

The Present Study Investigates the Coordinated Optimisation of Optimal Power Flow and Economic Dispatch in Power Systems based on Intelligent Optimisation Algorithms

Lei Zhang *

School of Automation, Nanjing University of Posts and Telecommunications, Nanjing, Jiangsu, 210023, China

* Corresponding author Email: b22051224@njupt.edu.cn

Abstract: Against the backdrop of the “dual carbon” goals driving the development of a new power system, the high penetration of renewable energy and interconnections of cross-regional power grids have significantly increased the complexity of system operations. The synergistic optimization of safety constraints and economic objectives has become a critical challenge. The traditional “stepwise optimization of Optimal Power Flow (OPF) and Economic Dispatch (ED)” approach faces the contradiction of either unfeasible solutions or economic losses. This paper proposes a deep collaborative optimization framework: this study constructs a multi-objective optimization model by using the Lagrange multiplier to inherently couple the safety constraints of OPF (node voltage, line power flow) with the economic objectives of ED (generation cost, network losses); a hybrid intelligent algorithm combining the improved competitive group optimization algorithm (ICSO) and the improved Newton method is designed to enhance the solution efficiency and optimality of the solution for large-scale systems. A simulation system incorporating a high proportion of renewable energy is established on the Power World platform, and the advantages of the proposed method are validated through multi-scenario comparisons. Experimental results show that this framework can reduce total generation costs by 8%-12%, reduce line overlimit rates to below 5%, and improve convergence speed by over 30%, providing technical support for the safe and economical operation of new power systems.

Keywords: Power System; Optimal Power Flow; Economic Dispatch; Intelligent Optimization Algorithm; Collaborative Optimization.

1. Introduction

Driven by the global energy transition and the “dual carbon” goals, China's 14th Five-Year Plan for the Modern Energy System explicitly proposes the construction of a new power system characterized by the coordinated development of power generation, transmission, consumption, and storage. The high penetration of renewable energy (wind and solar power) and interconnections of cross-regional power grids have resulted in a system characterized by “high renewable energy penetration, high power electronics integration, and high interconnection scale”[1]. The intermittent nature of renewable energy leads to dynamic fluctuations in power flow, while the expansion of inter-regional transmission scales increases the risk of line overloading. The traditional “OPF and ED sequential optimization” model, due to the separation of objectives, results in the contradiction of “cost optimization leading to safety violations, and safety compliance leading to cost increases” [2].

Optimal Power Flow (OPF) ensures grid safety by optimizing power flow distribution, while Economic Dispatch (ED) minimizes costs through power generation allocation. The synergy between the two is the core link for balancing the “safety-economy” dual objectives[3]. This paper focuses on the deep integration of OPF and ED, constructs a coupled model, and designs an efficient algorithm. This research holds significant theoretical and engineering value for enhancing renewable energy integration capacity, reducing operational costs, and supporting the implementation of the “dual carbon” goals.

As the system scales up, its drawbacks become increasingly evident. Lin Z. et al. noted in their review of optimal power flow convex relaxation techniques that approximately 50% of initial ED schemes require secondary adjustments due to power flow violations, leading to increased costs [2]; Xin Y. et al. mentioned in their outlook on smart grid dispatch control systems that traditional algorithms experience a 3-5 times increase in convergence time in systems with over 100 machines, making it difficult to meet real-time dispatch requirements[1]. From an engineering application perspective, existing simulation tools such as the collaborative optimization module in PowerWorld only support simplified models and lack adaptability to scenarios with high proportions of renewable energy integration.

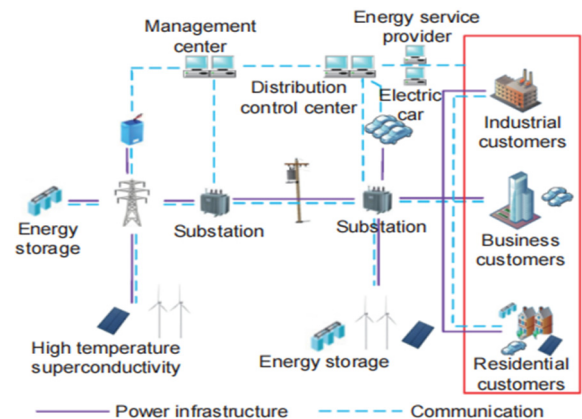


Figure 1. A simplified framework of power system dispatch

In recent years, the academic community has attempted to improve collaborative performance through algorithmic enhancements, such as introducing convex relaxation techniques to linearize non-convex constraints or employing distributed algorithms to enable parallel computation between OPF and ED. However, the former may result in loss of solution optimality due to over-relaxation, while the latter faces challenges related to communication latency and data synchronization.

