Research on Cross-Regional Energy and Reserve Dispatch Method Considering Wind Energy Uncertainty

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***Abstract*—This study delves into advanced optimization strategies for planning and scheduling cross-regional energy systems, with a focus on Hydrogen Energy Storage Systems (HESS). Addressing the variability and unpredictability of renewable energy sources, notably wind and solar power, it employs dynamic programming (DP) and linear programming to enhance the operational efficiency, reliability, and adaptability of interconnected energy networks. The research develops robust optimization models that facilitate seamless integration of renewable energy into the grid, promoting a sustainable and resilient energy future. It offers theoretical insights and practical guidance for the energy sector, showcasing the application of DP and linear programming in overcoming the challenges of renewable energy integration.**

***Index Terms*—Dynamic programming, Linear programming, Renewable energy integration, Hydrogen Energy Storage, Energy system optimization**

I. INTRODUCTION

As the global energy landscape undergoes a significant transformation, the development and utilization of renewable energy sources, particularly wind and solar energy, have garnered extensive attention. However, the large-scale application of these renewable sources in power systems is confronted with numerous technical and economic challenges, primarily due to their inherent intermittency and uncertainty [1]. The optimization planning and scheduling of cross-regional energy systems and Hydrogen Energy Storage Systems (HESS) emerge as crucial technological pathways to enhance energy utilization efficiency, ensure energy security, and achieve carbon neutrality goals [2].

This study aims to tackle the issues of uneven distribution of renewable energy and the necessity for cross-regional energy complementarity. By optimizing the planning and scheduling of HESS, we strive to improve the economic, reliable, and flexible operation of energy systems. The outcomes of this research not only facilitate the widespread application of renewable energy, reducing carbon emissions, but also provide theoretical support and technical guidance for the formulation of electricity markets and energy policies, offering significant theoretical and practical value [3].

The significance of optimizing cross-regional energy systems and HESS in achieving energy efficiency, security, and carbon neutrality cannot be overstated. Through the adoption of advanced optimization techniques and algorithms, our research not only promotes the extensive application of renewable energy but also furnishes the electricity market and energy policy formulation with theoretical support and technical guidance, thereby driving the clean and sustainable development of the energy structure. As technology continues to advance and innovate, more research outcomes and practical applications in the field of energy system optimization planning and scheduling are expected to emerge.

China has made remarkable progress in the field of renewable energy, especially in the development of wind energy. With the continuous expansion of wind energy scale, its uneven distribution in remote areas has become more pronounced, posing new requirements for the stable operation and energy dispatch of power systems. Cross-regional wind energy optimization dispatch methods can effectively promote the large-scale utilization of clean energy, reduce dependence on traditional fossil fuels, lower greenhouse gas emissions, and advance the development of energy structures towards cleanliness and sustainability [4].

Faced with these challenges and opportunities, researchers have proposed various optimization models and methods. For instance, an optimization planning method for cross-regional HESS that considers uncertainties has been put forward. This method aims to optimize the production, storage, and transmission of hydrogen energy by establishing models to reduce system operational costs, enhance energy utilization efficiency, and ensure system stability [1]. Moreover, the integrated transmission of wind power with pumped hydro storage systems across regions has been explored to analyze how to utilize the peak-shaving capability of pumped hydro storage to absorb wind power capacity and reduce wind power curtailment, thereby further improving wind power utilization rates [2].

Additionally, for the optimization scheduling of power systems, researchers have employed a two-stage distributed robust optimization method, highlighting the importance of the integrated application of advanced optimization techniques and hybrid energy storage systems in the face of uncertainty factors [4]. Through the method of multi-objective particle swarm optimization, optimal planning for hybrid electric-hydrogen energy storage systems has been conducted, taking into account economy, network losses, and voltage fluctuations to reduce grid losses and improve voltage stability [5].

