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Computational approaches to the optimization of operational strategies of energy storage systems with respect to generative artificial intelligence

Jiaxin Huang[1, 2], Xielin Shen[3] and Dongdong Chen[1, 2, *]

1 School of Electronics and Electrical Engineering, Minnan University of Science and Technology, Quanzhou, Fujian 362700, China;
[2]Key Laboratory of Industrial Automation Control Technology and Application of Fujian Higher Education, Quanzhou 362700, China;
[3]State Grid Fujian Electric Power Co.,Ltd.,Quanzhou Power Supply Company, Quanzhou 362011, China

Abstract

INTRODUCTION: The energy storage systems (ESSs) require the coordination of renewable generation, load demand, prices and safety constraints but operational strategy optimization is much dependent on manual modeling and is hard to change based on users preferences.
THE OBJECTIVES ARE: The study will come up with an automated and constraint-based optimization structure of ESS scheduling. It is proposed that a constraint-improved generative artificial intelligence (AI)-based model to optimize energy storage operation strategies, called CGAI-ESO, be developed.
METHODOLOGY: The model is based on natural language processing to understand the requests of energy management system (EMS) developers or end-users, retrieval-augmented generation (RAG) to fetch domain and optimization data, and a generative AI agent to develop objective functions, constraints, and executable optimization codes. The combination of an optimization solver with a digital twin feedback module checks the validity of economic performance, safety compliance, battery degradation and constraint satisfaction.
The results of experiments with public energy data and microgrid simulations demonstrate that CGAI-ESO minimizes operational cost by 18.72 percent, maximizes peak shaving rate to 28.5 percent, enhances the use of renewable energy to 96.0 percent and minimizes the level of constraint violation to 0.02 percent. It is also better than large language model (LLM)-only and LLM-RAG baselines in terms of model generation, constraint completeness and code executability.
CONCLUSION: CGAI-ESO provides a feasible route for intelligent and reliable ESS operation strategy optimization.

Keywords: Generative Artificial Intelligence, Energy Storage Systems, Microgrids, RAG, Operation Strategy Optimization, Large Language Models

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*Corresponding Author. Email: cdd1911@qq.com

1. Introduction

The growing penetration of renewable energy sources, electric cars and flexible loads in microgrids has made energy storage systems vital elements that can be used to improve system flexibility, peak shaving and valley filling performance, efficiencies of integrating renewable energy and cost-effectiveness of operations. Nonetheless, optimal energy storage operation strategy is not an easy economic dispatch problem but a complicated optimization problem which considers various interacting factors like load fluctuations, unpredictability of renewable energy supply, dynamic changes in electricity prices, safety limits on state-of-charge (SOC) and state-of-health (SOH), costs of battery degradation, and user preferences. Hence, the automated modeling, intelligent optimization, and dynamic feedback adjustment of energy storage operation strategies with the guarantee of adhering to engineering constraints still stand as the main research issue in smart microgrid energy management.

Over the past few years, improvements in large language models (LLMs) and generative artificial intelligence (AI) have created opportunities to improve energy systems. Majumder et al. used LLMs to examine tasks in the power domain and presented them as potentially useful in knowledge reasoning, interactive decision making, and operational assistance, although practical uses continue to be hindered by factors like reliability, professional limitation, and lack of safety validation [1]. The detailed analysis of energy systems also shows how the concept of LLMs may be applied to load forecasting, operational decision-making, planning support, and human-machine interaction, although their engineering application needs to be combined with domain-specific knowledge, optimization models, and safety constraints [2]. Other similar studies discuss modeling, optimization, and governance of sustainable energy systems by LLMs, and claim that the worth of generative AI must go beyond text generation to encompass task comprehension, model building, and making decisions on complicated energy systems [3]. Cheng came up with a LLM-driven solution to the problem of advanced power dispatching and showed that LLM could be used to help with operations adjustments, status monitoring, and sophisticated scheduling work, though it was still based on special datasets and physical restriction methods [4].

If generic AI is applied directly to the scheduling of energy storage, typical problems are encountered, including undefined variables, absent constraints, inconsistent parameters, and unexecutable code. As a countermeasure to these threats, retrieval-enhanced generation (RAG) methods have been applied to knowledge-intensive engineering operations. Hierarchical graph-enhanced RAG of power systems proves that structured retrieval leads to better knowledge traceability in long documents and complex rule-based situations [5]. Knowledge graph-enhanced RAG was used by Ghosh and Mittal to support engineering research tasks and it was found out that awareness of contexts will increase automation performance in engineering design and domain knowledge application [6]. Generative AI and large language models (LLMs) have been used in the renewable energy and smart grid fields in scenario generation, intelligent Q&A, data completion, operation assistance, and energy management but all the current publications keep highlighting that there is a significant necessity to have professional knowledge bases, model constraints, and verifiable execution mechanisms [7]. Studies on power system control and decision-making have shown that LLMs can be made more efficient in human-machine interaction, but they cannot be substituted with physical models, optimization algorithms, or safety verification modules [8].

The traditional mathematical optimization, intelligent optimization and deep reinforcement learning techniques have achieved great success in the area of optimizing microgrids and energy storage systems. As per the latest reviews, artificial intelligence is facilitating the transition between rule-based and adaptive intelligent control in microgrid design, operation, and maintenance, but multi-source uncertainties, model interpretability, and safety constraints are still central issues [9]. The optimization of renewable microgrids research indicates that AI can be used to predict, schedule, respond to demands, manage assets and it is currently being used in the form of non-unified interactive modeling frameworks and executable optimization solutions [10]. Stochastic programming was used by Alvarez-Arroyo to examine the role of flexible energy storage in microgrid energy management and found that storage flexibility lowered the operating costs of the system and increased the use of renewable energy [11]. Researches related to multi-energy microgrid communities show that the joint work of shared hybrid energy storage devices and electric cars enhances multi-stakeholder energy coordination performance and day-ahead operational economics [12]. Besides, the distributed energy management studies incorporating cyber threats and privacy protection indicate the fact that microgrid optimization is not just economically feasible but also resilient, secure, and capable of reliable implementation [13].

In addition to mathematical programming, meta-heuristic algorithms and multi-objective optimization approaches have found extensive use in scheduling problems related to energy storage. Studies that apply enhanced gradient optimizers to microgrid scheduling with energy storage integration show that smart optimization algorithms are capable of addressing complex nonlinear goals [14]. The findings of experiments on energy management models with electricity pricing, renewable energy, and coordinated energy storage operation suggest that pricing mechanisms and charging/discharge strategies have a significant influence on cost and system stability [15]. Manikandan evaluated the energy management strategies of DC microgrids with combined renewable energy sources and electric vehicle energy management systems and found that the best coordination between charging and discharging increases the energy efficiency of the system [16]. Multi-objective energy storage optimization studies also indicate that concentrating on reducing operational costs only is likely to increase degradation of the batteries, which should be balanced by considering an economic feasibility, emission minimization, reliability, and degradation of storage performance [17]. Nonetheless, such approaches often need the researcher to predefine the objective functions and constraint models hence the automatic adaptation of the model structure to meet natural language requirements of users is difficult.

The concept of deep reinforcement learning (DRL) is an information-driven method of online scheduling in energy storage systems. Studies related to microgrid energy management with renewable energy and electric vehicles have proven that DRL has the ability to learn dynamic charging/discharging policies [18]. Deep reinforcement learning can be successfully applied to market bidding situations that involve renewable energy and storage by effectively dealing with the problem of price uncertainty and strategy searching, but it is vulnerable to the amount of coverage of the training scenario and the structure of the reward function [19]. Zhu proposed a multi-time-scale deep reinforcement learning model to solve the island microgrid scheduling problem and the findings indicated that multi-time-scale control improves the operational performance [20]. Even though DRL has benefits of fast online inference and high flexibility, it also has disadvantages of strategy safety, explainability of constraints, and cross-scenario generalization especially when used in practice in engineering where severe constraints like energy storage state-of-charge (SOC), exclusivity of charging/discharging, and grid power limits are mandatory. These drawbacks require incorporation with explicit optimization models or safety correction measures.

The digital twin technology offers new opportunities to validate pre-deployment and refine the energy storage plans in a closed loop way. A study on digital twins in microgrids to optimize electric vehicle (EV) charging shows that synchronization and predictive optimization in real time would make scheduling of charging more efficient [21]. Sivaneasan created a cognitive digital twin system specific to real-life microgrids and found that the intelligent energy management and operations optimization can be achieved using a cloud-edge collaborative architecture [22]. The analysis of multi-energy microgrid optimization demonstrates that the combination of multi-energy coupling, controlled energy storage, and load response all contribute to the better performance of the economy of the system as well as the use of renewable energy [23]. It has been shown that strong economic dispatching studies of interconnected multi-microgrid systems show that strong optimization techniques improve the stability of the system in uncertain load and renewable energy conditions [24]. Also, stochastic optimization structures have been implemented in microgrid energy management with EVs, renewable sources, and energy storage, and it is shown that multi-scenario modeling is one of the efficient strategies to enhance the robustness of dispatches [25].

Flexible resources, including electric vehicles, hydrogen energy, and demand response mechanisms are often combined with energy storage systems to implement microgrid dispatching. Grid-connected EV charging systems and the use of renewables and storage technologies have been studied to find out how the appropriate implementation of energy storage can benefit the economy and reliability of the system [26]. The sophisticated scheduling method that integrates energy storage, renewable power production, hydrogen processing, and plug-in hybrid vehicle charging demonstrates that multi-energy synergy has a great positive effect on the flexibility of microgrid operation [27]. Coordinated renewable energy-electric vehicle operation comparative analyses explain how various market mechanisms and coordination strategies significantly affect system operating costs and stability [28]. Multi-objective economic optimization research on integrated renewable energy and demand response underscores even more on the fact that energy storage operation measures should be balanced with economic performance, environmental factors, and response capabilities of users [29]. Also, the quality of load forecasting is important to ensure effective planning of energy storage, and the combination of various learning methods in electricity consumption prediction indicates that multi-model fusion is useful not only in improving the accuracy of predictions but also in improving the stability of inputs [30].

To sum up, the current studies have established significant backgrounds in fields like generative AI, large language models to use in power systems, RAG knowledge improvement, microgrid mathematical optimization, deep reinforcement learning, and digital twin feedback but there are still a number of limitations: Firstly, the classical optimization algorithms generally depend on manually specified objective functions and constraints, which makes them hard to produce rapid personalized optimization models to suit the natural language needs of energy management system (EMS) developers or end-users; Secondly, although traditional LLM solutions can produce both text and code, they tend to be prone to such problems as hallucinations, omission of constraints and non-executability of code in complex energy storage conditions; Thirdly, existing RAG, digital twin and strong optimization algorithms are used as individual elements, not as a complete closed loop system aimed at optimizing energy storage operation plans.

