Research on Coordinated Optimization Control Strategies for Multi-energy Storage System

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Abstract: This paper studies the coordinated optimization control strategy of multi-energy storage system (MESS), especially improving the energy utilization efficiency and economic benefits of the system through model predictive control (MPC) and intelligent algorithm optimization methods. With the rapid development of renewable energy and smart grids, how to efficiently dispatch various energy storage devices has become a key issue. The paper analyzes the advantages and disadvantages of centralized and distributed control strategies, and proposes to optimize the collaborative scheduling of energy storage equipment through the multi-agent system (MAS). The simulation results show that distributed control performs better than centralized control in terms of energy loss, economic benefits and system stability. The distributed control strategy can significantly reduce the total energy loss and improve economic benefits. Finally, the research points out that in the future, the control strategy should be further optimized to enhance the robustness and adaptability of the system in order to cope with the challenges in complex dynamic environments.

Keywords: Multi-energy Storage System; Distributed Control Strategy; Energy Storage Equipment; Energy Utilization

1. Introduction

Multi-energy storage system (MESS) is increasingly widely applied in modern power systems, especially against the backdrop of large-scale access to renewable energy, the popularization of smart grids and electric vehicles. MESS achieve system optimization, improve energy utilization efficiency and reduce costs by coordinating different types of energy storage devices (such as battery energy storage, supercapacitors, flywheel energy storage, etc.). However, due to the diversity and complexity of energy storage technologies, their coordinated optimization control strategies have become one of the current research hotspots.

The coordinated optimization problem of multiple energy storage systems involves the application of various control methods. Zhao et al. [1] proposed a coordinated optimization method based on Model Predictive Control (MPC) by constructing a dynamic optimization model of MESS, aiming to minimize system costs and losses by real-time prediction and adjustment of the charging and discharging strategies of each energy storage device. Wang et al. [2] studied the optimization-based control strategy, combining the Particle Swarm Optimization Algorithm (PSO) and Support Vector Machine (SVM), and proposed a multi-objective optimization energy storage scheduling method to improve the efficiency of MESS. With the development of intelligent technology, more and more studies have applied machine learning methods to the optimal control of MESS. Li et al. [3] proposed an energy storage optimization control method based on deep learning. By training a neural network model to predict load demand and optimize the charging and discharging strategies of energy storage equipment, the accuracy of energy management and system efficiency can be improved. This method can respond quickly in a dynamic environment and effectively solve the limitations of traditional methods when dealing with nonlinear and uncertain problems.

In the coordinated control of MESS, the handling of constraint conditions has always been an important issue. Zhang et al. [4] conducted a detailed modeling of the MESS, considering multiple constraints such as the charging and discharging efficiency, capacity limit, and response time of the energy storage equipment, and proposed a control strategy based on constraint optimization. This strategy can effectively balance the scheduling and coordination among different energy storage devices and optimize the global energy efficiency. Khan et al.[5] proposed an optimization method based on cooperative game theory for the coordinated control problem in distributed energy storage systems. This method achieves the optimal coordination of the entire system by constructing a game model, enabling each energy storage device to make decisions based on its own needs and goals. This method avoids the computational bottleneck in the traditional centralized control method and improves the response speed of the system. In addition, considering the dynamic characteristics of MESS, researchers have also made many contributions to the stability and robustness of the systems. Chen et al. [6] adopted the robust control method to study the stability problem of MESS under uncertain conditions such as grid load fluctuations and energy storage equipment failures. Xu et al. [7] proposed a method based on Life Cycle Analysis (LCA), combined with environmental costs and economic benefits, to optimize the scheduling of MESS, aiming to reduce the carbon emissions and environmental impact of the systems. This method not only takes into account the economy of the system, but also takes into account the sustainable development goals, providing a new idea for the optimization of future MESS.

To sum up, although a large number of studies have proposed coordinated optimization control methods for MESS, there are still many challenges in aspects such as the complexity of system modeling, the computational requirements of real-time control, and the coordination strategies of different energy storage devices. Therefore, future research should continue to explore how to combine intelligence, distributed control and optimization algorithms to enhance the performance and reliability of MESS in practical applications.