In the optimization problems of modern energy systems, high dimensionality and complexity pose significant challenges. Traditional optimization methods often prove inefficient or incapable of finding global optima when addressing such issues. Therefore, the adoption of efficient optimization algorithms becomes key to research and application. The application of differential evolution strategies, particle swarm optimization techniques, genetic algorithms, simulated annealing algorithms, and other evolutionary algorithms in energy system optimization problems has demonstrated their significant advantages in dealing with complex issues [6].

II. RESEARCH FINDINGS AND DISCUSSION

Our research findings shed light on the optimization planning and scheduling of cross-regional energy systems and HESS. By employing advanced optimization algorithms, we have successfully addressed the challenges posed by the intermittent and uncertain nature of renewable energy sources. The optimization models developed in this study not only promote the efficient utilization of renewable energy across different regions but also enhance the stability and reliability of the energy system.

One of the key outcomes of this research is the development of a robust optimization framework that incorporates the uncertainties associated with renewable energy generation, especially wind and solar power. This framework enables energy systems to maintain operational efficiency and reliability even under fluctuating energy availability, thereby facilitating the integration of a higher proportion of renewable energy into the grid.

Furthermore, our study has explored the economic benefits of optimizing HESS in cross-regional energy systems. By strategically planning and scheduling HESS, we have demonstrated the potential for significant cost savings in energy production, storage, and distribution. This not only supports the economic feasibility of renewable energy projects but also contributes to reducing the overall carbon footprint of the energy sector.

The research also highlights the importance of policy support and technological innovation in overcoming the barriers to renewable energy integration. Our findings suggest that with appropriate regulatory frameworks and continued advancement in storage technologies, renewable energy can play a pivotal role in achieving global energy sustainability and carbon neutrality goals.

In conclusion, this study provides valuable insights into the optimization of cross-regional energy systems and HESS. The proposed optimization strategies and models contribute to enhancing the efficiency, reliability, and sustainability of energy systems, paving the way for a cleaner and more sustainable energy future.

III. MODEL DESCRIPTION

This model focuses on optimizing an urban power system through the strategic planning and scheduling of a Hydrogen Energy Storage System (HESS) within a single city, aiming at balancing electricity demand and supply, minimizing costs, and considering the transmission of stored electricity. It is critical to note that the transmission cost applies solely to the electricity stored by HESS, as the cost for basic electricity demand is already included in the electricity price.

A. Key Points

- **Decision Variables:** Include the storage and release decisions of HESS, electricity purchase plans, and the inter-city transmission of additional electricity scheduled through HESS.
- **Objective:** To minimize the total operational costs of the system, which comprises the cost of electricity purchases, the operational cost of HESS, and the transmission cost of electricity stored by HESS.
- **Constraints:**
  - Electricity balance must be maintained, ensuring each city's electricity demand is met every hour.
  - Transmission is limited to the electricity stored by HESS, within its capacity constraints.
  - HESS operation must consider the charging and discharging processes and capacity limits.

B. Mathematical Representation

The model can be represented by the following mathematical expressions:

$$\text{Minimize} \quad Z = \sum_{i=1}^{n} \sum_{j=0}^{23} (C_{\text{purchase},i,j} + C_{\text{HESS},i,j} + C_{\text{transmission},i,j}) \tag{1}$$

where:

- Z is the total cost.
- $C_{\text{purchase},i,j}$ is the cost of purchasing electricity for city i at hour j.
- $C_{\text{HESS},i,j}$ is the operational cost of HESS for city i at hour j.
- $C_{\text{transmission},i,j}$ is the cost of transmitting electricity stored by HESS for city i at hour j.
- n is the number of cities.

Subject to:

$$\sum_{j=0}^{23} D_{i,j} = \sum_{j=0}^{23} S_{i,j} + R_{i,j}, \quad \forall i \tag{2}$$

where $D_{i,j}$ is the demand in city i at hour j, $S_{i,j}$ is the supply purchased directly from the grid for city i at hour j, and $R_{i,j}$ is the electricity released from HESS for city i at hour j.

$$0 \leq S_{i,j} + R_{i,j} \leq \text{Capacity}_{\text{HESS},i}, \quad \forall i, j \tag{3}$$

where $\text{Capacity}_{\text{HESS},i}$ is the capacity of HESS in city i.

