancements in energy management practices.

The operational parameters of the multi-energy storage system in this study are derived from data provided in reference [18]. Waste heat recovery equipment typically exhibits conversion efficiencies ranging from 70% to 80% [19], and a conversion factor of 70% is adopted here to represent the efficiency of waste heat recovery. To accurately represent different types of generation units, the proposed model incorporates three distinct unit types, with their operational data sourced from reference [20]. Both the ESS and TSS are integrated into the model, with their parameters adjusted based on ERCOT scheduling data [21]. For a more comprehensive understanding of the system, detailed data on load information, value of lost load, and renewable resource outputs can be found in reference [22]. By utilizing these specific operational parameters and data sources, the study ensures the model's fidelity and provides insights into the performance and optimization of multi-energy storage systems in real-world scenarios.

The operational strategies of the ESS and TSS are visualized in Figures 1 and 2, respectively. Figure 1 demonstrates that the ESS is designed to

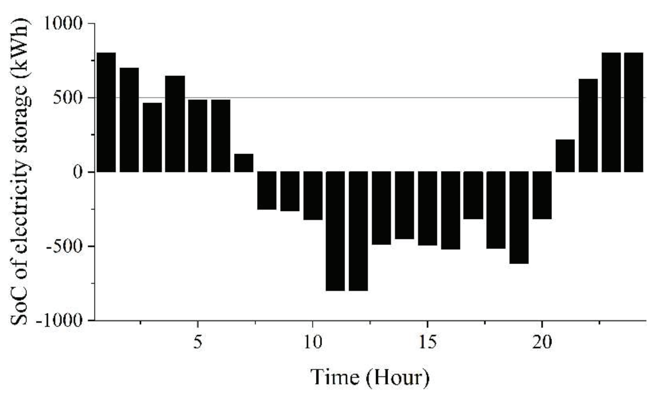

Figure 1 Electricity storage scheduling decisions.

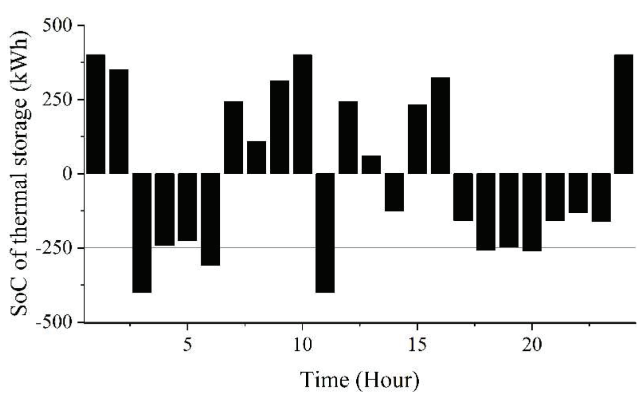

Figure 2 Thermal storage scheduling decisions.

optimize cost savings by charging during low spot price hours (0:00–7:00, 23:00–24:00) and discharging during peak hours (8:00–21:00) when electricity prices are high. This approach allows the ESS to store energy when it is less expensive and release it when it is more valuable, effectively reducing overall electricity costs. In Figure 2, the scheduling pattern of the TSS highlights its flexibility and independence from spot prices. The TSS is not directly influenced by electricity price fluctuations but focuses on efficiently managing heat demands. During off-peak hours of heat demands, the TSS takes advantage of the excess capacity by charging and storing thermal energy. Then, during peak hours, it releases the stored heat energy to fulfill the increased heat demand. This strategy optimizes the utilization of heat resources, improves energy efficiency, and ensures reliable heat supply during high-demand periods. Overall, the combination of ESS and TSS in the system allows for comprehensive optimization of both electricity and heat resources. By considering different pricing patterns and heat demand profiles, the system can achieve cost savings, reduce peak load on the electricity grid, and ensure reliable and efficient supply of both electricity and heat to meet consumer needs.

The study includes several test cases to examine the effects of waste heat recovery and electric-thermal decoupling in a multi-energy storage system's operational costs. The Optimal Case serves as a benchmark, where the model is optimized to minimize overall operation costs. In this scenario, the system incorporates waste heat recovery and maintains electric-thermal decoupling by integrating a TSS. By comparing the results of the Optimal Case with other test cases, the study aims to assess the impact of these factors on the operational costs of the multi-energy storage system. Case A focuses on analysing the effect of removing the waste heat recovery process from the system while keeping the electric-thermal decoupling intact. By comparing the cost of Case A to the Optimal Case, the study aims to quantify the cost savings achieved through waste heat recovery. Case B, on the other hand, explores the consequences of removing the TSS, leading to the coupling of power and heat production from the CHP unit. This configuration may result in different operational costs compared to the Optimal Case, as it eliminates the flexibility provided by the TSS. Lastly, Case C investigates the combined impact of removing both waste heat recovery and the TSS. This case serves as a reference point to evaluate the significance of each individual component and their combined effect on operational costs. Table 1 provides a cost comparison of total operation costs (in thousands of dollars, k$) among the base case, Case A, Case B, and Case C. The base case has the lowest