In order to solve the stated problems, this paper will suggest a constrained-improved optimization approach to energy storage action plans based on the generative AI model, which is called CGAI-ESO. The method relies on the use of RAG to access domain-specific knowledge and optimize implementation strategies based on a generative AI agent, automatically generating an energy storage schedule model and executable code. Furthermore, it also uses scenario-sensitive strategy generation and a digital twin feedback system to simulate, test and execute closed-loop improvement of energy storage operation plans. The research process diagram of the current work is presented in Fig. 1. In particular, there are three contributions: Firstly, in comparison to conventional rule-based and mathematical optimization, CGAI-ESO transforms natural language goals and constraints into executable schedule models, eliminating manual formulation dependency. Secondly, compared to LLM-only optimization, RAG introduces ESS domain rules and solver templates to eliminate hallucinated variables, missing constraints, and un-executable code. Thirdly, compared to LLM-RAG, digital-twin feedback layer conducts pre-deployment feasibility checks and feeds back violation data to modify model constraints, weights, and solver options to close the loop between generation and execution.

2. Methods

2.1. Overall Framework of CGAI-ESO

In order to meet difficulties in the optimal functioning strategy of energy storage systems, such as multi-source information coupling, complex operation constraints, changing customer preferences, and uncertainty in the output of renewable energy sources, we suggest a constraint-enhanced generative AI-based optimization approach to energy storage operation strategies referred to as CGAI-ESO. The proposed strategy combines natural language communication, RAG knowledge extension, generative optimization models, creation of executable code, optimization solvers, and digital twin feedback into one system allowing shifting the process of modeling manually to intelligent generation and feedback-based improvement of operation strategies.

Figure 2 shows that the CGAI-ESO initially gathers operational data, such as photovoltaic and wind power outputs, load demand, electricity prices, SOC/SOH levels, and weather conditions, of Internet of Things (IoT)-enabled energy storage microgrids, and it also receives natural-language optimization requests by EMS developers or end-users. The perception module of the system transforms the requests into semantic embeddings and accesses domain specific knowledge and optimization strategies using the RAG knowledge base. Thereafter, the generative AI agent automatically builds an energy storage optimization model with the help of the retrieved knowledge, historical data, real-time conditions and user preferences, produces executable optimization scripts, and calls a solver to find out optimal charging/discharging plans. Lastly, the digital twin environment assesses the economics of the strategies, safety compliance, battery degradation effect and constraint satisfaction and the feedback is used to refine the strategies further. In practice, the process consists of five interconnected steps: (1) user requirements are divided into objectives, preferences, and strict requirements; (2) the query embedding obtained is used to retrieve the ESS-domain rules and optimization templates; (3) the generative AI agent amalgamates the request, the retrieved context, and the current operating state to produce objective functions, constraints and an executable optimization model; (4) the solver calculates a candidate charging/discharging schedule; and (5) the digital twin replays the schedule, detects infeasible or risky behaviour and provides structured feedback to the generation and optimization steps. In case of violations, steps (3)-(5) are repeated until the strategy meets the given checks.

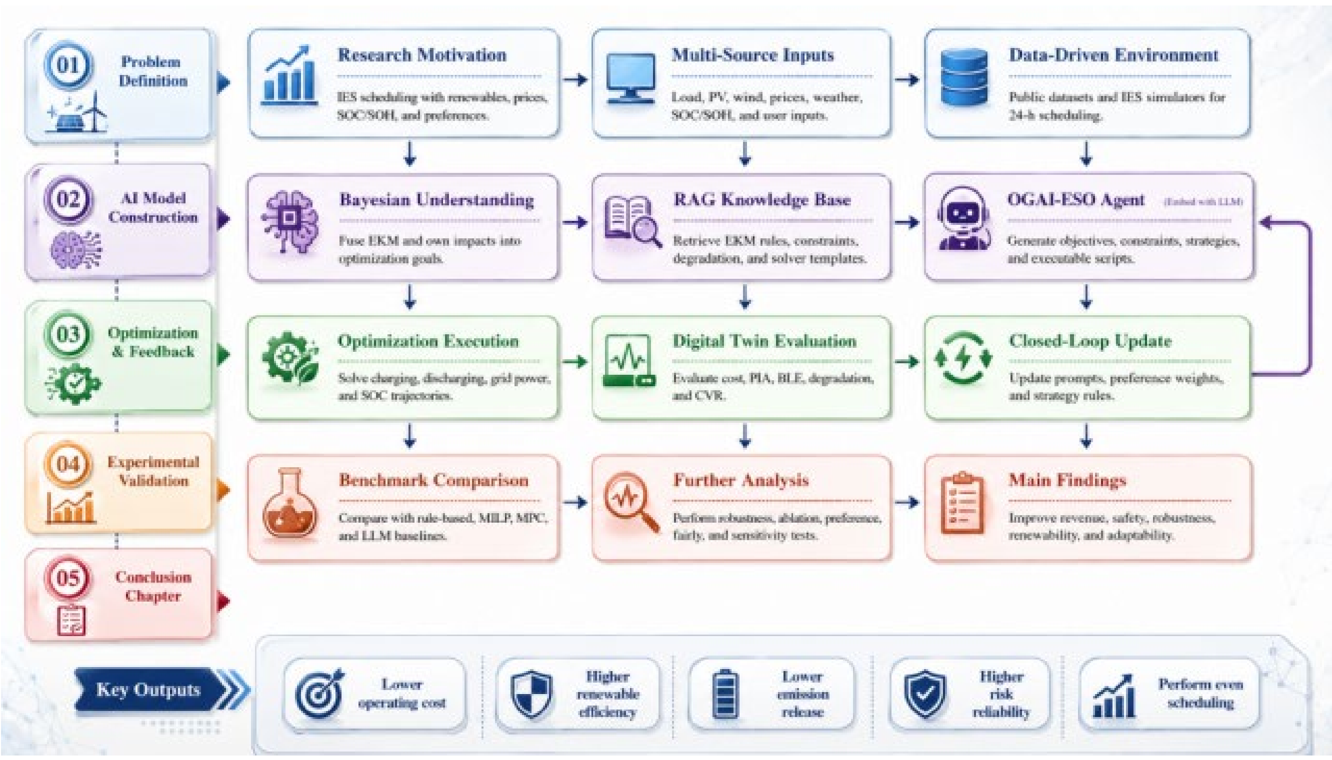


Figure 1. Research Flowchart

In contrast to conventional optimization strategies of energy storage, the main characteristic of CGAI-ESO is its optimization model, which is no longer dependent solely on manual factors but is instead self-generated by generative AI through operation scenarios, user goals, and expertise. Also, RAG retrieval and constraint optimization mechanisms reduce the likelihood of large-model hallucinations, so that engineering feasibility and reliability of results of the generated models can be achieved.

It consists of IoT-based energy storage microgrid environment, natural language processing module, RAG-enriched expert knowledge module, generative energy storage optimization module, and digital twin assessment with closed-loop feedback module. CGAI-ESO automatically builds energy storage optimization models, generates executable programs, executes solver computations and displays charging/discharging strategies in response to interactive requests by EMS developers and end-users, and strategy updates are done using digital twin feedback [31-32].

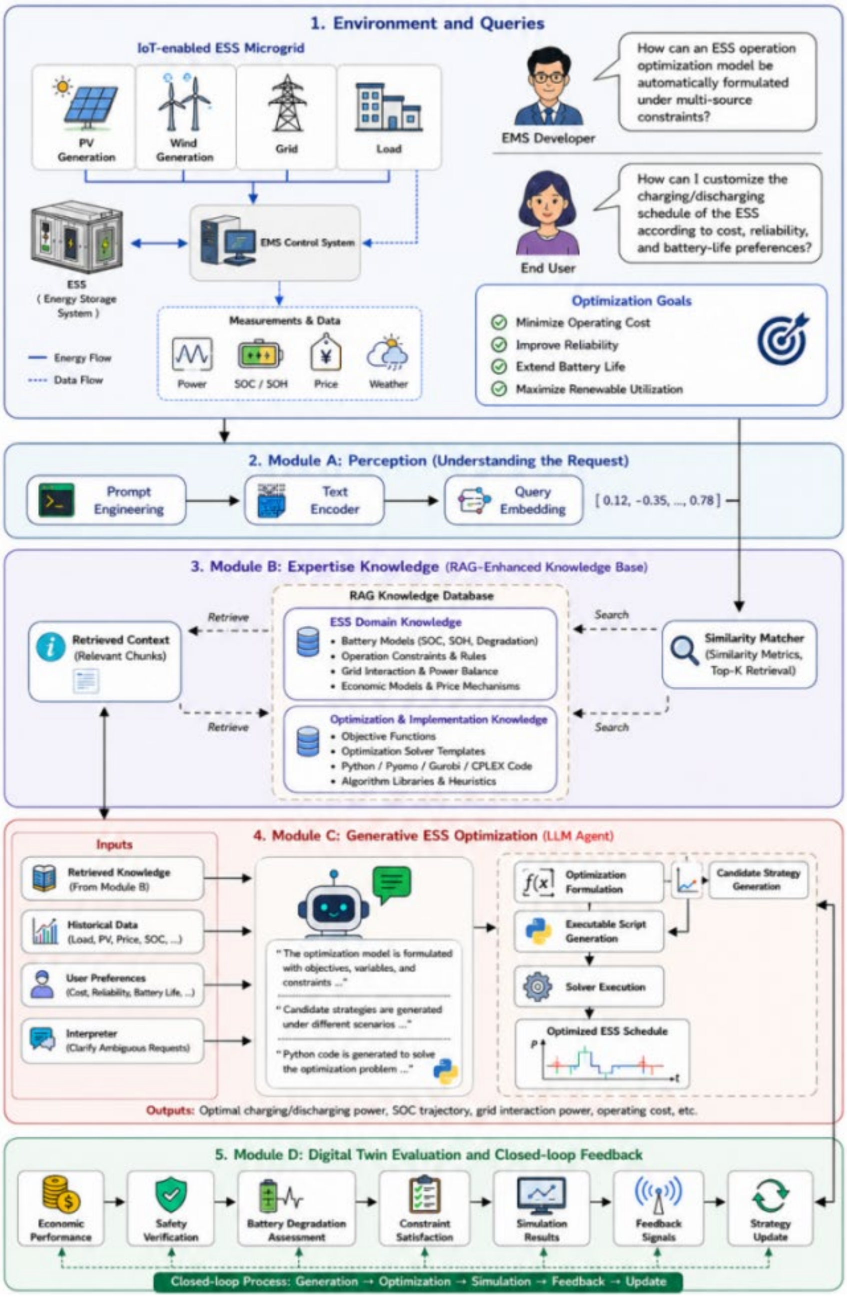


Figure 2. Framework architecture of CGAI-ESO

2.2. Problem Definition and State Modeling

The operating state of the energy storage microgrid at a given scheduling time t may be stated as:

$$X_t=[P_t^{pv},P_t^{wind},P_t^{load},C_t^{buy},C_t^{sell},SOC_t,SOH_t,W_t] \quad (1)$$

They are represented by P_t^{pv} and P_t^{wind} as the output of photovoltaic and wind power respectively, P_t^{load} is the load demand, C_t^{buy} and C_t^{sell} are the purchase and sale prices of electricity respectively, SOC_t and are the status of charge and health of the energy storage system respectively, and SOH_t is the weather and external environmental variables.

