

## Article

# A Hierarchical Distributed Method for Source-Grid-Load-Storage Coordinated Power and Energy Balance in Distribution Networks

Jingyu Liu <sup>1</sup>, Zhe Ming <sup>1,\*</sup>, Hongyun Shi <sup>1</sup>, Haihong Zhang <sup>1</sup> and Zifa Liu <sup>2</sup>

<sup>1</sup> Daqing Huanghe Photovoltaic-Storage Demonstration Research Co., Ltd., Daqing 163000, China; qoi8y8iop@126.com (J.L.); 18256491418@163.com (H.S.); 13950979130@163.com (H.Z.)

<sup>2</sup> School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 100000, China; tjubluesky@163.com

\* Correspondence: yx29916@163.com

## Abstract

The integration of distributed energy resources into modern multi-energy distribution networks introduces complexity, necessitating effective coordinated control to maintain stability. This study proposes a hierarchical distributed control strategy combining distributed autonomy with centralized coordination. A “self-balancing and self-smoothing” tie-line power control method is introduced for small-scale networks, while a coordinated optimization model is established for regional networks, solved using the Evolutionary Particle Swarm Optimization (EPSO) algorithm. Simulation results based on a real-world Zhejiang distribution network demonstrate that the proposed method effectively regulates power fluctuations. Compared to centralized optimization, the hierarchical approach reduced total system operating costs and exhibited improved computational scalability as the number of distributed entities increased. The proposed method achieves economic optimality for various stakeholders and enhances the operational efficiency of “Source-Grid-Load-Storage-Heat” systems, providing a robust solution for energy complementarity in new power systems.

**Keywords:** multi-energy distribution network; hierarchical distributed control; Source-Grid-Load-Storage; coordinated optimization; self-balancing and self-smoothing; Evolutionary Particle Swarm Optimization

## 1. Introduction

To achieve China’s “Dual Carbon” goals, it is essential to transition towards a New Power System dominated by renewable energy. This shift is transforming the structure of distribution networks, making it necessary to address new challenges in energy management and optimization. The integration of Distributed Energy Resources (DERs), energy storage, and Combined Cooling, Heating, and Power (CCHP) systems introduces complex interactions and demands innovative solutions to manage multi-energy systems efficiently [1–4]. The integration and interaction of large-scale Distributed Energy Resources (DERs), energy storage, and Combined Cooling, Heating, and Power (CCHP) systems on the distribution side have introduced new characteristics to modern multi-energy distribution networks [5–7]. These characteristics include stochastic fluctuations, bidirectional power flows, and multi-energy synergy [8–11]. Implementing centralized and efficient



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management for multi-energy distribution systems is a critical component of constructing the New Power System [12–14].

Modern multi-energy distribution networks integrate power, thermal, natural gas, and transportation networks. Compared to traditional “Source-Grid-Load-Storage” coordinated control, these networks involve distributed control objects, diverse user types, and complex user interaction patterns [15–17]. Conversely, the stochasticity and volatility of distributed renewable energy pose threats to the stable operation of distribution networks [18–21]. Therefore, research on “Source-Grid-Load-Storage-Heat” coordinated control methods is crucial to achieve mutual conversion and complementary advantages among different energy forms [22,23].

Currently, distribution network control methods mainly include centralized, decentralized, and distributed control [24–26]. Centralized control is widely used but faces challenges in modern networks where microgrid clusters are large-scale and geographically dispersed [27,28]. It requires frequent exchange of massive information, relying on high-reliability, long-distance real-time communication, which introduces significant technical and economic challenges. Furthermore, research on the coordinated control of modern multi-energy distribution networks is still in its infancy, often neglecting the constraints of information networks.

Existing research on hierarchical and distributed control of multi-energy or microgrid systems can be further categorized into centralized optimization methods, distributed optimization-based coordination schemes, and rule-based hierarchical control strategies. Centralized optimization methods can achieve global optimality but suffer from poor scalability in systems with high penetration of distributed resources. Distributed optimization approaches, such as ADMM- or consensus-based methods, improve scalability by decomposing large problems, yet they often rely on convexity assumptions and dual-variable coordination mechanisms, which limits their applicability when nonlinear coupling and mixed continuous–discrete decision variables are involved. Rule-based hierarchical control strategies, on the other hand, offer strong engineering practicality and fast response but typically lack explicit coordination between electrical and thermal subsystems and provide limited economic optimality.

Compared with these existing approaches, the framework proposed in this study emphasizes system-level integration rather than algorithmic novelty. By combining hierarchical coordination mechanisms, explicit electric–thermal coupling modeling, and locally autonomous regulation strategies, the proposed method seeks to balance economic performance, computational tractability, and practical applicability. In this way, it addresses several limitations observed in existing multi-energy distribution network control schemes.

Despite substantial progress in the literature, a clear gap remains in the practical and scalable integration of multi-energy systems. Many existing models fail to fully capture real-time interactions and synergistic relationships among different energy carriers, which are critical for optimizing energy flows and ensuring the stable and efficient operation of modern distribution networks. The integration of diverse energy types within distribution networks helps overcome the inefficiencies of traditional systems, where electrical, thermal, and gas subsystems are often treated in isolation. Enhanced coupling among multiple energy carriers enables improved renewable energy utilization, higher overall energy efficiency, and reduced system operating costs.

To address these challenges, this work develops a unified control strategy based on microgrid self-balancing and self-smoothing concepts. By defining clear operational metrics and corresponding boundary conditions, the proposed strategy coordinates distributed energy resources, energy storage systems, and controllable loads, thereby stabilizing microgrid operation and ensuring efficient energy flow regulation. In parallel, a multi-energy

flow system model is established to jointly consider supply- and demand-side flexibility, fully exploiting the potential of demand response and energy storage to enhance system coupling, stability, and efficiency.

Furthermore, collaborative power and energy balance mechanisms are introduced to support real-time coordination within distribution networks. This integrated approach improves the management efficiency of generation–network–load–storage–thermal systems and contributes to the development of intelligent control technologies for modern distribution grids. The primary contribution of this work lies in the coordinated system architecture and operational integration, rather than the development of new optimization theory.

## 2. Materials and Methods

### 2.1. Control System Structure

The proposed method adopts a hierarchical distributed microgrid architecture to coordinate the operation of multiple small-scale distribution networks. Each sub-microgrid is equipped with a Microgrid Energy Management System (MGEMS), which is responsible for monitoring device states and exchanging information with neighboring MGEMS units as well as with the Multi-Microgrid Energy Management System (MMGEMS). As the primary control node at the local level, each MGEMS maintains direct communication with the MMGEMS, enabling efficient information exchange across control layers.

At the cluster level, the MMGEMS performs centralized coordination of all connected sub-microgrids, while local regulation is achieved through peer-to-peer communication among MGEMS units. This hybrid control architecture combines cluster-level centralized coordination with local distributed autonomy, allowing the system to balance global optimization objectives with flexible local decision making.

### 2.2. Coordinated Control Method for Small-Scale Multi-Energy Distribution Networks

The small-scale distribution network operates as the lower layer of the hierarchical optimization framework. The monitoring system first regulates the output of fuel cells and energy storage units according to predefined self-balancing and self-smoothing ranges, ensuring that the system operates within acceptable stability and fluctuation limits.

Based on the control instructions issued by the regional distribution network, together with the real-time photovoltaic output and load demand, an optimization model for the small-scale distribution network is then established. Through its local energy management system, the outputs of fuel cells and energy storage units are further coordinated, enabling the network to achieve economically optimal operation while satisfying operational constraints.

#### 2.2.1. Local Objective Function

For coordinated operation within the small-scale distribution network, the output power of fuel cells and the charging/discharging power of electrical and thermal energy storage systems are selected as optimization variables. Each small-scale distribution network is optimized independently at the local level, with the objective of minimizing the total operating cost over a one-day scheduling horizon. The corresponding objective function of the small-scale distribution network is expressed as follows:

$$\begin{aligned}
\min C_{total}^{LN} &= \sum_{t=1}^{24} (C^{SOFC}(t) + C^{EES}(t) + C^{TES}(t) + C^{el}(t) + C^{ht}(t)) \\
C^{SOFC}(t) &= \rho^{SOFC}(t) \cdot P_{el}^{SOFC}(t) \\
C^{ESS}(t) &= \tau^{ESS}(t) \cdot (P_{el,dis}^{ESS}(t) + P_{el,cha}^{ESS}(t)) \\
C^{TES}(t) &= \tau^{TES}(t) \cdot (P_{ht,dis}^{TES}(t) + P_{ht,cha}^{TES}(t)) \\
C^{el}(t) &= \varepsilon^{el}(t) \cdot P_{el,TL}^{LN}(t) \\
C^{ht}(t) &= \varepsilon^{ht}(t) \cdot P_{el,TL}^{LN}(t)
\end{aligned} \tag{1}$$

where  $C_{total}^{LN}$  represents the total daily cost of the small-scale distribution network;  $C^{SOFC}(t)$ ,  $C^{ESS}(t)$ ,  $C^{TES}(t)$ ,  $C^{el}(t)$  and  $C^{ht}(t)$  denote the operational costs of the fuel cell, electrical/thermal energy storage, electricity purchase/sale, and heat purchase of a single small-scale distribution network at time  $t$ , respectively;  $\rho^{SOFC}$  is the unit operational cost coefficient of the fuel cell, encompassing both fuel costs and operation and maintenance (O&M) costs;  $\tau^{ESS}$  and  $\tau^{TES}$  are the O&M cost coefficients for the electrical energy storage system and thermal energy storage system, respectively;  $\varepsilon^{el}$  and  $\varepsilon^{ht}$  represent the unit price for purchasing/selling electricity from the regional distribution network and the unit price for purchasing heat, respectively.