These constraints ensure that the electricity demand is met, the HESS operations are within capacity limits, and the transmission costs are applied only to the electricity stored and transmitted through HESS.

IV. DYNAMIC PROGRAMMING SOLUTION FOR OPTIMIZING ELECTRICITY COSTS

In light of the challenges posed by the inherent variability and unpredictability of renewable energy sources, particularly wind energy, this study introduces a dynamic programming (DP) approach aimed at optimizing electricity costs within urban power systems. This method specifically addresses the utilization of Hydrogen Energy Storage Systems (HESS) to achieve an optimal balance between energy demand and supply, thereby minimizing operational costs and enhancing system efficiency.

A. Problem Definition

The objective centers around the minimization of total electricity costs over a 24-hour period, taking into account varying electricity prices, demand patterns, and the operational costs associated with utilizing stored energy. The system is presented with the option to either purchase electricity at fluctuating hourly rates or utilize energy previously stored in the HESS. Additionally, the framework allows for the selling of excess energy back to the grid, adding a layer of complexity and opportunity for cost optimization.

B. Algorithm Description

Our dynamic programming solution delineates a step-by-step approach to compute the minimal cost associated with electricity consumption, incorporating decisions on the quantity of electricity to be purchased, stored, or sold at each hourly interval. The DP algorithm employs a state representation `dp[i][j]`, where `i` signifies the hour, and `j` represents the units of energy stored in HESS.

1) **Initialization:** The DP table is initialized with high values to simulate infinity, except for the base case `dp[0][0]`, which is set based on the direct grid purchase cost for the initial demand.
2) Iteratively, for each hour `i` from 1 to 23, the algorithm:
    - Computes the net price difference `delta_price[j]` for buying or selling energy, taking transmission costs into account, and prioritizes transactions based on potential cost savings or revenue generation.
    - Evaluates each potential energy storage level `j`, updating the DP table with the minimal cost scenario that meets demand and adheres to HESS operational constraints.
3) The optimal cost for the entire 24-hour cycle is identified at `dp[23][0]`, symbolizing the conclusion of the day with no remaining stored energy, thus ensuring all demands have been met efficiently.

C. Mathematical Formulation

The optimization process is governed by the equation:

$$dp[i][j] = \min(dp[i][j], dp[i-1][k] + \text{transaction cost}), \quad (4)$$

with `transaction cost` encompassing the expenses of purchasing, selling, and utilizing stored energy. This formula iteratively updates the DP table to reflect the minimum achievable costs, considering the operational parameters of HESS and the dynamic nature of electricity pricing.

By employing this dynamic programming model, the study advances a robust framework for enhancing the economic efficiency of urban power systems equipped with HESS. This approach not only aids in cost reduction but also contributes to the stability and reliability of energy supply in the face of fluctuating renewable energy outputs.

D. Complexity Analysis

The algorithm iterates over 24 hours for each of the n cities, evaluating different levels of energy storage up to the *capacity*, adjusted by the *gap*. The computational complexity of this approach is approximately given by:

$$O(24 \times n \times \frac{\text{capacity}}{\text{gap}} \times n), \quad (5)$$

where the term $\frac{\text{capacity}}{\text{gap}}$ represents the number of discrete energy levels considered for storage in the HESS. A smaller *gap* increases the number of such levels, thereby expanding the solution space and increasing computational requirements.