The control variables of the energy storage system are defined as:

$$U_t=[P_t^{ch},P_t^{dis},P_t^{grid,+},P_t^{grid,-}] \quad (2)$$

Out of those, P_t^{ch} and P_t^{dis} are the charging and discharging power of energy storage whereas $P_t^{grid,+}$ and $P_t^{grid,-}$ are the power of buying electricity off the grid and selling electricity to the grid respectively. The purpose of this paper is to find the best charging and discharging plan in the upcoming dispatch processes, guaranteeing the safety of the energy storage systems operation and the balance of the grid power.

$$U^* = \arg\min_{U} J(U,X) \text{s.t.} \mathcal{C}(U,X) \leq 0 \quad (3)$$

One of them is J(U,X) which is the overall objective function of operations and C(U,X) which represents the collection of constraint sets in operating an energy storage system.

2.3. RAG-enhanced Generative Optimization Modeling

In cases where generative AI is used as a method of modeling optimization directly, there are common problems with missing constraints, incomplete variables, or even unrunnable code. In order to do that, this paper proposes an improved RAG-based expert knowledge base as an external knowledge source of generative AI, as shown in Figure 3. Knowledge base has two parts [33]:

$$K=K^{tech} \cup K^{exec} \quad (4)$$

Among these, K^{tech} covers the area of energy storage, such as SOC/SOH models, battery degradation models, charging and discharging constraints, power balance rules, electricity price mechanisms, and safety operation boundaries; K^{exec} has knowledge on how to implement optimization, such as templates of the objective functions, templates of constraints, methods of invoking solvers, and templates of codes written in Python, Pyomo, Gurobi or CPLEX.

To get the query embedding in the case of user query Q, the system first uses a text encoder to obtain the query embedding:

$$e_q=f_{enc}(Q) \quad (5)$$

Simultaneously, encode knowledge k_i fragments from the knowledge base into vectors:

$$e_i=f_{enc}(k_i) \quad (6)$$

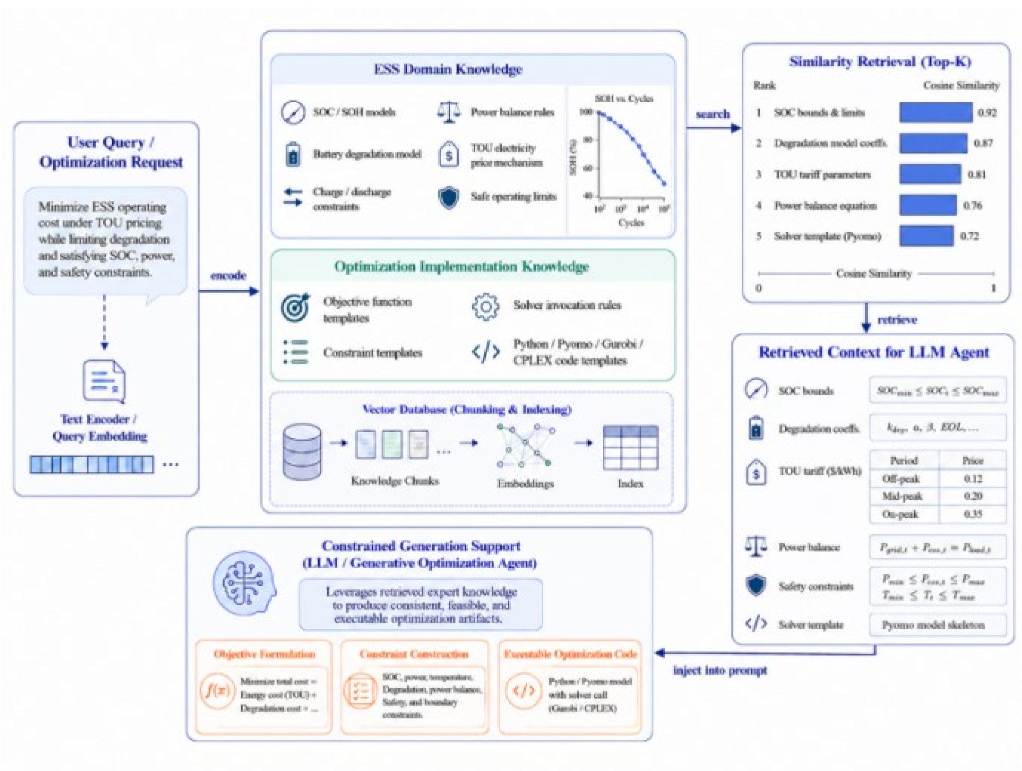


Figure 3. Diagram of the RAG-enhanced expert knowledge base framework

Retrieve the most relevant knowledge fragments for the current task using similarity matching:

$$\mathscr{R}(Q) = \mathrm{TopK}_{k_i \in K}\left(\mathrm{sim}\left(e_q, e_i\right)\right) \qquad (7)$$

The obtained knowledge context $\mathscr{R}(Q)$ is fed into the generative AI agent, which is used to limit the generation of optimization models and code generation. [34]. This mechanism makes sure that the output of the generative AI does not solely depend upon the internal parameters of the model but rather is limited by rules that are particular to the domain of energy storage, physical constraints, and solver-specific knowledge, as a result improving the accuracy and executability of the optimization models.

2.4. Optimization Model for Energy Storage Operation Strategies

Based on RAG knowledge improvement, the generative AI agent automatically detects the optimization variables, objective functions, constraints and user preferences [35] and builds an energy storage operation optimization model as in Figure 4.

Objective function is defined in the following way taking into consideration operational costs, battery degradation, penalty for constraint violation and advantages of using renewable energy:

$$\min J=\sum_{t=1}^{T}[C_t^{buy}P_t^{grid,+}-C_t^{sell}P_t^{grid,-}+\lambda_1 C_t^{deg}+\lambda_2 C_t^{vio}-\lambda_3 R_t^{ren}] \qquad (8)$$

One of them C_t^{deg} is the cost of battery degradation, another is a penalty term that penalizes constraint violations, the third is the revenue generated by using a new form of energy, and the last three are weight coefficients. The weight $\lambda_1, \lambda_2, \lambda_3$ vector can be altered automatically based on the preferences of the user to achieve user-customized scheduling:

$$\lambda=g_\theta(P^{user}) \qquad (9)$$

In this list, is the symbol of user preferences, and is the symbol that explains the work of the generative AI on the information about preferences.

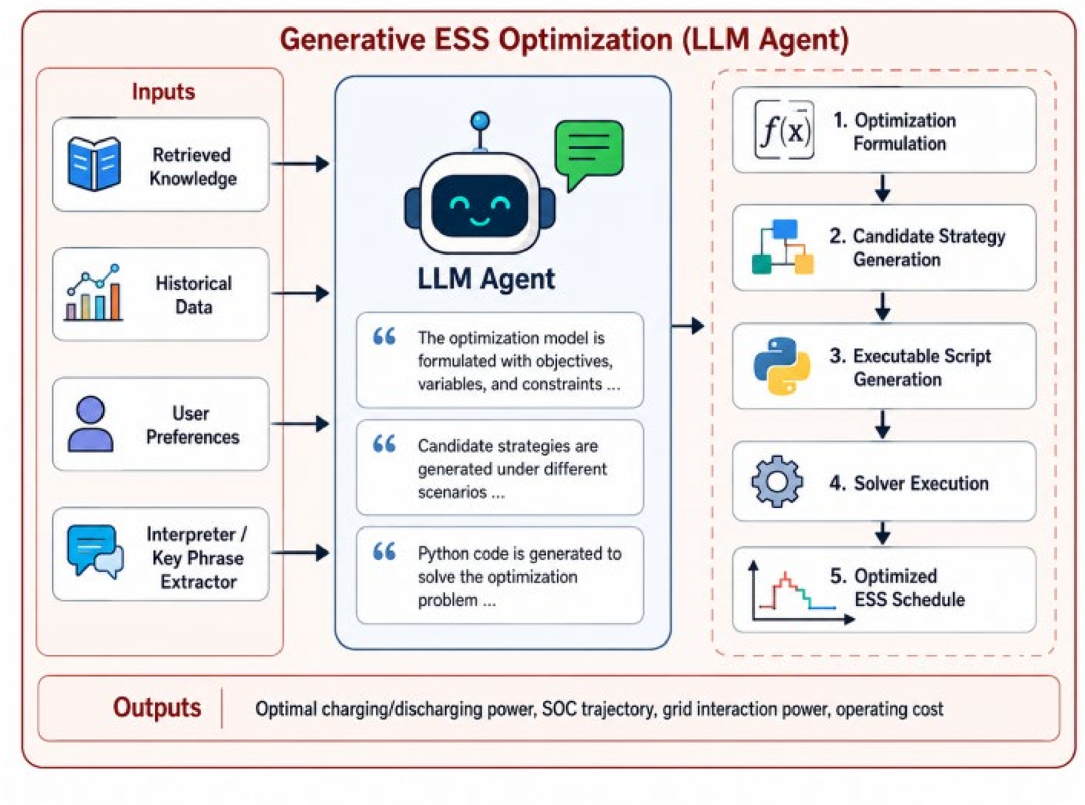


Figure 4. Generative AI Agent

The energy storage system must satisfy the power balance constraint:

$$P_t^{pv}+P_t^{wind}+P_t^{dis}+P_t^{grid,+}=P_t^{load}+P_t^{ch}+P_t^{grid,-}+P_t^{cur} \qquad (10)$$

Here, P_t^{cur} denotes the curtailed wind and solar power. The dynamic constraint of SOC is:

$$SOC_{t+1}=SOC_t+\frac{\eta_{ch}P_t^{ch}\Delta t}{E_{bat}}-\frac{P_t^{dis}\Delta t}{\eta_{dis}E_{bat}} \quad (11)$$

and meet the following requirements:

$$SOC_{min}\leq SOC_t\leq SOC_{max} \quad (12)$$

The charge-discharge power constraints are:

$$0\leq P_t^{ch}\leq b_t P_{ch}^{max} \quad (13)$$

$$0\leq P_t^{dis}\leq(1-b_t)P_{dis}^{max} \quad (14)$$

One of them, b_t indicates a binary variable that is an instrument to ensure the energy storage system will not charge and discharge at the same time.