## 2.2.2. Local Constraints

The constraints in this section jointly regulate the electrical and thermal subsystems through shared devices, such as the solid oxide fuel cell and electrical/thermal energy storage systems, as well as coupled power balance equations. As a result, the electrical and thermal subsystems are integrated into a unified coupled multi-energy optimization framework.

The optimization is subject to the following constraints:

### 1. Fuel Cell Constraints

$$I^{SOFC}(t) \times P_{el,min}^{SOFC} \leq P_{el}^{SOFC}(t) \leq I^{SOFC}(t) \times P_{el,max}^{SOFC} \tag{2}$$

$$-RD_l \leq P_{el}^{SOFC}(t) - P_{el}^{SOFC}(t-1) \leq RU_l \tag{3}$$

$$I^{SOFC} P_{ht,min}^{SOFC} \leq P_{ht}^{SOFC}(t) \leq I^{SOFC} P_{ht,max}^{SOFC} \tag{4}$$

$$-RD_{hl} \leq P_{ht}^{SOFC}(t) - P_{ht}^{SOFC}(t-1) \leq RU_{hl} \tag{5}$$

### 2. Energy Storage Constraints

$$-R^{ESS} D^{ESS} \leq SOC^{ESS}(t) - SOC^{ESS}(t-1) \leq R^{ESS} U^{ESS} \tag{6}$$

$$SOC_{min}^{TES} \leq SOC^{TES}(t) \leq SOC_{max}^{TES} \tag{7}$$

$$-R^{TES} D^{TES} \leq SOC^{TES}(t) - SOC^{TES}(t-1) \leq R^{TES} U^{TES} \tag{8}$$

$$\begin{aligned}
X(t) P_{el,dis}^{ESS,min} &\leq P_{el,dis}^{ESS}(t) \leq X(t) P_{el,dis}^{ESS,max} \\
Y(t) P_{el,cha}^{ESS,min} &\leq P_{el,cha}^{ESS}(t) \leq Y(t) P_{el,cha}^{ESS,max} \\
X(t), Y(t) &\in (0, 1)
\end{aligned} \tag{9}$$

$$\begin{aligned}
M(t) P_{ht,dis}^{TES,min} &\leq P_{ht,dis}^{TES}(t) \leq M(t) P_{ht,dis}^{TES,max} \\
N(t) P_{ht,cha}^{TES,min} &\leq P_{ht,cha}^{TES}(t) \leq N(t) P_{ht,cha}^{TES,max} \\
M(t), N(t) &\in (0, 1)
\end{aligned} \tag{10}$$

### 3. Power Balance

To ensure the secure and stable operation of a small-scale distribution network under multi-energy conditions, both electrical and thermal power balances must be satisfied. At the system level, the aggregated power balance relationships can be expressed as

$$P_{L,t}^e = P_{grid,t}^e + P_t^{pv} \quad (11)$$

$$P_{L,t}^h = P_{grid,t}^h \quad (12)$$

where  $P_{L,t}^e$  and  $P_{L,t}^h$  denote the electrical and thermal load demands of the small-scale distribution network at time  $t$ , respectively;  $P_{grid,t}^e$  represents the electrical power purchased from or sold to the upper-level distribution network;  $P_{grid,t}^h$  is the thermal power purchased from the upstream network; and  $P_t^{pv}$  denotes the photovoltaic generation output.

To represent the component-level realization of the above coupling, the detailed electrical and thermal power balance equations are formulated as

$$P_{el,L}^{LN}(t) = P_{el,TL}^{LN}(t) + P_{el}^{SOFC}(t) + P^{PV}(t) + P_{dis}^{ESS}(t) - P_{cha}^{ESS}(t) \quad (13)$$

$$P_{ht,L}^{LN}(t) = P_{ht,TL}^{LN}(t) + P_{ht}^{SOFC}(t) + P_{ht,dis}^{TES}(t) - P_{ht,cha}^{TES}(t) \quad (14)$$

where  $P_{el,L}^{LN}(t)$  and  $P_{ht,L}^{LN}(t)$  denote the electric and thermal load demands of the small-scale distribution network at time  $t$ , respectively;  $P_{el,TL}^{LN}(t)$  represents the power purchased or sold by the small-scale distribution network at time  $t$ ;  $P_{ht,TL}^{LN}(t)$  is the thermal power purchased by the small-scale distribution network at time  $t$ ; and  $P^{PV}(t)$  represents the photovoltaic power generation at time  $t$ .

The solid oxide fuel cell operates in a thermal-load-following mode, implying that its electrical output is constrained by thermal demand. As a result, the electrical and thermal subsystems are physically coupled through shared generation and storage devices. Equations (13) and (14) therefore constitute the component-level realization of the system-level coupling described in Equations (11) and (12).

Under such coupled conditions, synchronized forecasts of photovoltaic generation, electrical load, and thermal load are required to ensure the feasibility of the power balance constraints prior to optimization and dispatch. Accordingly, a long short-term memory network is adopted to jointly forecast solar irradiance, electrical load, and thermal load, providing reliable inputs for subsequent multi-energy coordinated optimization.

To ensure the reliability of the input data used in the coupled optimization model, the forecasting performance of the adopted LSTM model is evaluated by comparison with a support vector machine. The prediction errors for solar irradiance, electrical load, and thermal load are summarized in Table 1. The results demonstrate that the LSTM model provides consistently higher prediction accuracy across all variables, thereby offering reliable and synchronized inputs for the subsequent electric–thermal coordinated optimization.

**Table 1.** Comparison of forecasting errors between LSTM and SVM.

| Method | Solar Irradiance | Electrical Load | Thermal Load |
|--------|------------------|-----------------|--------------|
| LSTM   | 36.0932          | 211,320         | 29,821       |
| SVM    | 56.3541          | 472,060         | 78,770       |

#### 2.3. Control Method Based on Self-Balancing and Self-Smoothing

The self-smoothing degree of a small-scale distribution network describes the rate of change in electrical and thermal power exchanged with the regional distribution network. It

serves as a characteristic indicator of power fluctuation during energy exchange and reflects the dynamic interaction between the small-scale network and the upper-level system.

Based on this concept, two operational indicators are introduced in this section: the self-balancing degree and the self-smoothing degree. These indicators form the core of the coordinated control strategy for small-scale multi-energy distribution networks and provide a quantitative basis for regulating power exchange and fluctuation levels.

### 2.3.1. Self-Balancing Degree

The self-balance degree  $k(t)$  describes the ability of a small-scale distribution network to satisfy local load demand using internal distributed generation and energy storage resources. It is defined as the ratio of the available output power to the corresponding load demand.

The mathematical expressions of the self-balancing degree are given as follows:

$$k(t) = \frac{P_{el}^{LN}(t) + P_{ht}^{LN}(t)}{P_{el,L}^{LN}(t) + P_{ht,L}^{LN}(t)} \quad (15)$$

$$P_{el}^{LN}(t) = P^{PV}(t) + P_{el}^{SOFC}(t) + P_{el,dis}^{ESS}(t) - P_{el,cha}^{ESS}(t) \quad (16)$$

$$P_{ht}^{LN}(t) = P_{ht}^{SOFC}(t) + P_{ht,dis}^{TES}(t) - P_{ht,cha}^{TES}(t) \quad (17)$$

where  $k(t)$  is the total energy self-balance degree;  $P_{el}^{LN}(t)$  is the total power generation of distributed generation and electric energy storage in the small-scale distribution network; and  $P_{ht}^{LN}(t)$  is the total thermal power generation of distributed generation and thermal energy storage in the small-scale distribution network.

This metric ensures that the energy output from distributed generation and energy storage meets the local demand.

### 2.3.2. Self-Smoothing Degree

The self-smoothing degree  $s(t)$  refers to the rate of change in the electric/thermal exchange power in the small-scale distribution network. It is a characteristic value reflecting the fluctuation of the exchange power with the regional distribution network.

$$s(t) = \frac{d(P_{el,TL}^{LN}(t) + P_{ht,TL}^{LN}(t))}{dt} \quad (18)$$

$$P_{el,TL}^{LN}(t) = P_{el,L}^{LN}(t) - P_{el}^{LN}(t) = P_{el,L}^{LN}(t) - k^{el}(t)P_{el,L}^{LN}(t) \quad (19)$$

$$P_{ht,TL}^{LN}(t) = P_{ht,L}^{LN}(t) - P_{ht}^{LN}(t) = P_{ht,L}^{LN}(t) - k^{ht}(t)P_{ht,L}^{LN}(t) \quad (20)$$

where  $s(t)$  is the self-smoothing degree of the total exchange power;  $P_{el,TL}^{LN}(t)$  represents the power purchased or sold by the small-scale distribution network; and  $P_{ht,TL}^{LN}(t)$  is the thermal power purchased by the small-scale distribution network.