2. Design of Control Strategies

In the coordinated optimization control problem of multi-energy storage systems, the core objective is to achieve the optimization of system performance through reasonable control strategies. This includes but is not limited to maximizing energy utilization efficiency, reducing operating costs, and enhancing the stability and reliability of the system. With the rapid development of renewable energy, especially the volatility and uncertainty of solar and wind energy, how to efficiently schedule multiple energy storage devices to cope with load changes and the uncertainty of energy supply has become an urgent problem to be solved. multi-energy storage systems typically incorporate various types of energy storage devices (such as batteries, supercapacitors, flywheels, etc.), each with distinct charging and discharging characteristics, response speeds, and efficiencies [8]. Therefore, how to coordinate the working states of these devices to ensure the high efficiency and stability of the overall system operation is one of the core issues in this field of research. In addition, multi-energy storage systems need to maintain high operational reliability under various operating scenarios (such as grid failures, load fluctuations, or malfunctions of energy storage devices), avoiding risks like over-discharge or overcharging, and ensuring the safety and long-term stable operation of the system [9-11]. The coordinated and optimized control strategy of multiple energy storage systems is the key to ensuring their efficient operation. Due to the differences among various types of energy storage devices in terms of performance, response time, energy conversion efficiency, etc., how to design an appropriate coordinated and optimized control strategy to enable each energy storage device to work collaboratively at the entire system level is an important topic in current research. The design of control strategies must take into account the complexity of multi-energy storage systems, including the dynamic characteristics of the system, the coordination among various devices, system constraints, and changes in the external environment, etc. This section will introduce three main control strategies: model-based optimization control strategy, intelligent algorithm-based optimization control strategy, and distributed control-based coordination strategy. Each strategy will be combined with actual models and algorithms to analyze its application in multi-energy storage systems.

2.1 Model-based Optimization Control Strategy

The model-based optimization control strategy is to conduct system scheduling and optimization through dynamic modeling of multi-energy storage systems, combined with real-time data and system models. The most common models include linear models, nonlinear models and optimization-based scheduling models. MPC is one of the most widely used strategies in this type of method. The basic idea of MPC is to predict future behaviors through the dynamic model of the system and solve for the optimal control input within each control cycle. The MPC control strategy is usually divided into three main steps:

2.1.1 System modeling

Establishing a mathematical model based on the physical characteristics of the system, such as the charging and discharging characteristics of energy storage devices and energy conversion efficiency. Assuming that the charging and discharging processes of energy storage devices conform to certain dynamic equations, the state space model is usually adopted for representation:

$$x(k+1) = Ax(k) + Bu(k) \tag{1}$$

Among them, $x(k)$ represents the system status, such as the battery level of energy storage devices, charging and discharging power, etc. $u(k)$ represents the control input, that is, the charging and discharging power of the energy storage device.

2.1.2 Optimization objectives and constraints

Setting the optimization objective function, such as minimizing the total energy loss of the system, maximizing economic benefits or improving system stability. The common objective functions are:

$$J = \sum_{k=0}^{N} (\cos t(x(k),u(k)) + \lambda \cdot penalty(u(k))) \tag{2}$$

Constraint conditions include capacity limitations of energy storage devices, charging and discharging rate limitations, energy conversion efficiency, etc. Formally, they are:

$$Capacity \le x(k) \le MaxCapacity \tag{3}$$

$$Min/MaxChargingPower \le u(k) \le MaxChargingPower \tag{4}$$

2.1.3 Optimization solution

The existing optimization algorithms (such as linear programming, nonlinear programming or dynamic programming) are utilized to solve the optimal control input and applied to the next time step. The key to this process lies in how to solve optimization problems quickly and accurately, especially in large-scale systems.

The MPC method continuously adjusts the dispatching strategy of energy storage devices by updating the system status and optimization objectives in real time (as shown in Figure 1). In order to improve the computational efficiency, heuristic optimization algorithms (such as particle swarm optimization and genetic algorithm) are often adopted to accelerate the optimization process. These algorithms can search for the global optimal solution more efficiently and avoid the trouble of local optimal solutions.