The battery degradation cost can be expressed as:

$$C_t^{deg}=\alpha(P_t^{ch}+P_t^{dis})\Delta t+\beta|SOC_t-SOC^{ref}| \quad (15)$$

Of these, α and β are degradation coefficients and SOC^{ref} refers to the recommended SOC operating range. The given element allows the optimization model to focus more on the short-term operation costs as well as the effect on long-term battery life [36-37].

2.5. Scenario-aware Strategy Generation and Closed-Loop Feedback

Due to the unpredictability of new energy production output, load demand, and electricity prices, this paper also presents a scenario-aware strategy generation mechanism [38]. The generative AI agent creates various future operation scenarios using historical operation data, weather, electricity prices changes, and customer needs.

$$S=\{S_1,S_2,\ldots,S_N\} \quad (16)$$

All the scenarios are related to a possible operational mode, including high-load scenarios, low new energy output scenarios, high new energy output scenarios, electricity price fluctuation scenarios and extreme weather scenarios. In every case, the system offers candidate energy storage strategies $U^{(n)}$, which are chosen in a whole by the strong optimization objective.

$$minJ_{rob}=\sum_{n=1}^{N}\pi_n J\left(U^{(n)},S_n\right)+\rho Risk(U) \quad (17)$$

Of them, π_n is the scene weight, $Risk(U)$ is the strategy risk term and is the risk weight. The mechanism prevents the strategy from depending on a single prediction curve which increases the flexibility of the energy storage scheduling in uncertain conditions.

Once the optimization model has been developed, generative AI agent subsequently turns it into an executable script:

$$Code=G_{code}(M,R(Q),X_t) \quad (18)$$

Of these, M denotes the created optimized model and $G_{code}()$ denotes the code generation function. Next, the optimization solver is invoked to find the optimal scheduling strategy U^*.

To be reliable before any strategy is implemented, this paper creates the digital twin evaluation module that will allow the simulation and validation of the results of optimization. The metrics of evaluation are operational costs, peak shaving effectiveness, battery degradation, constraint satisfaction rate, and renewable energy integration rate. The feedback vector is given by: In particular, in case of each candidate schedule, the digital twin restores the SOC trajectory and determines if SOC stays in its set low and high limits; identifies the presence of charge/discharge conflicts when both the charging and discharging instructions are on at the same time; confirms the limits on charging, discharging and power exchange with the grid; and assesses the level of battery degradation based on the equivalent energy throughput and excessive SOC excursions.

$$F=[Cost,PSR,C^{deg},CV,R^{ren}] \quad (19)$$

In particular, Cost is the operating cost, PSR stands as the peak shaving rate, C^{deg} is the battery degradation cost, CV is the level of constraint violation, and R^{ren} is the use of new energy. The feedback findings are also applied to updating the prompt template, strategy generation rules, user preference weights, and solver parameters. Feedback information contains the information about the detected violation type, time index, violation magnitude, and degradation/economic indicators. Such signals are utilized to reinforce or introduce similar constraints, change penalty and objective-weight factors, modify user-preference mappings, and refresh solver parameters prior to solving again. Only those schedules which meet the hard operational constraints are allowed to be deployed.

$$\Theta^{new}=U(\Theta^{old},F,P^{user},R(Q)) \quad (20)$$

Hence, CGAI-ESO defines the cyclic process of generation-optimization-simulation-feedback-update that will allow the constant enhancement of energy storage operation plans depending on simulation assessment outcomes [39-40].

3. Experiments and Result Analysis

3.1. Experimental Setup

In order to confirm the efficiency of the suggested CGAI-ESO approach on the optimization of energy storage system operation strategies, this paper builds a microgrid energy storage dispatching experimental setup based on publicly accessible energy data resources. The user-side load data is based on residential electricity consumption data in the Pecan Street Dataport, which provides detailed information on energy usage and electric transportation habits of households, thus suitable to model the user-side energy behavior. The photovoltaic-related meteorological data are taken using the NREL National Solar Radiation Database (NSRDB) [41] which has solar irradiance and weather parameters that are important to model photovoltaic power generation. The NREL WIND Toolkit [42] is used to get wind power data to facilitate the simulation of time-series outputs of wind power and their connection to the grid. The electricity price data are based on Day-Ahead Hourly LMP data in the PJM Data Miner 2 that serves as the basis to develop predictive electricity prices.

Considering that public data sources generally cannot at the same time offer full load profiles, renewable energy production data, electricity prices, and energy storage operations status, the use of both publicly accessible information and energy storage system modeling is used in this research to develop an experimental setup. In particular, load curves of several residential customers in Pecan Street were combined and scaled to the appropriate microgrid loads; photovoltaic output curves were calculated using data on irradiation and temperature of solar panels provided by NSRDB; wind power output sequences were calculated using wind power capacity or the capacity factor provided by WIND Toolkit; day-ahead LMP of PJM was considered as the purchase price and the sale price was set at 80% of the purchase price to eliminate the irrational risk-free arbitrage. Every variable was represented with a resolution of 15 minutes, spanning a consecutive year and each variable consisted of 35,040 time points. The dataset was split sequentially into the training, validation and test sets in proportions of 70:15:15 to reduce information leakage in the future due to the random division.

The experiment has been implemented as a microgrid that comprises photovoltaic power generation, wind power generation, user loads, an energy storage system, a grid interaction unit, and an energy management system. The installed photovoltaic capacity is set to be 600 kW, the installed wind power capacity to be 400 kW, and the aggregated load peak to be scaled to 800 kW. There is a rated capacity of 1000 kWh in the energy storage system, which can be charged and discharged at a maximum rate of 500 kW each, initial state of charge (SOC) is 0.50, its operating range is 0.10-0.90, efficiency of charging and discharging is 0.95 and the maximum grid connected interaction power is 800 kW. Dispatch cycle is 24 hours and each dispatch is 96 time steps long with 1-hour rolling optimization.

The paper will compare CGAI-ESO with different methods such as the rule-based method, mathematical optimization, intelligent optimization, deep reinforcement learning, and generative AI techniques. The comparison includes Rule-based control, mixed-integer linear programming (MILP), stochastic programming-based mixed-integer linear programming (SP-MILP), model predictive control (MPC), particle swarm optimization (PSO), genetic algorithm (GA), deep Q-network (DQN), proximal policy optimization (PPO), long short-term memory-based model predictive control (LSTM-MPC), LLM-only, and LLM-RAG. Particularly: Rule-based utilizes a constant strategy of charging at low electricity rates and discharging during high rates, MILP stands as deterministic mixed integer linear programming, SP-MILP incorporates multi-scenario stochastic programming into MILP, MPC is based on rolling-time-domain optimization, PSO and GA make use of particle swarm optimization and genetic algorithms respectively to find out the sequences of energy storage charging/discharging, DQN and PPO are based on reinforcement learning to schedule tasks, LSTM-MPC initially forecasts load demand and renewable generation then optimizes using MPC, LLM-only depends exclusively on generative AI in order to optimize modeling and generate codes, LLM-RAG combines knowledge retrieval without the use of digital twin feedback, CGAI-ESO is the holistic approach being suggested in this paper. These baselines were chosen to represent a range of scheduling paradigms that do not necessarily include methods that are more supportive of the proposed framework: fixed-rule control; deterministic and stochastic mathematical programming; receding-horizon MPC; population-based metaheuristics; model-free DRL; forecast-assisted MPC; and generative-AI baselines. Formulations representative of the related energy-storage scheduling literature [11,18,20,40]. In order to be fair, all the methods are tested on the same test sequences, ESS parameters, price signals and physical constraints. Hyperparameters are trained on the validation set and held constant throughout testing. The MPC is implemented as a receding-horizon optimizer on the 24-h (96 steps) scheduling horizon with solutions recalculated every 1 hour and the SOC dynamics, power balance, charge/discharge exclusivity and grid-exchange limits imposed at each step; the LSTM-MPC applies the same MPC formulation after forecasting the load demand and renewable generation.

CGAI-ESO RAG knowledge base has two types of knowledge, which are as follows: the first type pertains to energy storage domain-specific knowledge, namely SOC/SOH models, charge/discharge power limits, power balance equations, battery degradation models, time-of-use pricing models, and safety limits of energy storage systems; the second type relates to optimization implementation knowledge, which includes templates of objective functions, constraints, and Python/Pyomo/Gurobi code templates, as well as ways of calling solvers. The fragment size is 512 tokens and the overlap size is 80 tokens, and the Top-K retrieval threshold is 5. The scenario generation module outputs 20 future operational scenarios per scheduling cycle to describe the uncertainties of load demand, renewable energy output, and electricity prices. To ensure implementation uniformity, the generative module is implemented using a fixed decoder-only instruction-following Transformer LLM configuration in all LLM-only, LLM-RAG or CGAI-ESO, and low-temperature decoding is applied to minimize the stochastic variance. The text encoder utilizes the Sentence-BERT-based model of embedding and cosine similarity is applied to retrieve vectors. The knowledge base is built by cleaning ESS-domain documents and optimization/solver templates, dividing them into 512-token pieces and overlapping them by 80 tokens, encoding the pieces into a vector index and finding the Top-5 passages per query. Optimized models are written in Python/Pyomo and run via a commercial mathematical-programming solver interface supporting the Gurobi/CPLEX templates that are present in the knowledge base.

Metrics used in the evaluation are operational cost (Cost), cost reduction rate (CRR), peak shaving rate (PSR), renewable energy utilization rate (RUR), battery degradation cost (Cdeg), constraint violation rate (CVR), code executability rate (CER), and average solution time. Precisely: Cost means operating costs; CRR is cost reduction rate; PSR is peak shaving efficiency; RUR is new energy utilization rate; C^{deg} is battery degradation cost; CVR is constraint violation rate; and CER is code executability rate.

$$\text{Cost}=\sum_{t=1}^{T}(C_t^{buy}P_t^{grid,+}-C_t^{sell}P_t^{grid,-}) \tag{21}$$

$$\text{CRR}=\frac{\text{Cost}_{\text{Rule-based}}-\text{Cost}_{\text{method}}}{\text{Cost}_{\text{Rule-based}}}\times 100\% \tag{22}$$

$$\text{PSR}=\frac{P_{peak}^{before}-P_{peak}^{after}}{P_{peak}^{before}}\times 100\% \tag{23}$$

$$\text{RUR}=\frac{\sum_{t=1}^{T}(P_t^{pv}+P_t^{wind}-P_t^{cur})}{\sum_{t=1}^{T}(P_t^{pv}+P_t^{wind})}\times 100\% \tag{24}$$

$$\text{CVR}=\frac{N_{vio}}{N_{total}}\times 100\% \tag{25}$$

N_{vio} here indicates the number of scheduling points where SOC boundaries are violated, charge/discharge power limits are exceeded, connections to the grid are made, or there is a charge/discharge conflict restriction and N_{total} is the total number of scheduling points. The battery degradation costs are estimated by an equivalent throughput model:

$$C^{deg}=c_{deg}\sum_{t=1}^{T}(P_t^{ch}+P_t^{dis})\,\Delta t \tag{26}$$

3.2. Comprehensive Experimental Results

A comparison of the general performance of different methods is shown in Table 1 on the test set. The table indicates that even though the rule-based method has the least computation time, it has the highest cost and the worst PSR and RUR values, which suggests that fixed rules cannot be easily adapted to changes in loads, fluctuating outputs of renewable energy, and changing electricity prices. MILP and MPC explicitly consider restrictions on operation of energy storage, which dramatically decrease costs relative to rule-based control, but MILP and MPC depend on manually developed optimization models and prediction curves. SP-MILP increases robustness as it uses a variety of operating conditions yet leads to significantly increased mean solution times. PSO and GA can solve nonlinear optimization problems, but it is relatively weak with respect to constraint processing and solution stability. DQN and PPO are very fast at online inference but have some limitations in CVR when faced with more complicated test conditions.