In principle, the self-smoothing degree can be described by the rate of change in the exchanged power. However, since the proposed control strategy is implemented under a discrete-time simulation framework, the self-smoothing degree is evaluated using a difference-based formulation to ensure consistency and reproducibility.

To maintain consistency in discrete-time simulations, the self-smoothing degree is calculated using the following difference-based formulation. In discrete time  $t = k\Delta t$ , the self-smoothing degree is defined as

$$s(k) = \frac{P_{tie}(k) - P_{tie}(k-1)}{\Delta t} \quad (21)$$

where  $\Delta t$  denotes the fixed simulation time step.

This strategy aims to smooth out fluctuations in energy flows, providing more stable system operation.

### 2.3.3. Unified Control Strategy and Boundary Constraints

The proposed control strategy employs the self-balancing and self-smoothing indices to regulate distributed generation, energy storage systems, and controllable loads within predefined operating ranges. The boundary values  $k_{\min}(t)$  and  $k_{\max}(t)$  specify the acceptable range of source–load deviation within the small-scale distribution network, while the limits  $s_{\min}$  and  $s_{\max}$  constrain the magnitude of tie-line power fluctuations exchanged with the regional distribution network. These boundaries collectively define the feasible and secure operating region of the proposed control strategy.

The boundary values  $k_{\min}(t)$ ,  $k_{\max}(t)$ ,  $s_{\min}$ , and  $s_{\max}$  are determined based on the actual operating conditions of the studied distribution network in Zhejiang Province. Specifically, local photovoltaic generation capacity, electrical and thermal load levels, and energy storage ratings are used to calculate the feasible operating envelope of the small-scale distribution networks. As a result, the selected boundary values represent the lower and upper limits required to ensure safe and reliable operation under typical load variations and renewable generation uncertainty, rather than arbitrarily selected thresholds.

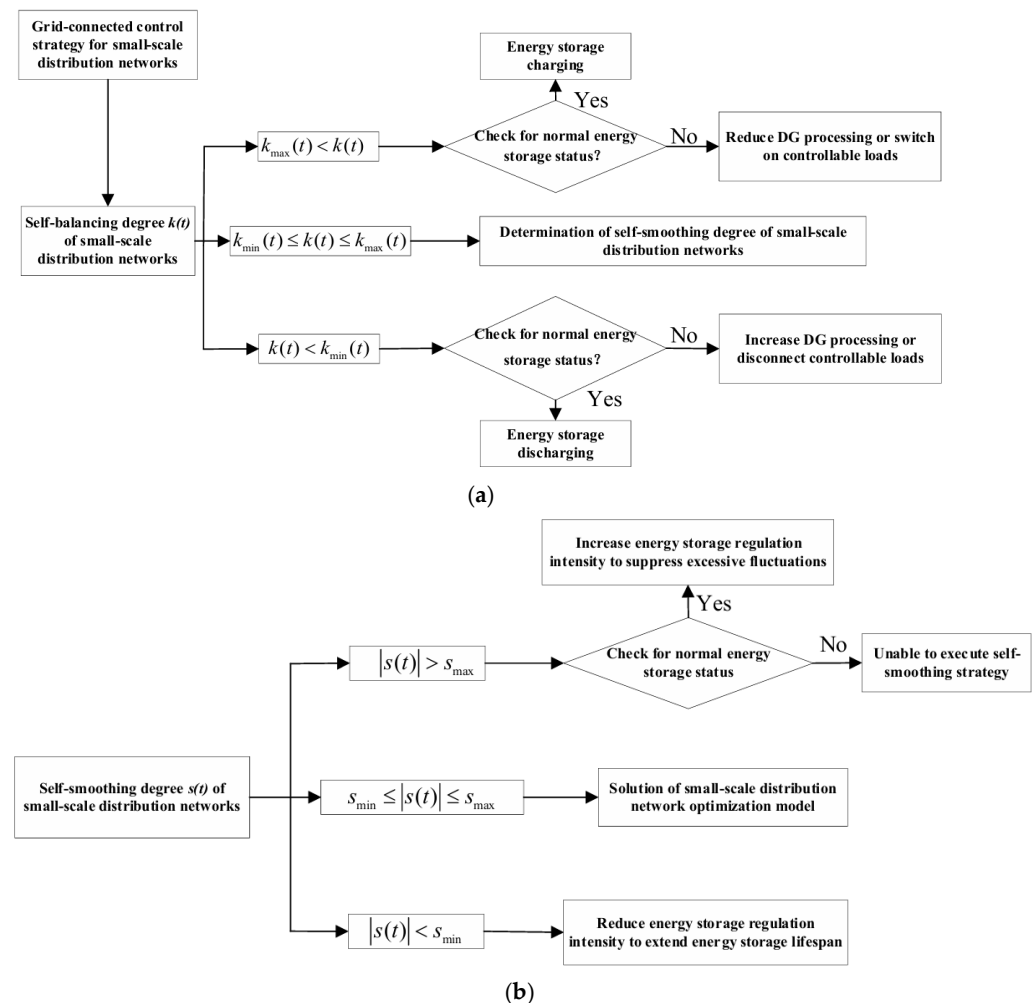
Numerical experiments show that moderate variations in these boundary values lead to only minor changes in system operating cost and tie-line power fluctuation levels, indicating that the proposed control strategy exhibits stable performance and limited sensitivity to parameter tuning within practical ranges. Equations (18)–(20) therefore define the quantitative decision regions for tie-line power exchange and provide the analytical basis for the control logic illustrated in Figure 1.

The overall control method based on the self-balancing and self-smoothing indices is illustrated in Figure 1, and the detailed control procedures are described as follows.

① Compare the real-time self-balancing degree  $k(t)$  of the small-scale distribution network with the self-balancing degree boundary curves  $k_{\min}(t)$  and  $k_{\max}(t)$ . When  $k_{\min}(t) \leq k(t) \leq k_{\max}(t)$ , it indicates that the output power fluctuates precisely within the prescribed range and can meet local or remote load demands; the system then proceeds to judge the self-smoothing degree of the small-scale distribution network. When  $k(t) \leq k_{\min}(t)$ , it indicates that the output power cannot meet the demands of local or remote loads. At this time, the system first determines if the energy storage status is normal. If it is normal, the electrical energy storage discharges; conversely, the distribution network output power is increased or controllable loads are shed. When  $k(t) \geq k_{\max}(t)$ , it indicates that the output power is greater than the demands of local or remote loads. At this time, if the energy storage status is normal, the energy storage charges; conversely, the distribution network output power is reduced or controllable loads are added.

② Compare the real-time self-smoothing degree  $s(t)$  of the small-scale distribution network with  $s_{\min}$  and  $s_{\max}$ . When  $s_{\min} \leq |s(t)| \leq s_{\max}$ , it indicates that the fluctuation of the exchange power on the grid-connection tie-line is within the allowable range, the power output is relatively stable, and the power curve is relatively smooth. On this basis, an optimization model for the small-scale distribution network is established and solved. When  $|s(t)| \leq s_{\min}$ , it indicates that the fluctuation of the exchange power on the grid-connection tie-line is small and the power output is relatively stable. Considering that frequent regulation will damage the service life of the energy storage device, the regulation intensity of the energy storage device should be minimized at this time. When  $|s(t)| \geq s_{\max}$ , it indicates that the fluctuation of the exchange power on the grid-connection tie-line is large. At this time, if the energy storage status is judged to be normal, the regulation intensity of

the electrical energy storage device is increased to reduce the disturbance impact on the regional distribution network. Conversely, the self-smoothing strategy cannot be executed.



**Figure 1.** Control flowchart of a small-scale distribution network. (a) Flowchart of Self-Balancing Control for Small Distribution Networks. (b) Networks Flowchart of Self-Smoothing Control for Small Distribution Networks.

#### 2.4. Collaborative Regulation Method for Regional Multi-Energy Flow Distribution Networks

##### 2.4.1. Regional Objective Function

The regional distribution network serves as the upper echelon. The optimization goal is to minimize the total economic cost of the system over one day. The objective function is as follows:

$$\min C_{total} = \sum_{t=1}^{24} \left( c(t) \cdot P_{el,pur}^{HN}(t) + c_{loss} \cdot \sum_{i=1}^N \sum_{j \in \Omega(i)} r_{ij} I_{ij,t} - \sum_{k=1}^M c(t) \cdot P_{el,TL}^{LN}(t) - \sum_{k=1}^M c_{ht}(t) \cdot P_{ht,TL}^{LN}(t) \right) \quad (22)$$

where  $C_{total}$  is the total cost of the regional distribution network within one day, which includes the cost of purchasing electricity from the main grid, the cost of network losses, the revenue/cost from purchasing/selling electricity to microgrids, and the revenue from selling heat to microgrids;  $P_{el,pur}^{HN}(t)$  is the amount of electricity purchased by the regional distribution network from the upstream grid at time;  $c(t)$  is the electricity price in that region;  $P_{loss}(t)$  is the active power network loss of the regional distribution network at time;  $N$  is the number of nodes in the distribution network;  $M$  is the number of microgrids; is the set  $\Omega(i)$  of child nodes in the distribution network branches with node as the parent

node;  $r_{ij}$  is the resistance of branch  $ij$ ; and  $I_{ij,t}$  is the current flowing through branch  $ij$  at time  $t$ .