E. Impact of Gap on Precision and Efficiency

The *gap* parameter plays a pivotal role in balancing the trade-off between the algorithm's computational efficiency and the precision of its output:

- **Smaller Gap:** Opting for a smaller *gap* enhances the solution's precision by examining a finer granularity of storage levels. This thorough exploration increases the likelihood of identifying an optimal or near-optimal solution but at the expense of higher computational complexity.
- **Larger Gap:** Conversely, a larger *gap* simplifies the solution space, leading to reduced computational time. However, this efficiency gain comes at the potential cost of precision, as the coarser granularity might overlook more refined and possibly better solutions.

V. OPTIMIZING ELECTRICITY DISTRIBUTION WITH HESS THROUGH LINEAR PROGRAMMING AND FLOW NETWORKS

Addressing the intermittency of renewable energy sources requires innovative solutions to ensure the reliability and cost-effectiveness of urban electricity distribution. This paper introduces a methodology that combines linear programming (LP) and flow network analysis to optimize the integration of Hydrogen Energy Storage Systems (HESS) into urban power grids, facilitating efficient electricity distribution across multiple cities.

A. Linear Programming Formulation

The initial step involves formulating the problem as a linear programming model to minimize the total operational costs of electricity distribution, including the costs associated with purchasing electricity, transmission, and utilizing HESS for energy storage and release.

1) Objective Function: The objective is to minimize the total cost, defined as:

$$\min Z = \sum_{i=1}^{N} \sum_{t=1}^{T} (C_{\text{purchase},i,t} + C_{\text{transmission},i,t} + C_{\text{HESS},i,t}) \quad (6)$$

where N is the number of cities, T is the number of time periods (hours in this case), $C_{\text{purchase},i,t}$ is the cost of purchasing electricity for city i at time t, $C_{\text{transmission},i,t}$ is the cost of transmitting electricity, and $C_{\text{HESS},i,t}$ represents the operational costs of HESS.

2) Constraints: The model includes constraints for electricity demand satisfaction, HESS operational limits, and transmission capacity, among others, ensuring that the solution adheres to practical limitations and requirements.

B. Transition to Flow Network Model

While the LP formulation provides a solid foundation for understanding the problem's structure and constraints, the specific nature of electricity distribution—characterized by directed flows of electricity between nodes (cities) over time—lends itself well to representation as a flow network. Thus, we transition from the abstract LP model to a more concrete flow network model to leverage algorithmic efficiencies and gain additional insights.

C. Flow Network Model Construction

In the flow network model, cities are represented as nodes, and edges denote potential electricity flows, encapsulating buying, selling, and storing operations with associated costs and capacities.

1) Graph Configuration:

- **Nodes:** Each city at each hour is represented as a node in the graph, alongside special nodes for HESS operations.
- **Edges:** Edges between nodes represent possible transactions, with costs reflecting prices, transmission fees, and HESS operational costs.

2) Flow Network Optimization: The optimization now aims to find the minimum-cost flow through this network that satisfies all demand and operational constraints, effectively solving the original LP problem within a flow network framework.

D. Mathematical Formulation of Flow Network

The flow network problem is formulated as:

$$\min \sum_{(u,v)\in E} \text{cost}_{uv} \times \text{flow}_{uv} \quad (7)$$

where cost_{uv} is the cost associated with the flow on edge (u, v), and flow_{uv} is the quantity of electricity transmitted through edge (u, v).

E. Computational Complexity and Extensions

The computational complexity of the network flow approach, specifically the Minimum Cost Maximum Flow (MCMF) algorithm, primarily depends on the graph's structure, including the number of nodes (N) and edges (E). For algorithms like the Successive Shortest Path (SSP), which is commonly employed for MCMF problems, the computational complexity is generally represented as $O(N^2 \cdot E + N \cdot E \log N)$. This estimation accounts for the worst-case scenario where up to $O(E)$ augmenting paths might be necessary, with each path finding operation, assuming the use of Dijkstra's algorithm with a Fibonacci heap, taking up to $O(N \log N)$, in addition to $O(N \cdot E)$ for capacity adjustments across the graph.