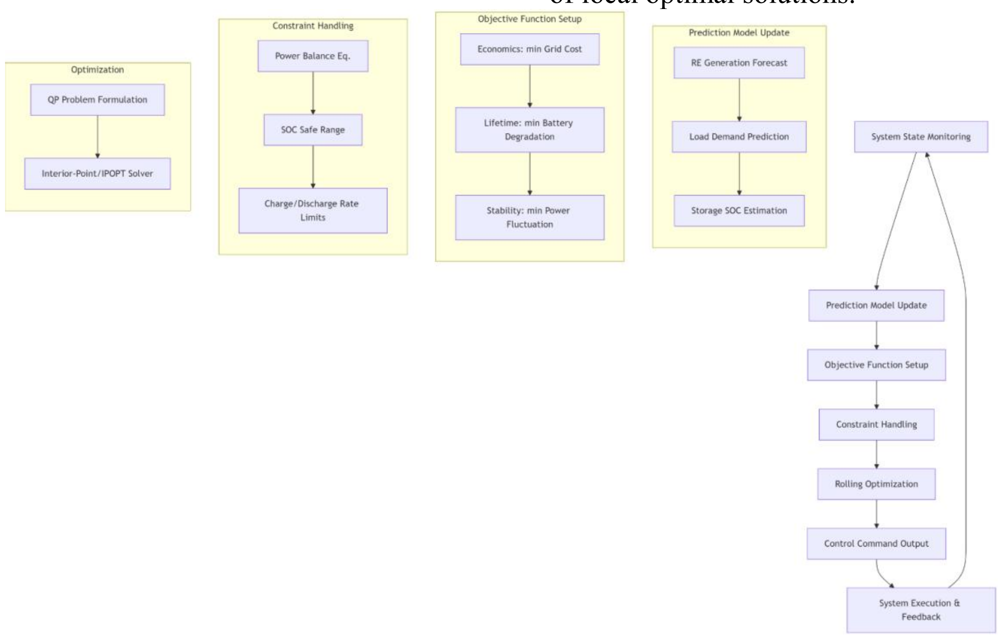

Figure 1. MPC Scheduling Flowchart

2.2 Optimization Control Strategy Based on Genetic Algorithm

Intelligent algorithms provide efficient tools for handling complex problems by simulating the evolutionary process in nature or swarm intelligence. Compared with traditional optimization algorithms, intelligent algorithms have a stronger global search ability and can effectively avoid getting trapped in local optimal solutions. Therefore, they are widely used in the optimal scheduling of multi-energy storage systems. Genetic algorithms search for the optimal solution by simulating the evolutionary processes of organisms (selection, crossover, mutation, etc.). In the scheduling problem of multi-energy storage systems, the main steps of the genetic algorithm are as follows:

Encoding and initial population generation: Firstly, encode each scheduling parameter of the system (such as the charging and discharging power, operating time, etc. of each energy storage device) as chromosomes. The initial population randomly generates several sets of solutions as the starting point of the search.

Selection operation: By calculating the fitness of each chromosome (i.e., the objective function value), individuals with higher fitness are selected for reproduction.

Crossover and mutation: Perform crossover and mutation operations on the selected individuals to generate new populations. These two operations simulate the recombination and mutation of genes, enhancing the diversity of the search space.

Termination condition: When the predetermined maximum number of iterations is reached or a certain convergence condition is met, the algorithm stops and outputs the optimal energy storage device scheduling scheme.

2.3 Coordination Strategy Based on Distributed Control

The distributed control strategy achieves the optimization of the entire system by allocating the control tasks in the system to each energy storage device and utilizing local information and self-decision-making capabilities. Compared with centralized control, distributed control has higher scalability and robustness, and can effectively reduce communication costs and improve the flexibility of the system. In distributed control, the coordination among energy storage devices is often achieved through multi-agent systems (MAS). multi-energy storage systems typically consist of multiple energy storage devices, each with distinct performance characteristics such as charging and discharging efficiency, maximum charging and discharging power, and storage capacity. How to coordinate various energy storage devices to optimize the operation of the entire system is an important issue in distributed control. Under the framework of MAS, the application of distributed control strategies can achieve the following goals.