Table 1 Cost comparison

	Total Operation Cost (k$)
Base case	56.26
Case A	162.32
Case B	85.20
Case C	285.62

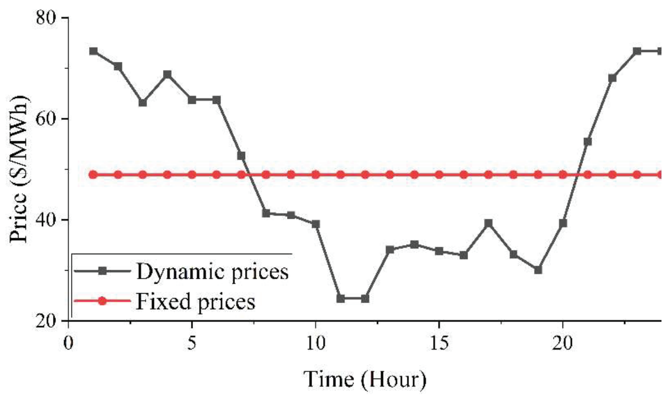

Figure 3 Dynamic prices and fixed prices.

cost at 56.26 k$, while Case A has the highest cost of 162.32 k$. Case B demonstrates a cost reduction compared to the base case, with a total operation cost of 85.20 k$. Case C stands out as the most expensive scenario, with a total cost of 285.62 k$. The table highlights the significant variations in costs among the different cases, indicating the impact of resource scheduling decisions on operational expenses. Further analysis of the specific factors and cost components involved would provide a more comprehensive understanding of the cost differences and potential areas for optimization.

In order to evaluate the performance of the proposed model, the study introduces two pricing modes: dynamic spot price and fixed price. The dynamic spot price is obtained from market data provided by PJM Interconnection LLC, while the fixed price is calculated as the weighted average of spot prices. Figure 3 presents a comparison between these two pricing modes, allowing for an assessment of their impact on the performance of the proposed model. By analyzing the results and differences between the dynamic spot price and fixed price scenarios, the study provides insights into the effectiveness and suitability of each pricing mode in optimizing the multi-energy storage system's operation. Meanwhile, Table 2 presents a cost

Table 2 Cost comparison

	Total Operation Cost (k$)
Base case	56.26
Case D	95.15

comparison between the base case and Case D in terms of total operation cost. The base case demonstrates a total cost of 56.26 k$, whereas Case D incurs a higher cost of 95.15 k$. This notable difference highlights that the resource scheduling decisions or modifications made in Case D have resulted in increased operational expenses. However, to gain a comprehensive understanding of the underlying reasons, further details from the corresponding study or analysis are necessary. Conducting additional analysis, including examining the methodology, resource allocation approach, impact evaluation, and sensitivity analysis, would provide a more thorough assessment of the cost comparison and the effectiveness of the resource scheduling decisions.

5 Conclusion

In conclusion, this study presents an innovative optimization method for resource scheduling in multi-energy storage systems, focusing on enhancing resource allocation while considering supply-demand flexibility and the integration of renewable energy. The proposed method utilizes a Markov dynamic model to capture the dynamic changes in energy supply and demand within the system. Furthermore, a reinforcement learning approach is employed to optimize resource scheduling decisions.

Through numerical simulations and case studies, the effectiveness and feasibility of the proposed method are validated. The results demonstrate its significant potential in improving the operational efficiency and reliability of multi-energy storage systems in the face of constantly changing energy patterns. By efficiently utilizing energy storage, achieving supply-demand balance, and maximizing renewable energy integration, the proposed method contributes to the overall goal of sustainable energy utilization.

This research provides valuable guidance and decision support for the design and operation of multi-energy storage systems. By optimizing resource allocation, these systems can enhance their performance, promote sustainable development, and contribute to the efficient and reliable utilization of renewable energy sources. The findings of this study have implications for the broader field of energy and offer insights into addressing the challenges posed by the increasing complexity of multi-energy systems.

The practical application potential is limited by factors such as scalability, sustainability, and cost-effectiveness. To address these challenges, future work should consider implementing more efficient algorithms and optimization techniques to enhance the approach's scalability, adopting adaptive algorithms and intelligent decision support systems to promote its sustainability, and conducting cost-benefit analysis and return on investment assessments to ensure its cost-effectiveness. By addressing these limitations, the practical application potential of this approach can be enhanced, making it suitable for broader applications.

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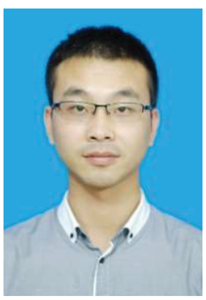

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