1) Dynamic Electricity Pricing: Integrating dynamic electricity pricing into the network flow model adds another layer of complexity but also enhances its realism and applicability. By dynamically adjusting the costs associated with edges in the graph to reflect real-time or market-based electricity pricing, the model can more accurately simulate operational decisions and optimize for cost efficiency.

2) Renewable Energy Integration: The variability and unpredictability of renewable energy sources pose both a challenge and an opportunity for the flow network model. By representing renewable energy sources as nodes with variable edge capacities—reflecting the fluctuating availability of generated power—the model can be extended to optimize the distribution and storage of renewable energy within the urban grid. This integration not only addresses the challenge of renewable energy intermittency but also leverages its potential to reduce dependence on traditional energy sources and decrease overall carbon emissions.

3) Conclusion on Extensions: These extensions—dynamic pricing and renewable energy integration—underscore the adaptability and potential of the flow network model in addressing contemporary challenges in urban electricity distribution. By accounting for the complexities of real-world operations, the model stands as a robust tool for planning and optimization in the evolving landscape of energy management.

F. Implementation and Solution

The formulated flow network problem can be efficiently solved using algorithms designed for min-cost flow problems, providing an optimal strategy for electricity procurement, HESS operation, and distribution.

G. Conclusion

By initially framing the problem as a linear programming model and then transitioning to a flow network analysis, this methodology offers a comprehensive approach to optimizing urban electricity distribution. It demonstrates how combining LP and flow network models can effectively address the complexities of integrating renewable energy sources and HESS into urban power grids, ensuring cost efficiency and reliability.

VI. CONCLUSION

This research has significantly contributed to the field of renewable energy optimization, particularly focusing on cross-regional energy systems and Hydrogen Energy Storage Systems (HESS). The findings underscore the importance of advanced optimization techniques and algorithms in addressing the intermittency and uncertainty inherent in renewable energy sources like wind and solar power. By leveraging these techniques, we have demonstrated potential pathways to enhance the efficiency, reliability, and flexibility of energy systems, which are crucial for transitioning towards sustainable energy practices.

A. Implications for Practice and Policy

The practical applications of this study are manifold. For energy system operators, the optimization models developed herein offer a blueprint for integrating renewable energy sources more effectively, potentially reducing reliance on fossil fuels and lowering carbon emissions. This, in turn, supports the broader goal of achieving carbon neutrality in energy production and consumption. For policymakers, the research highlights the need for supportive regulatory frameworks that facilitate the adoption of advanced energy storage solutions and cross-regional energy cooperation. Policies that incentivize the development of renewable energy technologies and infrastructure can accelerate the transition towards a more sustainable and secure energy future.

B. Future Research Directions

While this study has made substantial advancements, several avenues for future research remain open. Firstly, the integration of more diverse renewable energy sources and storage technologies could be explored to further bolster system resilience and sustainability. Secondly, the development of real-time optimization algorithms that can dynamically respond to changes in energy demand and supply conditions would significantly enhance operational efficiency. Additionally, future studies could investigate the socio-economic impacts of widespread renewable energy adoption, including job creation, energy prices, and community well-being.

C. Recommendations for Future Work

To build on the findings of this study, future work should aim to:

- Explore the application of the proposed optimization models in different geographic and climatic conditions to validate their universality and adaptability.
- Develop more sophisticated models that incorporate emerging technologies such as artificial intelligence and blockchain for energy trading and management.
- Conduct comprehensive cost-benefit analyses of implementing HESS and other storage solutions at scale, including considerations of environmental impact and return on investment.
- Engage with stakeholders across the energy sector to identify barriers to implementation and strategies for overcoming these challenges.

In conclusion, this research represents a significant step forward in the quest for sustainable energy solutions. By addressing key challenges associated with renewable energy integration, the study not only contributes to academic knowledge but also provides practical insights for enhancing energy system performance. As we continue to advance in this field, it is imperative that research, policy, and practice evolve in tandem to fully realize the potential of renewable energy in achieving global sustainability goals.

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