#### 2.4.2. Regional Constraints

Constraints include fuel cell and energy storage limits, as well as

##### 1. Distribution Network Operation Security Constraints:

$$-5\% \leq V(t) \leq 5\% \quad (23)$$

where  $V(t)$  is the voltage magnitude of each node in the regional distribution network at time  $t$ .

##### 2. Constraints on Power Exchange with the Upstream Grid

$$0 \leq P_{el,pur}^{HN} \leq P_{el,pur,max}^{HN} \quad (24)$$

In the power interaction constraints, it is required that photovoltaic power generation be completely consumed within the regional distribution network, and the transmission of electrical energy to the upstream grid is not allowed, thereby reducing the impact of photovoltaic power generation on the upstream grid.

##### 3. Small-scale Distribution Network Power Purchase/Sale Constraints

$$P_{el,TL,min}^{LN} \leq P_{el,TL}^{LN}(t) \leq P_{el,TL,max}^{LN} \quad (25)$$

##### 4. Small-scale Distribution Network Heat Purchase Constraints

$$P_{ht,TL,min}^{LN} \leq P_{ht,TL}^{LN}(t) \leq P_{ht,TL,max}^{LN} \quad (26)$$

##### 5. Power Balance Constraints

$$P_{el,L}^{HN}(t) = P_{el,pur}^{HN}(t) + P_{el}^{SOFC}(t) + P^{PV}(t) + P_{dis}^{ESS}(t) - P_{cha}^{ESS}(t) - P_{el,TL}^{LN}(t) \quad (27)$$

$$P_{ht,L}^{HN}(t) = P_{ht}^{SOFC}(t) + P_{ht,dis}^{TES}(t) - P_{ht,cha}^{TES}(t) - P_{ht,TL}^{LN}(t) \quad (28)$$

where  $P_{el,L}^{HN}(t)$  is the electrical power demand of the regional distribution network at time  $t$ ;  $P_{ht,L}^{HN}(t)$  is the thermal power demand of the regional distribution network at time  $t$ .

#### 2.5. Hierarchical Distributed Collaborative Control Strategy and Algorithm

This project adopts a hierarchical control strategy for the coordination and optimization of a multi-energy flow distribution network containing multiple small-scale distribution networks. The specific control flow is shown in Figure 2.

Step 1: The distributed monitoring system of the small-scale distribution network sends the current load demand and distributed power output information to the distributed monitoring system of the regional distribution network.

Step 2: The distributed monitoring system of the regional distribution network constructs its optimization model and solves it using the Particle Swarm Optimization (PSO) algorithm based on a hybrid power flow calculation method. Step 3: Determine whether the results satisfy the operational constraints of the regional distribution network. If they are satisfied, the tie-line thermal/electrical power values are issued to the distributed monitoring system of the small-scale distribution network; otherwise, return to Step 2 to solve again.

Step 4: Since the operation of the small-scale distribution network adopts a “thermal-load-following” mode (power determined by heat), the distributed monitoring system of the small-scale distribution network first calculates the output of the fuel cell and thermal energy storage system based on the issued thermal power and then calculates the output of the electrical energy storage combined with the issued electrical power.

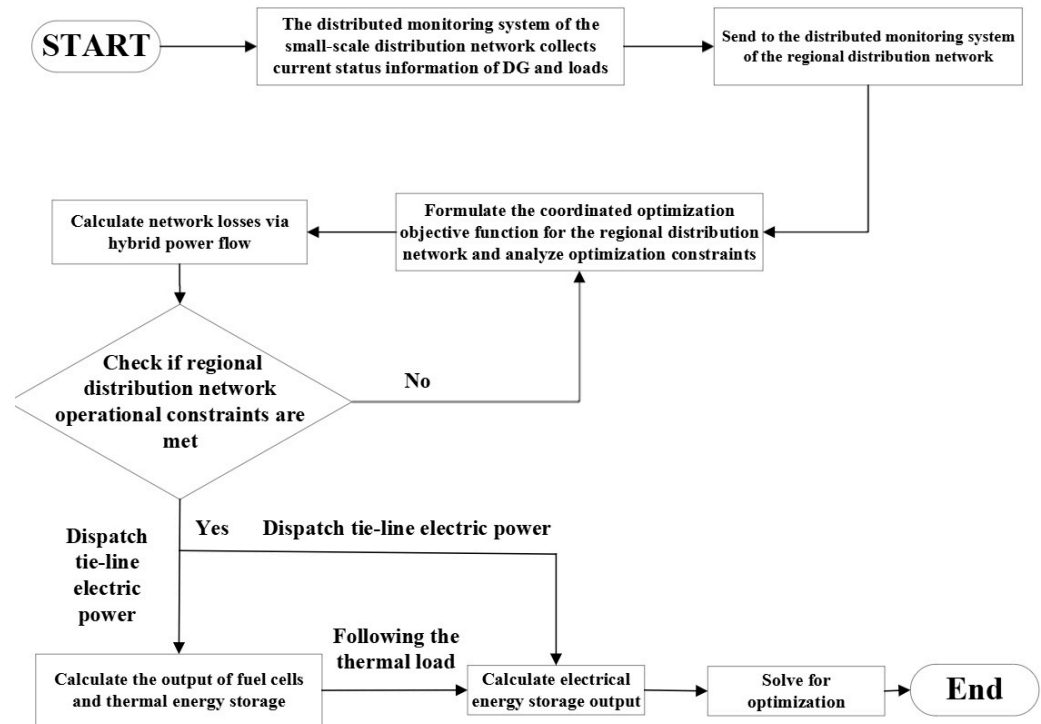


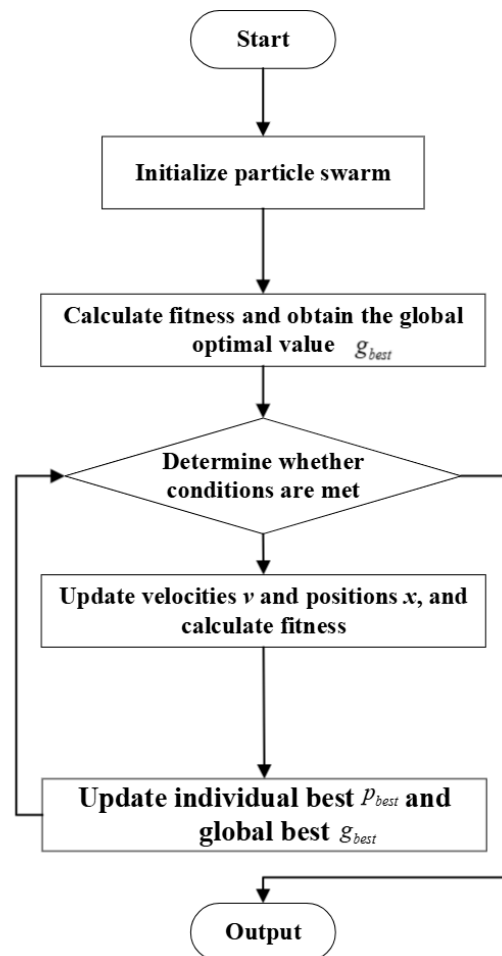
Figure 2. Control strategy flowchart.

The optimization problem formulated in this study involves nonlinear coupling between electrical and thermal subsystems, together with mixed discrete and continuous decision variables. Such characteristics make many conventional gradient-based or convex optimization methods difficult to apply effectively in practice.

In addition to the EPSO-based solution framework described above, two representative distributed optimization methods, namely the alternating direction method of multipliers (ADMM) and difference in convex programming (DCA), are considered for comparative analysis. ADMM decomposes large-scale optimization problems through dual-variable coordination and is effective for convex or weakly coupled systems. However, its convergence performance may deteriorate when strong nonlinear coupling and mixed discrete–continuous decision variables are present, as in the studied electric–thermal coordinated optimization problem.

DCA addresses nonconvex optimization by iteratively solving a sequence of convex subproblems. While DCA can achieve fast convergence under certain conditions, its performance depends on the quality of convex approximations and may be sensitive to initialization, particularly in highly coupled multi-energy systems with complex operational constraints.

For the regional-level optimization in Step 2, PSO is adopted as the solver. As illustrated in Figure 3, the algorithm initializes the particle swarm, evaluates fitness, and iteratively updates particle velocity and position as well as  $p_{best}$  and  $g_{best}$  until the stopping criterion is satisfied.