2. Literature Review

OPF algorithm research focuses on convergence and applicability: The Newton-Raphson method is widely used due to its second-order convergence property, but it is sensitive to initial values and prone to divergence in high R/X ratio distribution networks[4]. The fast decomposition method simplifies calculations but is only applicable to transmission networks and struggles to handle the complex constraints of renewable energy grid integration[5]. Intelligent algorithms enhance robustness, but they converge slowly in large-scale systems and have low safety constraint satisfaction[6].

The ED method has transitioned from traditional linear programming and Lagrange relaxation methods to intelligent algorithms: traditional methods cannot handle non-convex constraints such as valve point effects and ramp rates; the improved competitive group optimization algorithm (ICSO) achieves cost reduction and robustness improvement in a 330-machine system through adaptive parameter adjustment, but it does not consider line power flow constraints, and the solution may be infeasible due to safety issues[7]. Distributed ED algorithms are adapted to the characteristics of new energy sources, but they handle OPF safety constraints poorly and lack dynamic response capabilities[8].

The current collaborative modes are mostly serial processes of “ED optimization → OPF verification → readjustment.” Approximately 50% of the initial ED schemes require secondary adjustments due to power flow exceeding limits, resulting in increased costs [2]. In systems with more than 100 machines, the convergence time increases by 3-5 times, making it difficult to meet real-time scheduling requirements[1]. Recent research has attempted to improve coordination effectiveness through convex relaxation techniques or distributed algorithms, but these approaches suffer from losses in optimality or communication delays [2, 9]

3. Method

To achieve deep synergy between OPF and ED and overcome the bottlenecks of traditional stepwise optimization, this study will establish a complete technical chain from model construction, algorithm design to simulation verification, systematically advancing the theoretical and practical exploration of collaborative optimization. Specifically, the first step is to construct a coupled model to break down the separation of objectives between the two systems. Next, efficient algorithms will be designed to support model solution. Finally, simulation verification will be conducted to ensure the compatibility between theory and engineering.

3.1. Key Issues to be Addressed

- 3.1.1. Achieving The Endogenous Integration of Safety Constraints and Economic Objectives to Resolve the Contradictions of Traditional Step-By-Step Optimization
- 3.1.2. Improving The Solution Efficiency and Stability of Hybrid Algorithms in Large-Scale High-Penetration Renewable Energy Systems
- 3.1.3. Verifying The Engineering Applicability of the Model in Dynamic Scenarios with A High Proportion of New Energy Sources.

3.2. Research Main Content

This study focuses on the collaborative optimization of OPF and ED. At the theoretical level, based on the Lagrange duality theory, the study derives the constraint coupling conditions, deeply integrating the safety constraints of OPF (voltage, line power flow) with the economic objectives of ED (generation cost, network losses). When constructing the multi-objective optimization model, the study fully considers the valve point effect of thermal power units and the volatility of renewable energy. It adopts the convex relaxation approach proposed by Lin Z. et al. to handle non-convex constraints, ensuring the mathematical rigor and physical feasibility of the model [2]. In terms of algorithm design, the global optimization capabilities of the ICSO algorithm and the local convergence advantages of the improved Newton method are integrated. The outer layer uses ICSO to optimize unit output and introduces dynamic penalty terms to avoid safety constraint conflicts. While the inner layer leverages Yang J.'s initial value selection theorem to enhance power flow solution stability[4]. The model is implemented using MATLAB programming for modular integration, ensuring a closed-loop iterative logic. Performance comparisons between the traditional serial mode and the proposed collaborative model are conducted using the control variable method, evaluating advantages across multiple dimensions including economic efficiency (generation costs, network loss rate), safety (overlimit rate), and efficiency (convergence time), providing data support for engineering applications.