Figure 5 demonstrates that CGAI-ESO reaches optimal or almost optimal results in Cost, PSR, RUR, Cdeg, and CVR. Unlike rule-based approaches, CGAI-ESO saves 18.72% of Cost, gains 15.7 percentage points of PSR and 9.7 percentage points of RUR. In comparison to the MILP approach, CGAI-ESO saves 8.94% of Cost and adds 6.9 percentage points of PSR. Compared with the LLM-only strategy, CGAI-ESO minimizes the CVR of 2.12% down to 0.02% indicating that using generative AI alone to directly generate models and code can be associated with problems like the omission of constraints, insufficient definition of variables, or the unfeasibility of the approach.

Table 1. Overall performance comparison on the test set

Method	Cost/CNY	CRR/%	PSR/%	RUR/%	Cdeg/CNY	CVR/%	Time/s
Rule-based	12864.7	0.00	12.8	86.3	421.5	2.84	0.08
MILP	11483.2	10.74	21.6	91.4	386.7	0.04	4.72
SP-MILP	11026.4	14.28	23.8	92.7	378.4	0.03	13.58
MPC	11217.9	12.80	22.9	92.1	374.8	0.05	5.41
PSO	11846.5	7.91	19.3	89.5	405.6	1.37	18.42
GA	11935.8	7.22	18.7	89.1	411.3	1.61	24.36
DQN	11608.2	9.77	20.4	90.6	397.5	1.08	0.16
PPO	11394.6	11.43	22.1	91.8	389.2	0.74	0.19
LSTM-MPC	10972.8	14.71	24.6	93.2	371.6	0.04	6.85
LLM-only	11762.4	8.57	19.9	90.3	403.8	2.12	7.46
LLM-RAG	10894.7	15.31	25.2	93.6	365.1	0.32	8.94
CGAI-ESO	10456.3	18.72	28.5	96.0	347.9	0.02	9.67

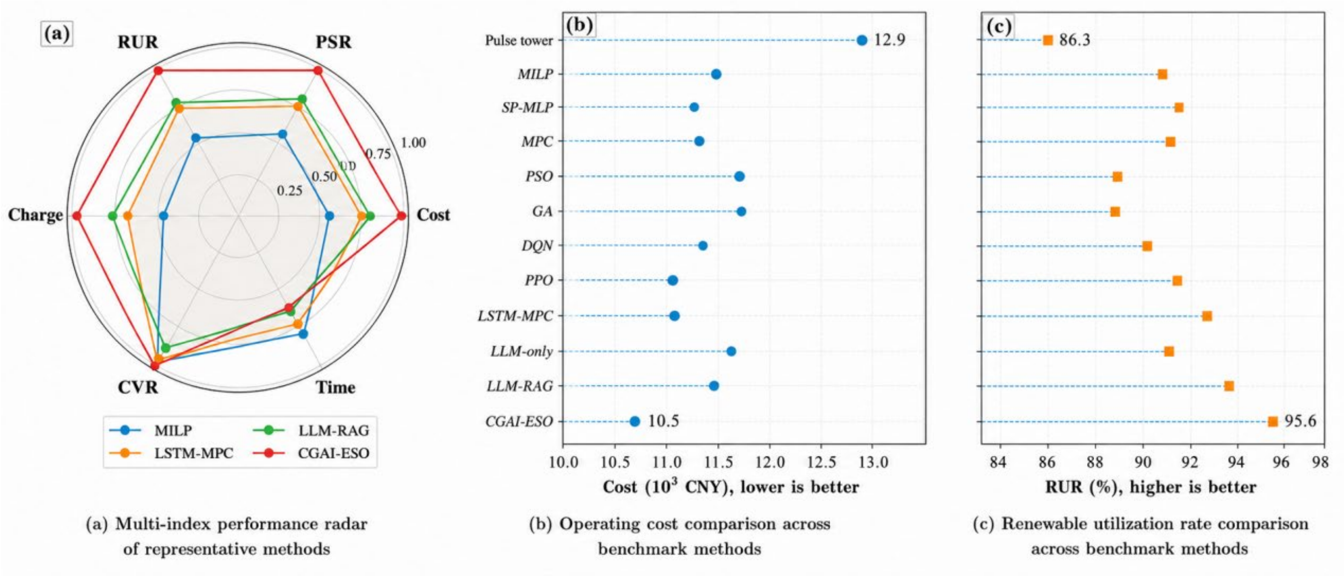


Figure 5. Multi-index comprehensive performance comparison between CGAI-ESO and typical methods

LLM-RAG shows much better performance than LLM-only, which means that integrating domain-specific knowledge into energy storage and optimizing implementation templates is a good way to improve the modeling reliability of generative AI. But its CVR is still 0.32% indicating that knowledge retrieval cannot be used as the sole strategy to guarantee the safety of policy implementation. Based on LLM-RAG, CGAI-ESO also incorporates digital twin assessment and a feedback loop control with which secondary validation of SOC exceedances, power limit breaches, battery degradation, and economic viability can be done prior to policy implementation, hence minimizing the CVR to 0.02%.

In order to further justify the strength of the different approaches in complex working environments, this paper creates five test conditions: under normal operation, high load, low renewable energy production, electricity price volatility, and extreme weather. This high-load scenario is achieved by adding 15 percent to the total load of the test set, whereas the low-renewable-output scenario consists of decreasing photovoltaic and wind energy generation by 20 percent, the electricity price volatility scenario includes 20 percent random perturbation of peak-hour rates, and the extreme weather scenario incorporates increased load, decreased renewable energy generation, and amplified peak-rate price perturbation. The costs of each method under these scenarios are shown in Table 2.

Figure 6 shows that CGAI-ESO has the lowest cost in all five scenarios, and its benefit is especially significant in the case of heavy load and severe weather. When it comes to extreme weather situations, CGAI-ESO saves 665.7 yuan over LSTM-MPC and 524.6 yuan over LLM-RAG, which confirms that the combination of scenario-aware policy generation and digital twin feedback control can greatly improve the model flexibility in response to complex operating conditions. The conventional MILP and MPC methods are found to be steady at normal operation but extremely sensitive to prediction errors and environmental perturbations as renewable energy production drops or load consumption spikes sharply, causing large cost escalations. Despite the fact that PPO shows a certain level of flexibility, its ability to generalize policies does not reach the level necessary to act in extreme conditions.