**Figure 3.** EPSO algorithm flowchart.

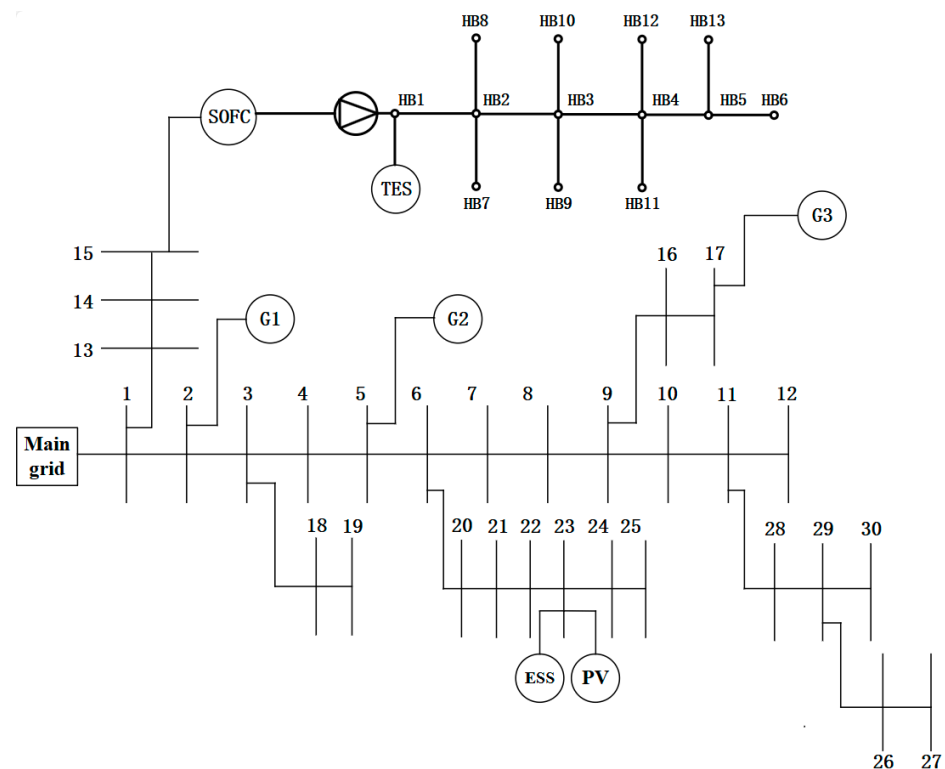
## 2.6. Simulation Setup and Parameters

To verify the effectiveness of the established optimization model for multi-energy flow distribution networks, this paper conducts a case study simulation using a distribution network system in a city in Zhejiang Province, which contains three small-scale distribution networks. Its topological structure is shown in Figure 4. The regional distribution network in this area is composed of two parts: an electrical power network and a thermal network. The electrical power network has a voltage level of 10 kV and a rated capacity of 100 MW. The thermal energy of the thermal network is mainly provided by fuel cells within the regional distribution network, and heat exchange can also occur with the thermal networks in each small-scale distribution network. The small-scale distribution network system is similarly composed of a thermal network and an electrical power network. The main equipment within the system includes PV systems, fuel cells, and thermal/electrical energy storage systems, as shown in Figure 5.

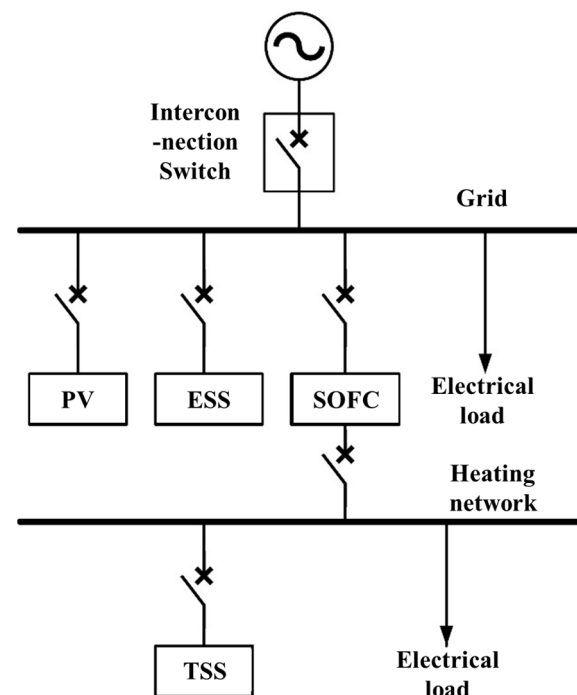
The rated power of the devices within the regional distribution network and each small-scale distribution network is shown in Table 2.

**Table 2.** Rated power of devices in the distribution network.

| Region                             | PV (kW) | Fuel Cell (kW) |
|------------------------------------|---------|----------------|
| Regional Distribution Network      | 3000    | 1500           |
| Small-scale Distribution Network 1 | 500     | 300            |
| Small-scale Distribution Network 2 | 500     | 300            |
| Small-scale Distribution Network 3 | 500     | 300            |



**Figure 4.** Topology of a distribution network with a thermal system in a specific area of Zhejiang.



**Figure 5.** Topology of the small-scale distribution network.

The time-of-use electricity price information is shown in Table 3. The cost of network loss is set at 0.73 CNY/kW·h.

In addition to evaluating economic performance and power balance behavior, the simulation framework is also designed to assess closed-loop dynamic response, feasibility preservation across hierarchical levels, parameter sensitivity, and communication robustness. These aspects are further investigated in Section 4 to provide a comprehensive validation of the proposed hierarchical distributed control framework.

**Table 3.** Time-of-use electricity price information.

|               | Time        | Electricity Price (CNY/kWh) Purchase (Sale) |
|---------------|-------------|---------------------------------------------|
| Peak Period   | 18:00~23:00 | 1.322                                       |
| Flat Period   | 7:00~18:00  | 0.839                                       |
| Valley Period | 23:00~7:00  | 0.556                                       |

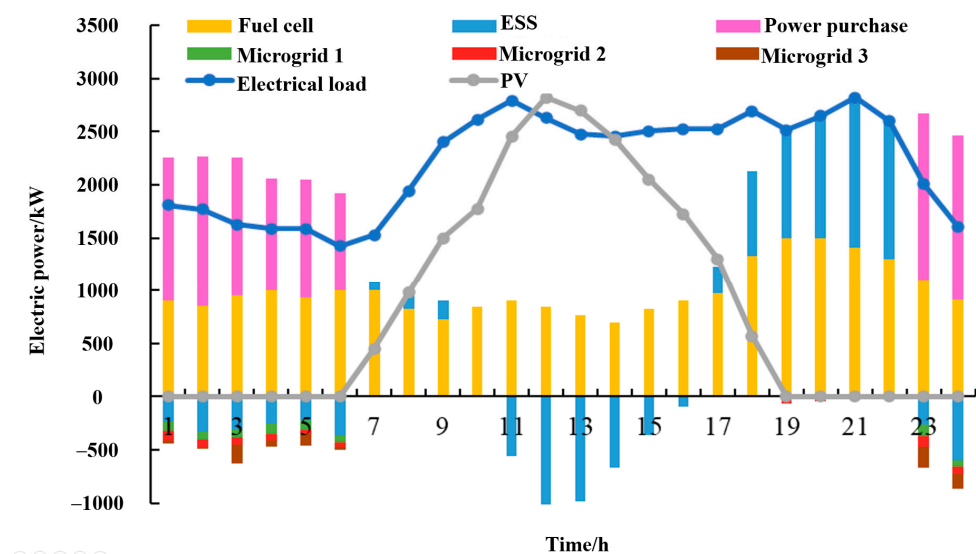
### 3. Results

This section presents the simulation results of the proposed hierarchical distributed control framework under typical operating conditions. The analysis focuses on power balance behavior, energy exchange characteristics, and economic performance at both regional and small-scale distribution network levels. Further validation regarding dynamic stability, feasibility preservation, parameter sensitivity, and communication robustness is presented in Section 4.

#### 3.1. Regional Distribution Network Power Balance

The model establishment and simulation were carried out using MATLAB R2023a, and the simulation results are analyzed as follows.

As shown in Figure 6, photovoltaic generation is zero from 23:00 to 06:00. During this period, the regional distribution network relies heavily on electricity purchased from the upstream grid. Meanwhile, the solid oxide fuel cell operates in a thermal-load-following mode, with its output primarily determined by heat demand. As a result, its electrical output fluctuates with the thermal load and is insufficient to fully satisfy the electrical demand of the network.

**Figure 6.** Electric power balance of the regional distribution network.

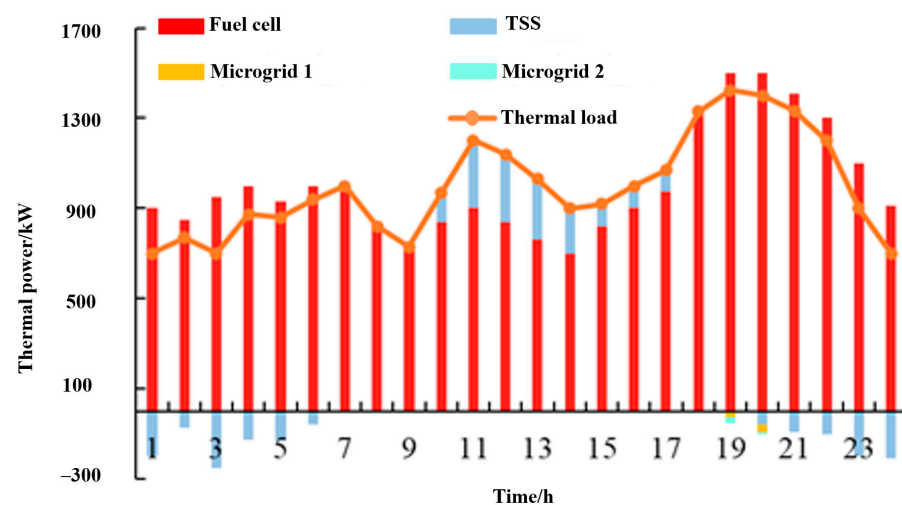
Since this time interval corresponds to the valley electricity price period, the electrical energy storage system is charged in preparation for discharging during peak load periods, thereby reducing overall operating costs. In addition, the storage system absorbs excess electrical energy during periods of high photovoltaic output.