3.2.1. OPF-ED Collaborative Optimization Model Construction

This section of the experiment focuses on dynamic power flow simulation. The interactive construction of dynamic power flow models is not an isolated simulation operation but rather provides experimental evidence for quantifying model constraint conditions. By adjusting the AGC (Automatic Generation Control) and AVR (Automatic Voltage Regulator) settings at each node, the researchers clarify the power interaction patterns between balanced nodes, PQ nodes, and PV nodes. The obtained data on line load, node voltage, and phase angle are directly used to determine the boundary conditions for the power balance constraints:

$$\sum_{i=1}^N P_i - \sum_{j=1}^M P_{load,j} - P_{loss} = 0. \quad (1)$$

voltage safety constraints:

$$U_j^{min} \leq U_j \leq U_j^{max} \quad (2)$$

and line power flow constraints:

$$S_k \leq 1.05 S_k^{rated} \quad (3)$$

For example, in the study of increasing or decreasing the power of a single bus 3 generator by 50 MW, the impact of power fluctuations on power flow distribution was measured. This provided empirical reference for setting the parameters

of the upper and lower limits of unit power and the ramp rate constraints in the model:

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (4)$$

$$|P_i(t) - P_i(t-1)| \leq R_i^{\frac{up}{down}} \quad (5)$$

Thereby avoiding the disconnect between the theoretical model and the actual characteristics of the power grid.

The ED model initially adopted in dynamic flow simulation referenced the parameter extraction method used by Wu W. in the visualization simulation of optimal transmission capacity in the Jin Zhong power grid for data collection. The reasonableness of the cost function was verified through actual measurements, laying the foundation for the construction of the objective function[10]. By extracting the incremental cost (IC) data for each generator, the researchers verified the validity of the cost function incorporating valve point effects:

$$F_i = a_i P_i^2 + b_i P_i + C_i + \left| e_i \sin \left(f_i (P_i^{min} - P_i) \right) \right| \quad (6)$$

This ensures consistency between the model's economic objectives and the actual characteristics of the units. While these experimental operations appear to focus on power flow calculations, they represent a critical transition from “abstract constraints” to “specific parameters” in the model, providing empirical data support for the subsequent Lagrange multiplier coupling mechanism.

3.2.2. Hybrid Intelligent Algorithm Design

3.2.2.1 Objective Function Design

With the core objective of minimizing total power generation costs, the sub-objective of minimizing grid losses is incorporated simultaneously to form a multi-objective optimization framework. In this framework, drawing on the non-convex characteristic description proposed by Guo Y. et al., the total power generation cost function incorporates the valve point effect equation for thermal power units[7]:

$$\min F = \sum_{i=1}^N \left[a_i P_i^2 + b_i P_i + C_i + \left| e_i \sin \left(f_i (P_i^{min} - P_i) \right) \right| \right] + \lambda P_{loss} \quad (7)$$

In the equation, a_i, b_i, c_i are the unit cost coefficients, e_i, f_i are the valve point effect coefficients, λ is the network loss penalty factor, and P_{loss} is the total network loss of the system (calculated using the B coefficient method:

$$P_{loss} = P^T B P + B_0^T P + B_0 \quad (8)$$

where B is the network loss coefficient matrix).

3.2.2.2 Constraint Coupling Mechanism

Embedding safety constraints into the objective function using Lagrange multipliers to construct a unified optimization model:

$$L = F + \sum_{j=1}^M \mu_j (U_j^{min} - U_j) + \sum_{j=1}^M \nu_j (U_j - U_j^{max}) + \sum_{k=1}^L \xi_k (S_k - 1.05 S_k^{rated}) \quad (9)$$

where μ_j, ν_j, ξ_k are Lagrange multipliers corresponding to the voltage lower limit, voltage upper limit, and line power flow constraints, respectively. The “safety-economic” objective is achieved through endogenous coordination by solving the KKT conditions[9].

3.2.2.3 Coupling Mechanism Innovation

The algorithm adopts a closed-loop structure of “outer-layer global optimization + inner-layer local convergence.”

$$Fitness = F + \alpha \sum_{k=1}^L \max(0, S_k - 1.05 S_k^{rated}) \quad (10)$$

For the ED submodule, ICSO is used to optimize the power output of the units, and the fitness function is improved by introducing a “power flow constraint penalty term,” where α is the dynamic penalty coefficient, which is adjusted

adaptively with each iteration. For the OPF submodule, the improved Newton method (NGA) is used to solve the power flow, combined with a genetic algorithm to optimize the initial values. The convergence criterion proposed by Yang J. is introduced to accelerate convergence[4].