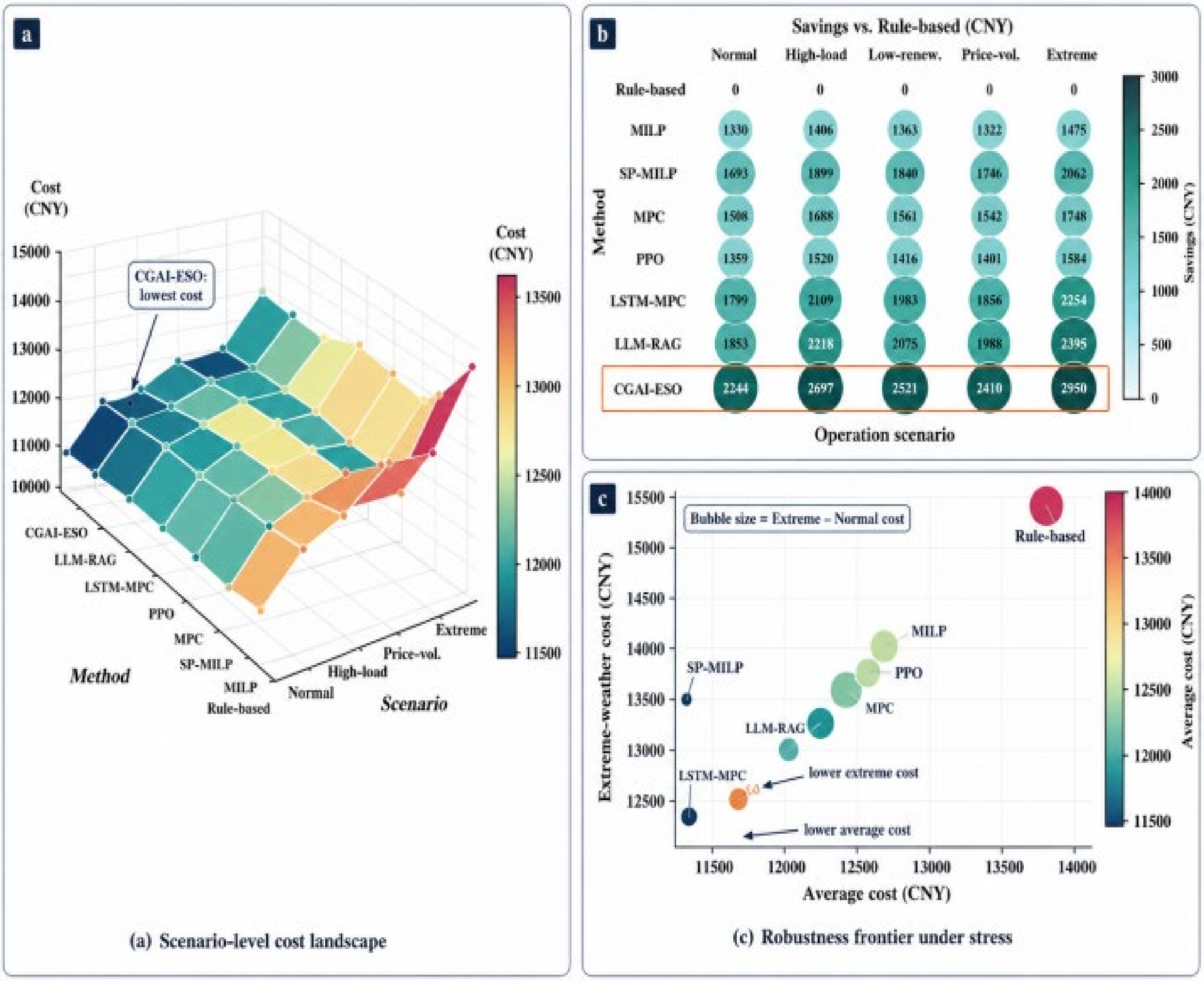


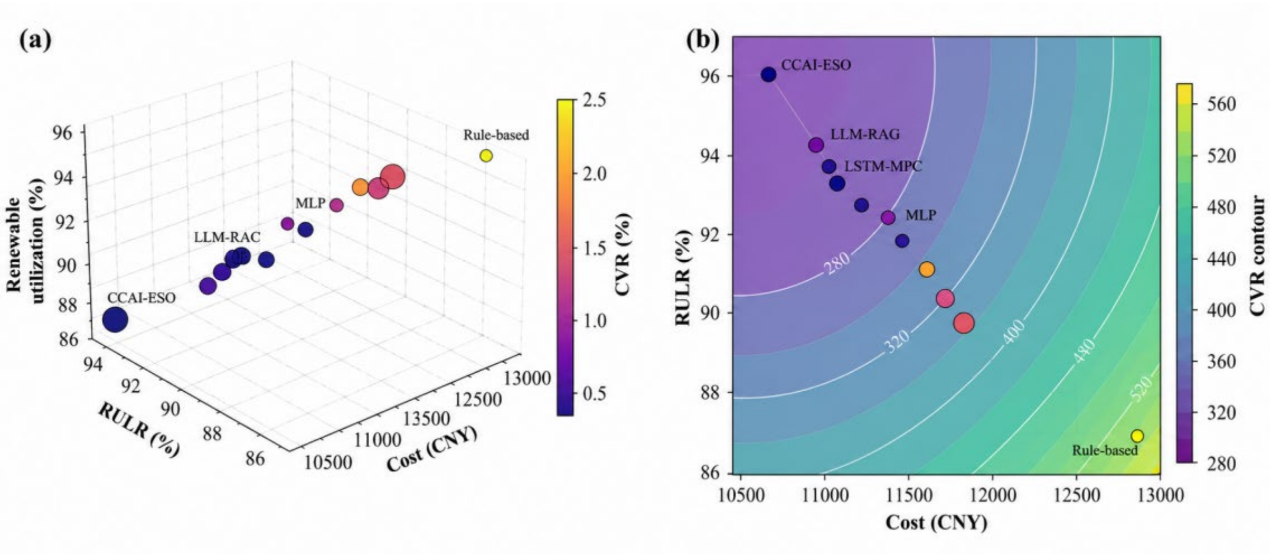
Figure 6. Robustness analysis of CGAI-ESO under different operating scenarios

The comparison of CVR of various methods in five scenarios is depicted in Table 3. It is clear that Rule-based, PSO, GA, DQN, PPO, and LLM-only all have some level of constraint violations which can be observed when SOC reaches the boundary, grid-connected power exceeds the limits, or cannot be resolved due to charge-discharge conflict constraints. Although LLM-RAG greatly minimizes CVR, slight violations are still recorded during high-load situations and extreme weather phenomena. CGAI-ESO has the least CVR of all the scenarios, with a constraint violation rate lower than 0.05 percent, which shows that constraint-enhanced optimization along with digital twin validation devices can indeed improve the safety of energy storage scheduling approaches. Figure 7 also illustrates the trade-off between operating cost, PSR, RUR, and CVR and indicates that CGAI-ESO performs more balanced than the benchmark methods.

Table 2. Cost under different operation scenarios

Method	Normal/CNY	High-load/CNY	Low-renewable/CNY	Price-fluctuation/CNY	Extreme-weather/CNY	Avg.Cost/CNY
Rule-based	12635.2	14582.6	13947.4	13284.5	15326.8	13955.3
MILP	11304.8	13176.3	12584.7	11962.1	13851.5	12575.9
SP-MILP	10942.5	12683.4	12107.9	11538.8	13264.6	12107.4
MPC	11126.7	12894.6	12386.2	11742.5	13579.3	12345.9

Method	Normal/CNY	High-load/CNY	Low-renewable/CNY	Price-fluctuation/CNY	Extreme-weather/CNY	Avg.Cost/CNY
PPO	11275.9	13062.1	12531.8	11883.6	13742.4	12499.2
LSTM-MPC	10836.4	12473.8	11964.6	11428.9	13072.5	11955.2
LLM-RAG	10782.1	12364.5	11872.8	11296.7	12931.4	11849.5
CGAI-ESO	10391.6	11885.2	11426.3	10874.9	12406.8	11397.0



(a) Three–dimensional trade-off among cost, renewable utilization, battery degradation, and CVR

(b) Cost–renewable-utilization contour projection with method distribution

Figure 7. Three-dimensional trade-off analysis of energy storage optimization methods

Table 3. CVR under different operation scenarios

Method	Normal/%	High-load/%	Low-renewable/%	Price-fluctuation/%	Extreme-weather/%
Rule-based	1.86	3.42	2.95	2.67	4.31
PSO	0.94	1.62	1.48	1.25	2.09
GA	1.16	1.83	1.62	1.38	2.31
DQN	0.71	1.24	1.07	0.96	1.58
PPO	0.42	0.83	0.71	0.65	1.08
LLM-only	1.37	2.46	2.08	1.89	2.81
LLM-RAG	0.21	0.38	0.34	0.27	0.52
CGAI-ESO	0.01	0.03	0.02	0.02	0.04

3.3. Ablation Experiment and Further Analysis

In order to determine the impact of every component module of CGAI-ESO on performance enhancement, the study came up with four ablation models which are CGAI-ESO without RAG (expert knowledge retrieval), CGAI-ESO without scenario generation (multiscenario candidate strategy generation), CGAI-ESO without digital twin feedback and CGAI-ESO without battery degradation cost. The outcomes of the ablation experiment are indicated in Table 4.

As it can be seen in Figure 8, the removal of RAG had a significant impact on the cost of the model, which increased, and CVR went up to 1.94 percent and CER decreased to 82.3 percent. It shows that the expert knowledge provided by the RAG is an important aspect of improving the quality of generative AI models. Generative AI without information about the operating principles of energy storage, constraint templates, and solver implementations is susceptible to problems like lack of complete variable definition, absence of SOC constraints, absence of charge-discharge conflict constraints, or non-executable code.

With elimination of the multi-scenario strategy generation, the model cost rose by 10,456.3 yuan to 10,983.7 yuan, and the RUR fell by 96.0 percent to 93.1 percent. It means that there is a single prediction scenario that is unable to fully reflect all the uncertainties related to load demand, production of renewable energy and electricity prices, but the scenario-aware mechanism can improve the strength of energy storage dispatching. The removal of digital twins feedback increased the CVR to 0.27% which shows that even with the use of optimization models alone there can be locally infeasible strategies when operating in a complex environment and simulation feedback allows secondary validation and optimization of strategies. After excluding battery degradation expenses, the overall expense had reduced by $10,294.8, yet the Cdeg had greatly risen up to 426.3, implying that only concentrating on short-term economic gains will worsen the degradation of the lifespan of the energy storage system over time.

Table 4. Ablation study of CGAI-ESO

Method	Cost/CNY	PSR/%	RUR/%	Cdeg/CNY	CVR/%	CER/%
w/o RAG	11694.5	20.6	90.7	401.6	1.94	82.3
w/o scenario generation	10983.7	24.9	93.1	365.8	0.18	96.4
w/o digital-twin feedback	10876.2	25.4	93.8	362.7	0.27	97.1
w/o battery degradation cost	10294.8	28.9	95.5	426.3	0.04	98.5
CGAI-ESO	10456.3	28.5	96.0	347.9	0.02	98.8

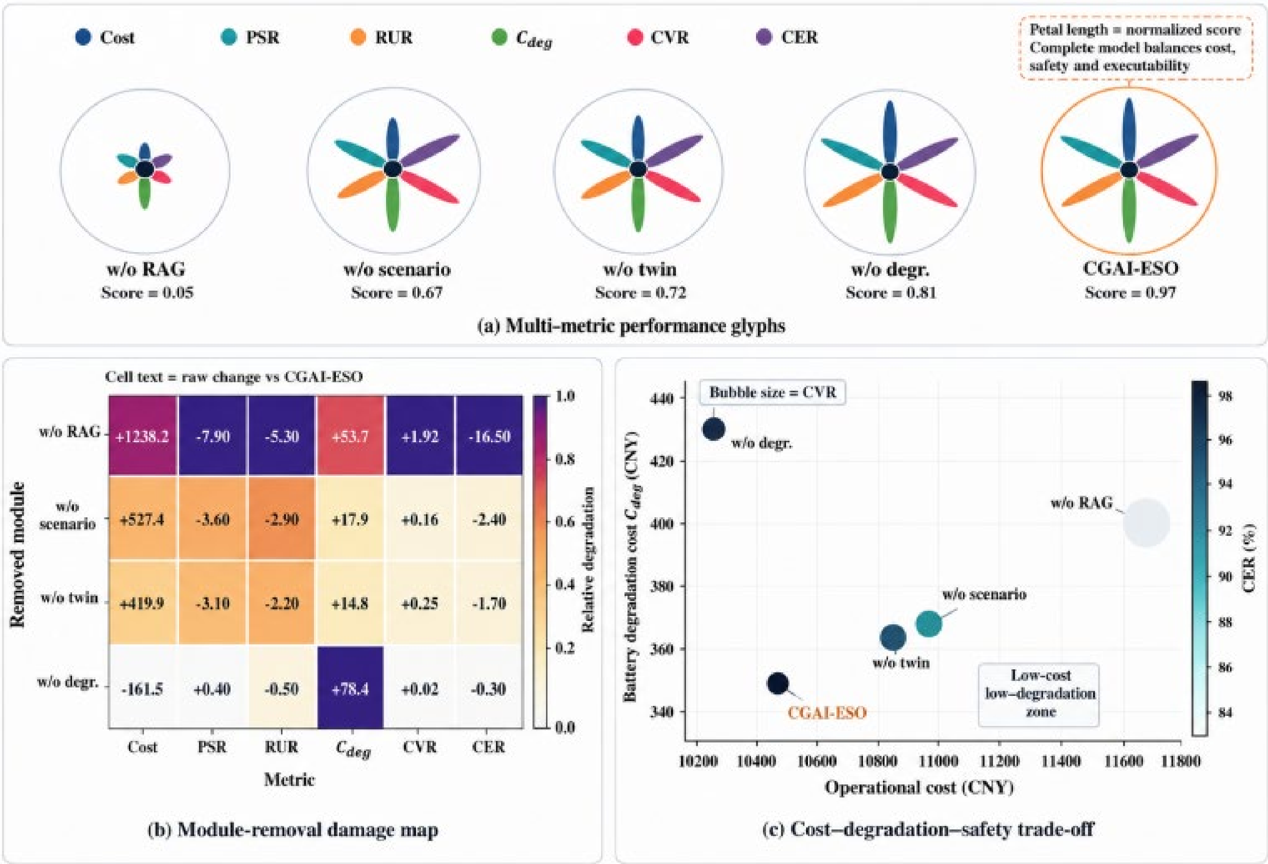


Figure 8. Ablation experiment results of key modules in the CGI-ESO model

In order to confirm the soundness of generative AI in optimization modeling problems, there are 200 sets of natural language optimization requests created by this study involving five types of requests, namely, cost priority, lifespan priority, reliability priority, new energy integration priority, and comprehensive balance. The measures that were used in evaluation were: success rate of model generation, rate of variable completeness, rate of constraint completeness, CER and average number of revision rounds. CER is described as:

$$CER=\frac{N_{exec}}{N_{total}}\times 100\% \tag{27}$$

In this case, N_{exec} refers to the number of requests that were successfully creating and running the optimized code, and N_{total} is the total number of requests. Comparison of modeling capabilities of different generative AI methods is given in Table 5.