At 12:00 and 13:00, the photovoltaic generation reaches high levels, while the thermal-driven generation units are unable to adjust their output strictly in accordance with the thermal load demand. Consequently, the surplus electrical power exceeds the rated capacity of the energy storage system, leading to photovoltaic curtailment and reduced economic efficiency.

This operating behavior directly reflects the electric–thermal coupling imposed by the solid oxide fuel cell and the coupled power balance constraints established in the proposed model.

The model establishment and simulation were carried out using MATLAB, and the analysis of the simulation results is as follows:

As shown in Figure 7, Small-scale Distribution Networks 1 and 2 purchase heat from the regional distribution network at 19:00 and 20:00. By combining the thermal load characteristics of both, it is evident that the SOFC is insufficient to meet the load demand at these moments. Therefore, according to the program settings, the system can choose to supply heat via local thermal energy storage or purchase heat from the up-stream network. In contrast, for Small-scale Distribution Network 3, the thermal load demand throughout the day never exceeds the maximum output power of the SOFC; therefore, it does not need to purchase heat from the regional distribution network.



**Figure 7.** Thermal power balance of the regional distribution network.

### 3.2. Small-Scale Distribution Network Operation

Taking Small-scale Distribution Network 1 as an example, this section analyzes the output of distributed energy resources and the power purchasing/selling situation within the grid based on the method proposed in this paper. As can be seen from Figure 8, the self-balancing degree exceeds the preset range during certain time periods. At these times, the small-scale distribution network system utilizes the self-balancing and self-smoothing control strategies to bring the self-balancing degree back within the set range through the charging and discharging of electrical energy storage.

Figure 9 displays the self-smoothing degree of Small-scale Distribution Network 1 at each time step. It can be observed that the value falls below the preset range during only one time period within the day. Considering the goal of minimizing the output of the energy storage system to extend its service life, the storage system is not activated to adjust the self-smoothing degree at this specific time.

The above analysis primarily focuses on the electric power balance during sunny days. When conditions such as overcast weather occur, resulting in insufficient photovoltaic output, the output status of various components involved in the electric power balance within the small-scale distribution network is shown in Figure 10.

By comparing the data results with those of a sunny day, it can be observed that due to insufficient PV output, the output of fuel cells and electrical energy storage in Small-scale Distribution Network 1 increases significantly. Consequently, the power purchased from the grid increases to compensate for the power deficit. Simultaneously, to reduce

the operating costs of the small-scale distribution network, the electrical energy storage charges during valley electricity price periods, such as at hours 1, 2, 3, and 4. During peak electricity price periods, as the output of electrical energy storage is insufficient to fully compensate for the power deficit within the small-scale distribution network, the control strategy operates to limit the power purchased from the grid, as seen at hours 9, 10, and 13.

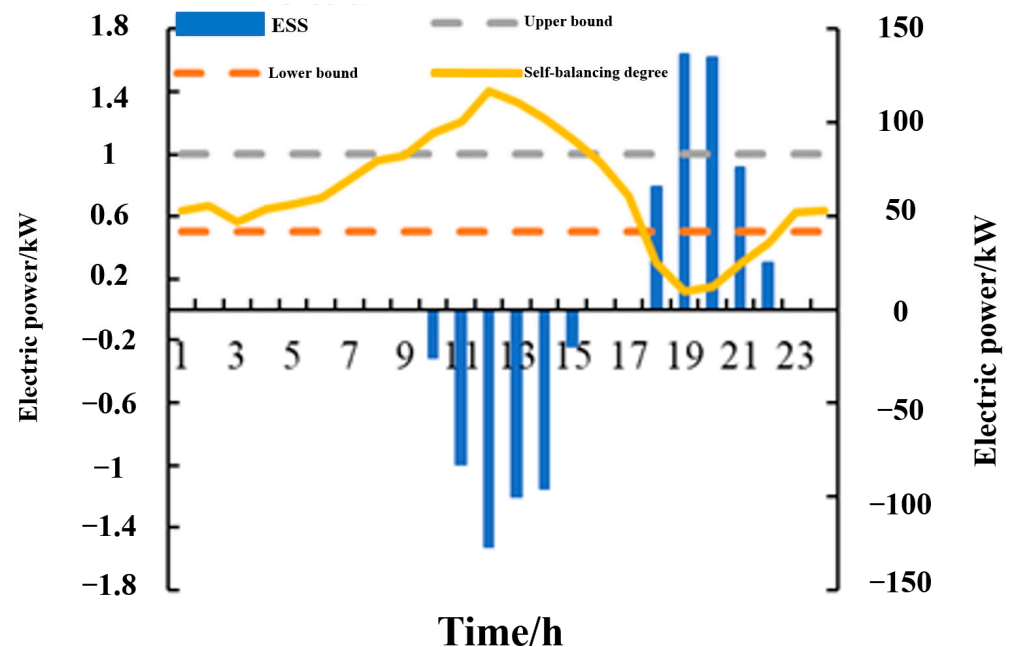


Figure 8. Self-balancing degree curve of Small-scale Distribution Network 1.

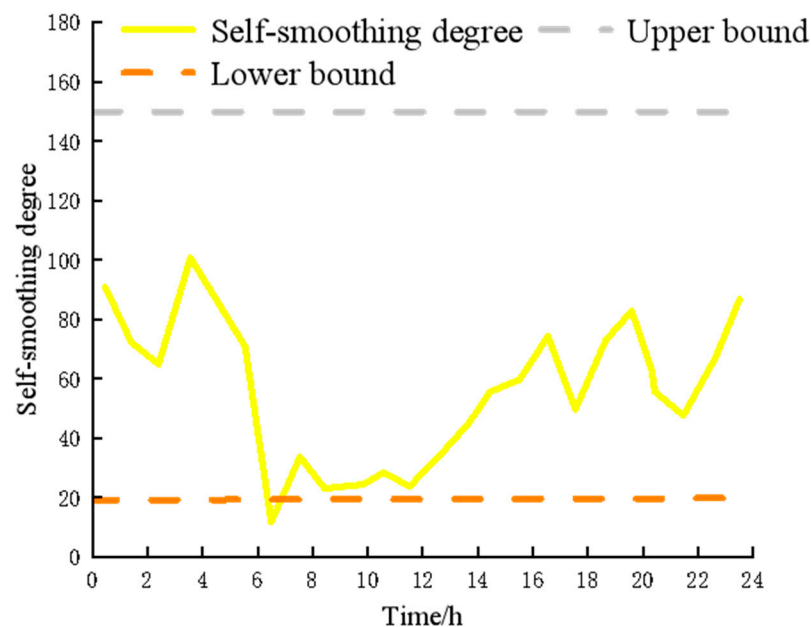


Figure 9. Self-smoothing degree curve of Small-scale Distribution Network 1.

To further verify the effectiveness of the hierarchical distributed collaborative control method proposed in this paper, a comparative analysis of different control methods was conducted. Specifically, the centralized optimization of the multi-energy flow distribution network refers to aggregating the optimization objectives and constraints of both the small-scale distribution networks and the regional distribution network to solve for a global optimum.

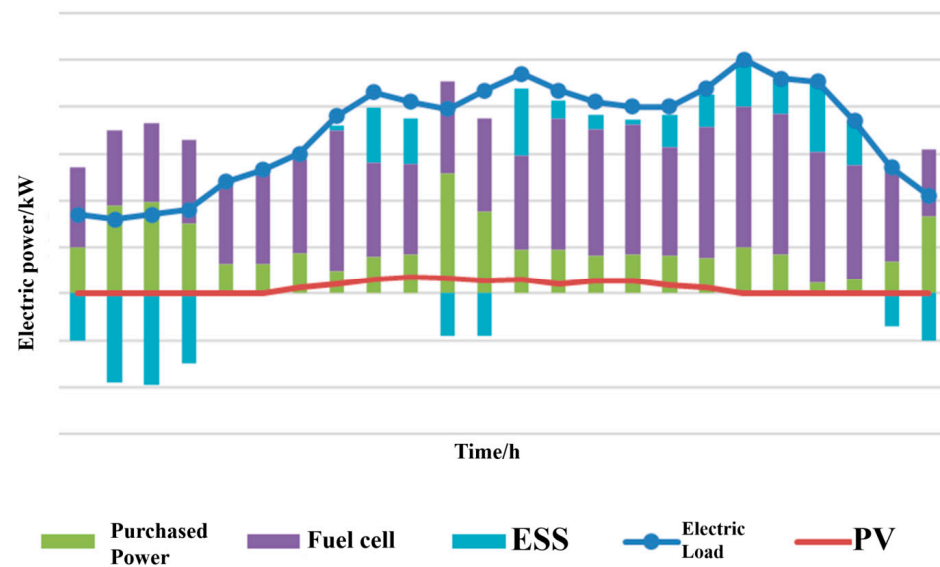


Figure 10. Electric power balance of Small-scale Distribution Network 1 on a rainy day.