2.3.1 Optimizing the dispatching of energy storage equipment

In a MESS, each energy storage device can be regarded as an agent, responsible for making decisions based on its own state, demands and environment. Through the collaborative mechanism of MAS, agents can exchange information with each other, understand the overall load of the system, equipment status and other information in real time, and thereby optimize the charging and discharging strategies of each device. The goal of each energy storage device is to maximize its own benefits, for instance, by making the most of the price difference in the electricity market to achieve economic benefits, while ensuring that it does not exceed the constraints such as the maximum charging power and battery capacity of the device.

For instance, suppose there are multiple energy storage devices in the system. Each device can choose to charge, discharge or be in standby mode, and each device makes decisions based on its own status and market demand. Through the MAS model, each energy storage device (agent) will execute a local optimal strategy and collaborate with other agents by sharing information, ultimately achieving global optimal scheduling.

2.3.2 Load forecasting and demand response

The dispatching of multi-energy storage systems not only depends on the characteristics of the equipment itself, but also needs to take into account the external load demand and changes in the power market. Under the framework of MAS, each agent can make predictions based on historical load data and formulate appropriate response strategies. For instance, when it is predicted that the load demand will increase, the system can activate more energy storage devices for charging, and when the demand decreases, the system can choose to discharge the energy storage devices to balance the power supply and demand.

The advantage of MAS lies in that each agent can make adaptive adjustments based on local demand information instead of relying on a central control system, thereby avoiding bottlenecks in the information transmission and decision-making process. Furthermore, MAS can cope with changes in the external environment (such as fluctuations in electricity market prices, fluctuations in electricity demand, etc.), respond quickly, and enhance the flexibility and robustness of the system.

2.3.3 Coordination and game theory

In multi-energy storage systems, there may be resource competition and target conflicts among multiple energy storage devices. For instance, multiple energy storage devices may compete for the same charging resources or profits in the electricity market. To coordinate the behaviors of these devices, MAS can introduce game theory models. Game theory helps each agent optimize based on the decisions of other agents by setting the strategy space and payment function, and ultimately reaches an equilibrium state. The application of game theory can be divided into two categories: cooperative games and non-cooperative games. In cooperative games, various agents reach a consensus strategy through negotiation and information sharing, thereby maximizing the overall benefits. In non-cooperative games, each agent makes decisions based on its own benefits. Eventually, the Nash equilibrium state is reached through the game, that is, each agent selects the optimal strategy, and no agent can obtain higher returns by unilaterally changing the strategy.

3. Simulation and Verification

In the research and application of multi-energy storage systems, simulation and verification are important means to test the effectiveness of control strategies. Through simulation tests, the operation of the system can be simulated based on actual data (such as load demand, energy price fluctuations, etc.) to evaluate the performance of different control strategies, especially the advantages and disadvantages of distributed control and centralized control. In this study, we adopted simulation tools such as Matlab/Simulink to implement the control strategy of the MESS and conduct performance verification.

3.1 Simulation Environment and Model Establishment

The simulation environment is usually established on the basis of a known system dynamic model, including factors such as the charging and discharging characteristics of energy storage devices, load requirements, energy prices, and control constraints. We established the simulation environment through the following steps:

3.1.1 Energy storage system model

The energy storage system is composed of multiple different types of energy storage devices (such as batteries, supercapacitors, flywheels, etc.), each of which has different parameters such as charging and discharging power limits, maximum capacity, and charging efficiency. The system model takes into account the interactions among various devices and uses the state space model for dynamic description:

$$x(k+1) = Ax(k) + Bu(k) \tag{5}$$

Among them, $x(k)$ represents the state of the energy storage system at time at time k, $u(k)$ is the control input, that is, the charging and discharging power of each energy storage device, and A and B are the state transition matrix and control matrix of the system respectively.

3.1.2 Load demand and energy price model

In order to be closer to practical applications, load demand and energy price fluctuations are factors that cannot be ignored in the system. Load requirements are usually simulated based on actual load data and are typically modeled using time series prediction models. The fluctuation of energy prices simulates the pricing mechanism of the electricity market and predicts the future trend of price changes based on historical data of market prices.

In the simulation, the load demand and energy price are passed into the control system as input signals to test the performance of different scheduling strategies in the face of different market environments and load fluctuations.