Illustration 9 shows that CGAI-ESO performs better than LLM-only and LLM-RAG in terms of model generation success rate, variable completeness, constraint completeness, and CER. Although LLM-only has elementary natural language understanding and code generation abilities, it is likely to miss important variables and constraints when dealing with sophisticated engineering demands. Though LLM-RAG enhances the quality of the generated results significantly by retrieving knowledge, it does not have execution result validation and simulation feedback. Utilizing a closed-loop process of knowledge retrieval - optimized modeling - code execution - digital twin feedback, CGAI-ESO also decreases the percentage of unexecutable models and impractical strategies.

The paper also specifies three standard cases of user preferences that will be used to assess the personalized scheduling properties of CGAI-ESO. Cost-first mode: cost minimization is the highest priority, lifespan-first mode: minimizing the number of battery depth cycles and large SOC changes are the main priorities, and renewable energy integration-first mode: improving RUR is the goal. The results of optimizations in each case of preferences are shown in Table 6.

Table 5. Generative optimization modeling capability comparison

Method	Model generation/%	Variable completeness/%	Constraint completeness/%	CER/%	Revision rounds
LLM-only	84.5	81.7	76.2	78.9	2.41
LLM-RAG	94.8	93.1	91.6	94.2	1.27
CGAI-ESO	98.6	97.9	96.8	98.8	0.64

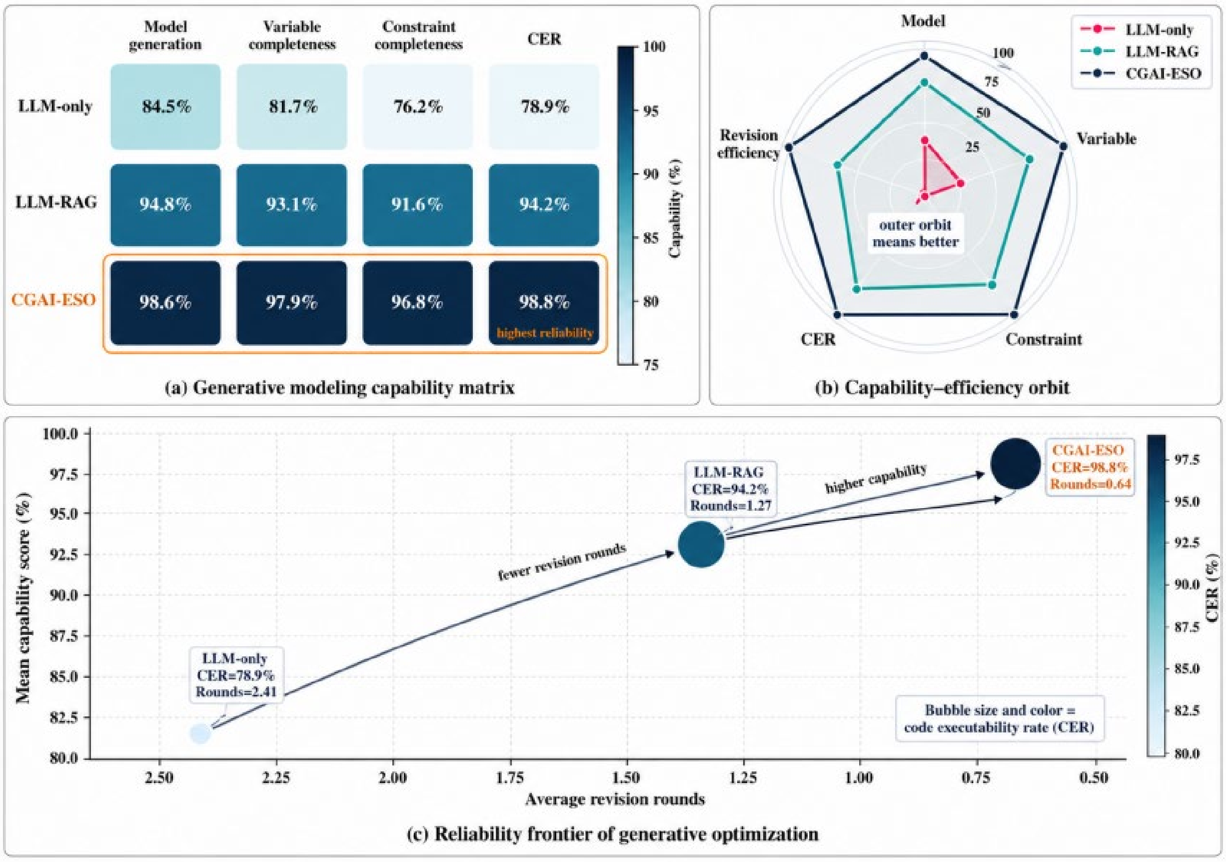


Figure 9. Comparison of generative AI's modeling optimization capabilities

Table 6. Optimization results of CGAI-ESO under different Puser settings

Puser setting	Cost/CNY	Cdeg/CNY	RUR/%	PSR/%	SOC fluctuation
Cost-priority	10184.6	386.2	94.1	27.6	0.214
Lifetime-priority	10876.3	318.4	93.5	25.9	0.136
Renewable-priority	10642.8	352.7	97.4	28.1	0.188
Balanced	10456.3	347.9	96.0	28.5	0.171

As illustrated by Figure 10, CGAI-ESO automatically computes objective function weights depending on user preferences and delivers personalized scheduling solutions. With Cost-Priority mode, the model focuses on exploiting the peak-valley electricity price difference as a way of reducing the costs which leads to the lowest cost with large SOC values and higher Cdeg. Lifetime-Priority mode minimizes the number of deep charging/discharging cycles, and minimizes SOC fluctuations to 0.136; this results in the lowest Cdeg. The model increases the capability of energy storage to store PV and wind power output in Renewable-Priority mode, where the RUR attained is 97.4%. Balanced mode is the one that balances the cost, PSR, RUR, and Cdeg in a balanced manner.

To sum up, the experiment findings prove that CGAI-ESO has benefits in addition to reducing costs, but in many areas such as CVR, strategy robustness, CER, and user preference flexibility. In comparison with the traditional mathematical optimization techniques, CGAI-ESO minimizes the use of manual models; in comparison with intelligent optimization and reinforcement learning strategies, it is more efficient in terms of incorporating safety constraints of the energy storage system; and in comparison with traditional generative AI strategies, it integrates RAG expert knowledge and digital twin feedback which greatly decreases model artifacts and strategy infeasibility risks. Thus, CGAI-ESO is especially appropriate in operational strategy optimization problems of energy storage systems with complex constraints, multi-objective targets and interactive optimization needs.

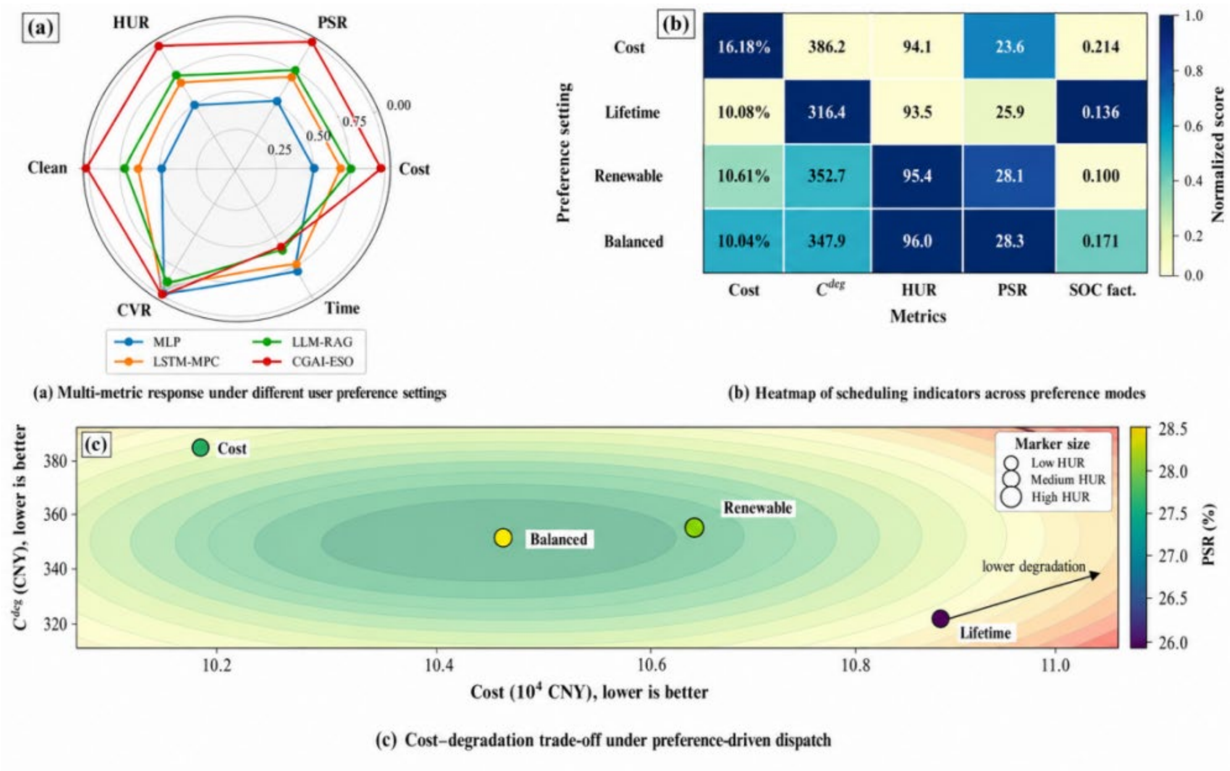


Figure 10. Response of energy storage scheduling strategies under different user preferences

3.4. Typical Scheduling Behaviors and Parameter Sensitivity Analysis

In order to also illustrate the energy storage dispatching behavior of CGAI-ESO, this paper provides the normal daily dispatch outcomes and parameter sensitivity evaluation due to overall performance comparison. The graph in Figure 11 shows the changes in the load, photovoltaic (PV), wind power, energy storage charging/discharging power and State of Charge (SOC) throughout a 24-hour period of operation.