Figure 11 presents the residual convergence curve of the hierarchical optimization. It can be seen from the figure that in the initial stage of iteration, each small-scale distribution network seeks optimization in the direction of minimizing its own operating costs. At this point, the operating costs of each small-scale distribution network are at their lowest, but the primal and dual residuals of the shared variables are at their maximum. As the multiplier coefficients are continuously updated during the iteration process, the proportion of the multiplier penalty term in the objective function value gradually increases. This forces the optimization problem of each small-scale distribution network to seek an energy flow coordinated dispatch scheme that reduces the residuals of the shared variables. Correspondingly, the operating costs of each small-scale distribution network increase. Through multiple iterations and coordinated calculations, the algorithm finally converges and obtains a dispatch scheme that satisfies the requirements for both primal and dual residuals.

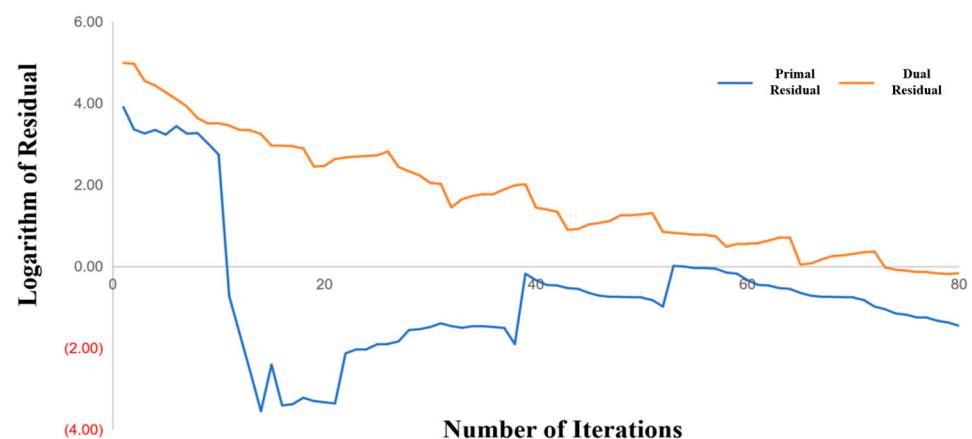
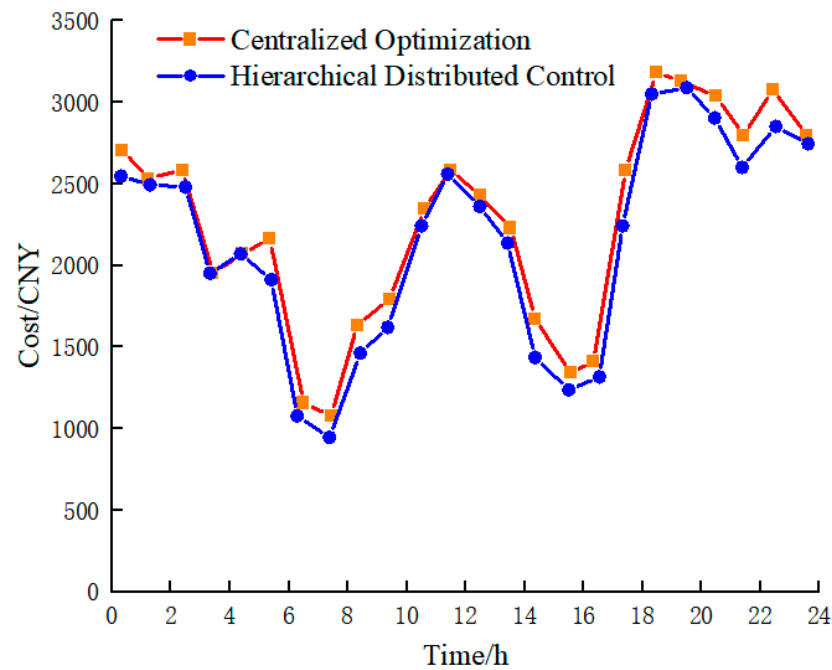


Figure 11. Residual convergence curve.

Figure 12 compares the results of hierarchical optimization and centralized optimization at different time periods. The results show that, compared with centralized optimization in multi-energy distribution networks, the hierarchical optimization method can reduce system operating costs during certain periods.



**Figure 12.** Comparison of total costs between hierarchical optimization and centralized optimization at each time step.

Table 4 presents the operating costs and computation times under hierarchical optimization and centralized optimization. Since centralized optimization does not require distributed iterative computation, it achieves a shorter computation time. However, this approach is less suitable for the decentralized and autonomous decision-making environment of modern distribution networks.

**Table 4.** Operating costs and computation time of small-scale distribution networks.

| Algorithm                | Small-Scale Grid 1 | Small-Scale Grid 2 | Small-Scale Grid 3 | Distribution Count | Time (s) |
|--------------------------|--------------------|--------------------|--------------------|--------------------|----------|
| Centralized              | 11,104             | 12,391             | 14,125             | -                  | 1.26     |
| Hierarchical Distributed | 10,857             | 12,184             | 13,956             | 3                  | 1.98     |

Table 5 shows the computation time required for centralized optimization and distributed optimization under different distribution quantities (numbers of entities). It can be observed that as the number of distributed entities further increases, the time required for centralized optimization gradually approaches that of hierarchical optimization.

**Table 5.** Optimization computation time for small-scale distribution networks (Time/s).

| Algorithm                | 3    | 6    | 9    | 12   | 15   | 18   |
|--------------------------|------|------|------|------|------|------|
| Centralized              | 1.26 | 2.43 | 3.51 | 5.27 | 6.86 | 8.21 |
| Hierarchical Distributed | 1.98 | 2.57 | 3.53 | 4.98 | 6.53 | 8.09 |

Table 6 presents the total costs of individual networks within the system using both hierarchical optimization and centralized optimization methods. Compared with centralized optimization, hierarchical optimization can significantly reduce the operating cost of the regional distribution network, while slightly reducing the operating cost of the small-scale distribution network. It is evident that the results of hierarchical optimization are more beneficial to the economics of the upper-level optimization entity, which is consistent with the

mathematical interpretation of hierarchical optimization. That is, it achieves the optimality of lower-level objectives while ensuring the optimality of the upper-level optimization entity, exhibiting distinct hierarchical characteristics.

**Table 6.** Comparison of Total Costs for Each Network: Hierarchical Optimization vs. Centralized.

| Item                                     | Centralized Optimization | Bi-Level/Hierarchical Optimization |
|------------------------------------------|--------------------------|------------------------------------|
| Regional Distribution Network (CNY)      | 16,292.49                | 14,717.18                          |
| Small-scale Distribution Network 1 (CNY) | 11,103.72                | 10,856.67                          |
| Small-scale Distribution Network 2 (CNY) | 12,391.29                | 12,183.71                          |
| Small-scale Distribution Network 3 (CNY) | 14,125.5                 | 13,955.93                          |
| Total Cost (CNY)                         | 53,913                   | 51,699.39                          |

#### 4. System Performance and Analysis Validation

In order to comprehensively evaluate the performance of the proposed hierarchical distributed control framework, this section conducts experimental validation and analysis from four aspects: closed-loop dynamic characteristics, feasibility preservation across hierarchical levels, parameter sensitivity, and communication robustness. All experiments are based on real-world distribution network data from Zhejiang Province, as described in Section 2.6, and were carried out in the MATLAB environment.

##### 4.1. Closed-Loop Stability and Dynamic Response Analysis

For closed-loop stability analysis, although a strict control law is not constructed in this study, simulations show the system's dynamic behavior under external disturbances. To simulate real-world uncertainties, step disturbances were introduced during typical scheduling periods:

- $t = 12:00$ : Electric load increased by 10% (simulating the activation of temporary industrial load).
- $t = 19:00$ : Photovoltaic output dropped by 50% (simulating cloud coverage).
- $t = 22:00$ : Thermal load dropped by 15% (simulating heating regulation).

Simulation results demonstrate that under the self-balancing strategy, the sub-microgrid successfully restores the self-balancing degree  $k(t)$  within the prescribed boundary  $[k_{min}, k_{max}]$  after 2–4 scheduling cycles ( $\Delta t = 15$  min). The self-smoothing degree  $s(t)$  initially peaks, but it returns to the range of  $[s_{min}, s_{max}]$  within 3–5 cycles, aided by energy storage regulation and upper-layer coordination. The voltage deviation  $V(t)$  of the regional distribution network remained within  $\pm 5\%$  at all times, with no violations.