3.1.3 Control strategy model

We conducted simulation verification on two control strategies: centralized control and distributed control (based on Multi-agent System MAS). Centralized control usually involves a single central controller making all decisions, while distributed control makes decisions through multiple agents (energy storage devices). These agents exchange information through communication to jointly optimize the overall benefits of the system.

3.2 Simulation Results and Performance Comparison

3.2.1 Simulation settings

To compare the advantages and disadvantages of centralized and distributed control strategies, we have designed the following simulation Settings:

Simulation time: 24 hours (a complete power load cycle)

Number of energy storage devices: 5 energy storage devices (batteries, supercapacitors, flywheels, etc.)

Load demand fluctuation: Simulate a typical 24-hour load demand curve, including morning rush hour, evening rush hour and off-peak hours.

Energy price fluctuations: Modeling based on historical electricity market price data to simulate price fluctuations.

3.2.2 Control strategy 1: centralized control

In centralized control, the scheduling of all energy storage devices is determined by a central controller. The central controller monitors the global status in real time (i.e., the status information and load demand of all energy storage devices), and generates dispatching instructions based on the optimization objective function (such as minimizing total energy loss or maximizing economic benefits). Suppose the objective function is:

$$J = \sum_{k=0}^{N} (C_{total}(x(k),u(k)) + \lambda \cdot P(u(k))) \quad (6)$$

Among them, $C_{total}(x(k),u(k))$ is the total cost of the system, and $P(u(k))$ is the penalty term for controlling the input.

3.2.3 Control strategy 2: distributed control (MAS)

In distributed control, energy storage devices participate in the decision-making process as agents. Each energy storage device selects its own charging and discharging strategy based on local information and communication with other devices. The goal of each agent is to maximize its own benefits and achieve the optimization of the overall goal through cooperation and competition with other agents. The optimization model is:

$$u_i^*(k) = \arg\min (J_i(x_i(k),\ k_i(k))) + \lambda \cdot P_i(u_i(k)) \quad (7)$$

Among them, $J_i(x_i(k),\ k_i(k))$ are the local cost functions of the energy storage device i , $P_i(u_i(k))$ is the penalty for the control input that does not conform to the constraints.

3.3 Simulation Result Analysis

3.3.1 Comparison of total energy loss

The simulation results show that when the distributed control strategy (MAS) is adopted, the total energy loss of the system is reduced by approximately 12% compared with the centralized control strategy. The specific data are shown in **Table 1**.

Table 1. Comparison of Total Energy Losses of Two Control Strategies

Control strategies	Total energy loss (kWh)	Energy loss saved (%)
Centralized control	45.6	-
Distributed control strategy (MAS)	40.1	12%

As can be seen from Table 1, the distributed control strategy can effectively reduce the total energy loss. This is mainly attributed to the coordination and optimization of each energy storage device, enabling the energy storage devices to allocate charging and discharging tasks more reasonably during different load demand periods.

3.3.2 Comparison of economic benefits

Considering the impact of energy price fluctuations, distributed control strategies also perform well in optimizing economic benefits. When distributed control is adopted, the system can charge when the electricity price is low and discharge when the electricity price is high, thereby maximizing economic benefits. The specific data are shown in **Table 2**.

Table 2. Comparison of Economic Benefits of Two Control Strategies

Control strategies	Total economic benefit (USD)	Enhanced economic benefits (%)
Centralized control	120	-
Distributed control strategy (MAS)	138	15%

Table 2 shows that distributed control can not only reduce energy loss but also improve the

economic benefits of the system by 15%.

4. Conclusion

Simulation tests show that the distributed control strategy (MAS) has significant advantages over centralized control. Distributed control can not only effectively reduce energy loss and improve the economic benefits of the system, but also maintain the stability of the system when dealing with load fluctuations and changes in market prices. Through simulation and verification, we have verified the effectiveness of the proposed control strategy in multi-energy storage systems, providing strong support for practical applications. Future research can further optimize the communication mechanism of MAS, reduce the delay of information transmission, and introduce more dynamic factors (such as environmental changes, equipment failures, etc.) at the same time, making the control strategy more robust and adaptive.

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