This fact is clear that the highest PV generation occurs in the daytime midday period, when CGAI-ESO focuses on energy storage charging to increase the use of renewable energy and reduce the risk of curtailing solar power; in the evening peak demand times, the energy storage system switches to discharge mode, which relieves the pressure on grid power purchases and enhances peak shaving performance. During the entire dispatch procedure, SOC stayed within permissible limits with little fluctuations, which indicates that CGAI-ESO can strike a balance between the integration of renewable energy, peak shaving needs, and the limitation of operational costs and meet the safety conditions of energy storage.

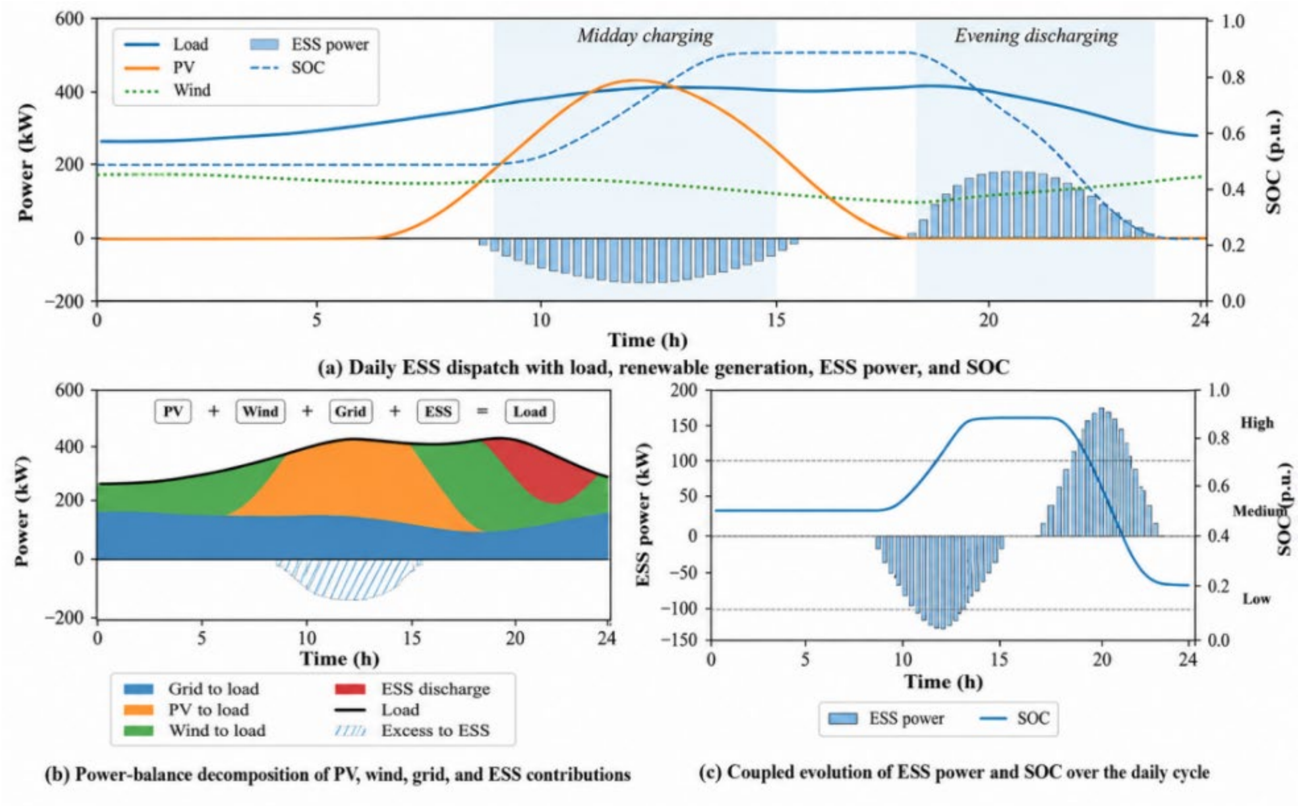
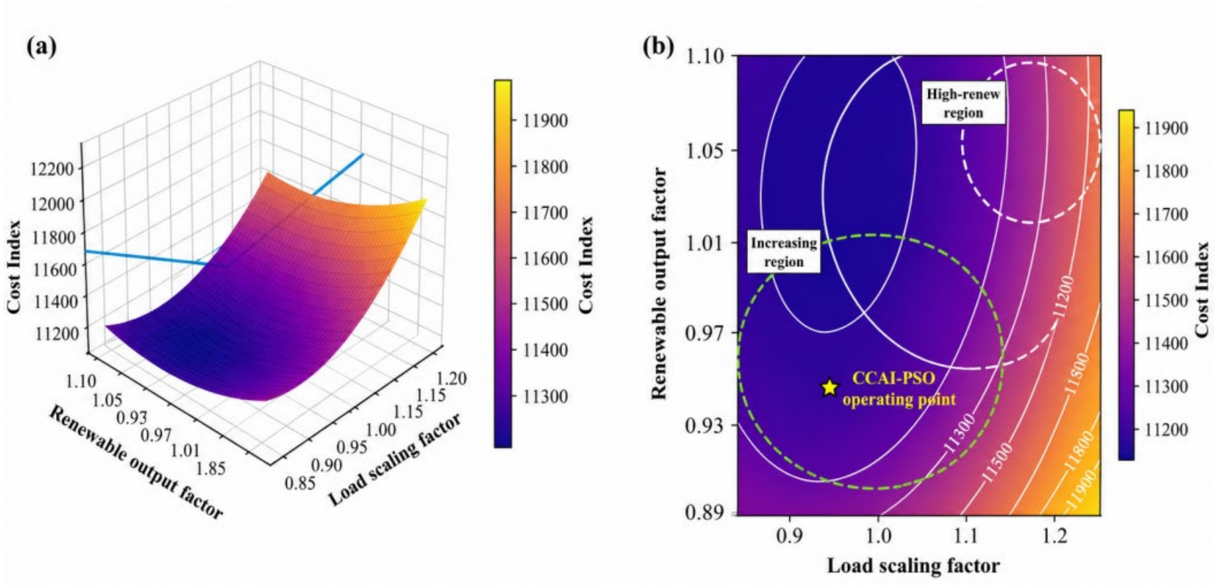


Figure 11. Sensitivity analysis of operating costs under load and new energy disturbances

Figure 12 also helps to illustrate how load variations and changes in output of renewable energy affect operating costs. The load scaling factor represents a growth or reduction in load demand whereas renewable energy output factor denotes improvements or decreases in photovoltaic and wind power production. As illustrated in Figure 12, with an increase in load demand and a decrease in renewable energy output, the system becomes more dependent on grid electricity purchase which causes a sharp rise in operating costs; alternatively, in case of low load pressure and high renewable energy output, the energy storage system is capable of better usage of renewable energy and thus, the operating costs are relatively less. The normal operating point as shown in the figure is in the area of low cost, showing that CGAI-ESO has high flexibility to changes in loads and renewable energy output.



(a) 3D operating cost surface under load and renewable output variations

(b) Operating cost contour map with representative operating regions

Figure 12. Sensitivity analysis of operating costs under load and new energy disturbances

4. Conclusion

The present paper suggests a generative artificial intelligence model of energy storage operation strategy optimization with constraint enhancement, that is, CGAI-ESO. The combination of natural language requirement parsing, RAG-based expert knowledge retrieval, automated optimization model creation, executable code generation, solver invocation and digital twin feedback enables providing an intelligent and verifiable answer to the problem of energy storage planning in the face of complex engineering constraints.

As demonstrated by the experimental findings, CGAI-ESO demonstrates superior overall performance over rule-based control, mathematical optimization, intelligent optimization, DRL-based approaches, LLM-only modeling, and LLM-RAG modeling. CGAI-ESO has lower operating cost (by 18.72%) compared to rule-based control, higher PSR (28.5) and RUR (96.0), and lower CVR (0.02). When performing generative optimization modeling problems, CGAI-ESO has a model generation success rate of 98.6 per cent, a constraint completeness rate of 96.8 per cent, and a CER of 98.8 per cent, which means that RAG knowledge augmentation and digital twin feedback may be used to effectively mitigate the omission of constraints, non-executable code, and unfeasible scheduling strategies. The robustness experiments also prove that CGAI-ESO can sustain an operating cost level of less than 0.05% when it experiences high load, low renewable output, electricity price fluctuations and extreme weather conditions. The results of ablation indicate that the retrieval of expert knowledge, scenario-aware strategy generation, digital twin validation, and battery degradation modeling are all factors to improve economic performance, safety compliance, robustness, and reliable operation over long-term.

Nonetheless, there are multiple drawbacks of this work. Firstly, the experimental setup was built based on publicly available energy data and simulation of microgrids, and the suggested approach has not been entirely tested in a physical energy storage microgrid or an operational industrial power system. Secondly, CGAI-ESO reliability is affected by the thoroughness and correctness of the RAG knowledge base, solver templates, scenario-generator settings, and the quality of input data. Thirdly, even though CGAI-ESO increases the reliability of the models and feasibility of the strategies, the mean solution time it needs is greater compared to the rule-based control and some reinforcement learning algorithms, which might make it less deployable in ultra-fast real-time scheduling environments. Fifth, the current experiments have a single fixed LLM backbone. Since model capability, context length, decoding behavior, and code-generation reliability will differ between LLMs, the absolute performance of LLM-only, LLM-RAG, and CGAI-ESO would be different depending on the chosen backbone; cross-

LLM validation is thus necessary before concluding model-independent improvements.

The future work ought to be done towards field validation of real energy storage system, updating the RAG knowledge base online, integration of more detailed battery degradation and thermal safety models, and extension to multi-energy microgrids with hydrogen storage, electric vehicles, and demand response and distributed renewable resources. Also, uncertainty quantification, cybersecurity limitations, data interaction that preserves privacy, and edge-cloud collaborative implementation needs to be added to enhance the engineering applicability, scalability, and reliability of generative AI-based energy storage operation optimization.

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