For theoretical stability analysis, the electric-thermal coupled model was linearized at the selected operating point, and a state-space representation was constructed. The eigenvalues of the Jacobian matrix were computed, and the results showed that all the real parts of the eigenvalues were negative, with the maximum real part being  $-0.12$ , indicating that the system is locally asymptotically stable at this operating point.

##### 4.2. Feasibility Preservation Across Hierarchical Levels

Matching rate = Number of time periods where the instructions fall within the feasible domain / Total number of scheduling periods  $\times 100\%$

The feasibility matching results for the typical-day scheduling, including the electric- and thermal-power command match rates, are reported in Table 7.

In rare mismatched periods (e.g., during rapid fluctuations in photovoltaic output or energy storage SOC limits), the MGEMS units provide real-time feasible domain feedback to the MMGEMS, which adjusts the commands in the next round of optimization. After an

average of 2.3 iterations, all commands are adjusted to feasible solutions. This confirms that the proposed framework incorporates an online feasibility coordination mechanism, effectively avoiding command conflicts.

**Table 7.** Electric and thermal power command match rates of sub-microgrids.

| Sub-Microgrid ID | Electric Power Command Match Rate | Thermal Power Command Match Rate |
|------------------|-----------------------------------|----------------------------------|
| 1                | 96.30%                            | 97.90%                           |
| 2                | 95.80%                            | 98.20%                           |
| 3                | 97.10%                            | 99.10%                           |

#### 4.3. Sensitivity and Robustness Analysis

The results indicate that the system is insensitive to changes in the boundary parameters, with a total cost change rate of less than 2%, as shown in Table 8. However, the self-smoothing boundary  $s_{max}$  has a significant impact on tie-line fluctuation, and careful tuning is required based on the grid's tolerance level.

**Table 8.** Sensitivity and Robustness Analysis.

| Parameter Change | Total Cost Change | Tie-Line Fluctuation Change |
|------------------|-------------------|-----------------------------|
| $k_{min} +10\%$  | 1.20%             | −0.80%                      |
| $k_{min} -10\%$  | −0.90%            | 1.10%                       |
| $s_{max} +10\%$  | −0.50%            | 12.30%                      |
| $s_{max} -10\%$  | 0.70%             | −9.60%                      |

Simulation results show that communication performance degrades as packet loss increases, as summarized in Table 9. When packet loss exceeds 10%, the system switches to a local autonomous mode, relying solely on self-balancing strategies. In this mode, the total cost increases by approximately 8.2%, but the system still maintains basic power supply reliability.

**Table 9.** Communication Delay and Packet Loss Robustness.

| Communication Conditions                         | Average Convergence Iterations | Average Total Cost in CNY | Convergence Success Rate |
|--------------------------------------------------|--------------------------------|---------------------------|--------------------------|
| Ideal Communication                              | 45                             | 51,699.39                 | 100%                     |
| Delay $\leq 2$ cycles,<br>Packet loss $\leq 3\%$ | 48                             | 51,845.62                 | 100%                     |
| Delay $\leq 5$ cycles,<br>Packet loss $\leq 5\%$ | 52                             | 52,210.37                 | 95%                      |
| Delay $\leq 5$ cycles, Packet loss $\leq 10\%$   | 67                             | 53,189.43                 | 82%                      |

Analysis conclusion: EPSO outperforms ADMM and DCA in economic cost, convergence speed, and communication data volume. ADMM, while having good theoretical convergence properties, performs less efficiently when handling the non-convex coupling constraints in this problem. DCA converges faster but requires frequent global communication, which increases communication overhead and leads to higher costs. These observations are supported by Table 10, which reports the total cost, convergence iterations, and communication data volume of EPSO, ADMM, and DCA.

**Table 10.** Performance comparison of EPSO, ADMM, and DCA.

| Optimization Method | Total Cost in CNY | Iterations for Convergence | Communication Data Volume (MB/Day) |
|---------------------|-------------------|----------------------------|------------------------------------|
| EPSO                | 51,699.39         | 45                         | 12.7                               |
| ADMM                | 52,110.28         | 62                         | 18.3                               |
| DCA                 | 52,890.45         | 38                         | 22.5                               |

## 5. Discussion

The proposed hierarchical distributed control framework effectively addresses the coordination challenges of modern multi-energy distribution networks, in which electrical and thermal subsystems are tightly coupled through shared generation and storage devices. Rather than emphasizing algorithmic novelty, the framework focuses on system-level coordination between local autonomy and regional optimization, which is consistent with the practical operational characteristics of real-world multi-energy distribution systems.

The economic performance of the proposed framework demonstrates clear advantages, particularly at the regional distribution network level. By enabling small-scale distribution networks to optimize their operation locally while respecting system-level power balance constraints, the hierarchical structure achieves a more balanced allocation of operating costs. This result highlights a fundamental benefit of hierarchical coordination, as purely local optimization may conflict with overall system efficiency in coupled multi-energy environments.

From a computational perspective, the hierarchical distributed approach exhibits favorable scalability characteristics. Centralized optimization performs efficiently in small-scale systems but becomes increasingly computationally demanding as the number of distributed entities grows. In contrast, the hierarchical structure decomposes decision-making responsibilities and reduces coordination complexity at the local level, thereby maintaining relatively stable computational performance in larger systems with high penetration of distributed resources.

At the operational level, the self-balancing and self-smoothing strategies play a key role in regulating power exchange and mitigating the propagation of local fluctuations. These mechanisms allow small-scale distribution networks to respond autonomously to renewable variability and load changes while remaining compatible with regional optimization objectives. As a result, disturbances caused by local uncertainty are effectively attenuated before propagating to the upper-level network, contributing to improved system robustness.

The optimization problem involves nonlinear coupling between electrical and thermal subsystems as well as mixed continuous and discrete decision variables, which increases solution complexity. Under such conditions, population-based optimization methods exhibit practical advantages in terms of robustness and adaptability. The choice of the evolutionary particle swarm optimization approach is therefore motivated by the structural characteristics of the formulated problem rather than by claims of algorithmic optimality. Compared with gradient-based or dual-variable-driven distributed optimization methods, EPSO provides stable convergence behavior and satisfactory economic performance within the hierarchical framework. Accordingly, the focus of this study is placed on the effectiveness of the proposed hierarchical coordination architecture rather than on demonstrating the superiority of a specific optimization algorithm.

Despite the demonstrated effectiveness of the proposed framework, several simplifications remain. The thermal subsystem is modeled using a steady-state representation, which does not explicitly capture thermal inertia and dynamic heat storage effects. In addition,

communication delays and data uncertainties are not explicitly considered. Future work will focus on incorporating more detailed thermal dynamics, modeling communication constraints, and validating the proposed approach through hardware-in-the-loop testing or field-level demonstrations.

## 6. Conclusions

This paper presents a hierarchical distributed control framework for the coordinated optimization of multi-energy flows in distribution networks. By integrating self-balancing and self-smoothing strategies at the small-scale distribution network level with coordinated optimization at the regional level, the proposed framework effectively addresses the coupling between electrical and thermal subsystems in multi-energy distribution systems.

Simulation results based on a real-world distribution network in Zhejiang Province demonstrate that the proposed method achieves significant economic benefits. Compared with centralized optimization, the total system operating cost is reduced from 53,913 CNY to 51,699.39 CNY, corresponding to a reduction of approximately 4.1%. The regional distribution network benefits most significantly, with an operating cost reduction of 9.7%, while small-scale distribution networks also achieve moderate cost savings.

In addition to economic improvements, the proposed hierarchical distributed approach exhibits superior computational scalability. While centralized optimization performs efficiently in small-scale systems, its computation time increases rapidly as the number of distributed entities grows. In contrast, the hierarchical framework maintains relatively stable performance in larger-scale scenarios, making it more suitable for decentralized multi-energy distribution networks with high penetration of distributed resources.

The incorporation of self-balancing and self-smoothing strategies further enhances operational robustness by regulating power fluctuations and enabling autonomous local regulation under renewable uncertainty. Future work will focus on refining the modeling of thermal dynamics, incorporating communication delays and uncertainties, and validating the proposed framework through hardware-in-the-loop testing or field-level demonstrations, thereby improving its applicability to practical multi-energy distribution systems.

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## Abbreviations

The following abbreviations are used in this manuscript:

|        |                                             |
|--------|---------------------------------------------|
| DERs   | Distributed Energy Resources                |
| CCHP   | Combined Cooling, Heating, and Power        |
| MGEMS  | Microgrid Energy Management System          |
| MMGEMS | Multi-Microgrid Energy Management System    |
| SOFC   | Solid Oxide Fuel Cell                       |
| EPSO   | Evolutionary Particle Swarm Optimization    |
| PV     | Photovoltaic                                |
| O&M    | Operation and Maintenance                   |
| SOC    | State of Charge                             |
| ESS    | Electrical Energy Storage System            |
| TSS    | Thermal Energy Storage System               |
| EMS    | Energy Management System                    |
| ADMM   | Alternating Direction Method of Multipliers |
| $s(t)$ | Self-smoothing Degree                       |
| $k(t)$ | Self-balancing Degree                       |
| DCA    | Difference of Convex Programming            |

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