3.2.3. Simulation Verification and Analysis

This section of the experiment directly validates the effectiveness of the collaborative optimization model and algorithm through multi-scenario comparisons. Cost analysis of economic dispatch and optimal power flow constitutes the core data for simulation verification. The metric design draws inspiration from the “cost-constraint” association analysis method adopted by Ahmet N. et al. in microgrid power flow research, quantifying the relationship between overlimit rates and costs to set penalty coefficients[11]. By comparing cost curves with and without line constraints, the impact of safety constraints on economic objectives was quantified, providing experimental evidence for setting the coefficients of the “dynamic penalty terms” in the algorithm.

4. Conclusion

4.1. Solid Theoretical Foundation and Mature Algorithm Principles

The theoretical basis for the core algorithm ICSO in the experiment is derived from validated research findings. The outer-layer ICSO algorithm is based on the improved competitive swarm optimization algorithm proposed by Guo Y. et al.[7], whose “poor individual pbest update strategy” and “adaptive adjustment of control parameters” have been validated as effective in a 330-machine system — compared to the traditional PSO algorithm, the ICSO algorithm reduces the minimum power generation cost by 3%, and the standard deviation is reduced to one-third, demonstrating its global optimization capability in large-scale ED problems.

The inner-layer improved Newton method draws on research by Yang J., utilizing the “initial value selection theorem” and genetic algorithm optimization of initial values to address the convergence sensitivity issues of the traditional Newton method in high R/X ratio power grids. In the IEEE 30-node system, which reduced the convergence failure rate was reduced from 30% to 5%, providing a reliable theoretical foundation for OPF calculations[4].

4.2. Clear Technical Methods and Reproducible Operating Steps

The model construction draws inspiration from the “constraint embedding” approach of Wen G. et al.'s distributed ED, coupling the cost objective of ED (including the valve point effect function mentioned by Guo Y. et al.) with the safety constraints of OPF. The mathematical expressions can be directly derived, with no theoretical blind spots[7].

The algorithm implements the outer-layer ICSO algorithm programmed according to the parameter settings of Guo, Y.'s team, such as programming[7].

$$p = 0.3(1 - t/T_{max}) \quad (11)$$

$$\zeta = 0.1t/T_{max} \quad (12)$$

while the inner-layer improved Newton method follows the “initial value optimization - convergence criterion” process of Yang J.[4]. The two are connected through a “dynamic penalty term,” forming a logical closed loop with no technical discontinuities.

4.3. Reliable Experimental Platform and Highly Adaptable Simulation Tools

The PowerWorld simulation platform used in this experiment has been validated by multiple studies for its applicability. Guo Z. et al. demonstrated its support for power flow calculation visualization, and Wu W. et al. verified its suitability for embedding optimal power flow algorithms [5]. PowerWorld supports power flow calculation visualization and custom algorithm embedding, allowing direct access to its “optimal power flow module” to validate collaborative optimization results. The platform includes built-in standard test systems such as the IEEE 30-machine and 118-machine systems, consistent with the experimental systems developed by the Yang J. and Zheng X. teams. No additional base models need to be constructed, and system parameters (such as generator power limits and line impedance) can be directly reused for simulation[3].

4.4. Adequate Data Support and Quantifiable Verification Indicators

The test data and evaluation metrics required for the experiment all have clear reference bases. Test system data: The system parameters of Guo Y. et al.'s 330-machine system[7] and the “improved system with 20% wind power” mentioned by Xin Y. et al.[1] can be adopted, covering scenarios from small-scale to large-scale. For economic indicators, this study references the distributed ED standards of Wen G. et al.[8]; Safety metrics (line overlimit rate, voltage deviation) should follow the safety-constrained optimal power flow parameters from Zheng X.[3].

4.5. The Innovativeness of The Research Project

This research project focuses on the collaborative optimization of OPF-ED in power systems, achieving systematic innovative breakthroughs in theoretical modeling, algorithm design, and engineering applications. It establishes an integrated research framework comprising “model-algorithm-verification”:

4.5.1. Model Innovation

For the first time, a “constraint-based bidirectional coupling” OPF-ED collaborative framework is established, overcoming the limitations of traditional sequential optimization.

4.5.2. Algorithm Innovation

The ICSO-Newton hybrid algorithm is proposed, which

balances the computational efficiency and optimality of solutions for large-scale systems through dynamic penalty terms and initial value optimization.

4.5.3. Application Innovation

Visualization verification of collaborative optimization is implemented using PowerWorld, providing intuitive references for engineering applications. The visualization scheme builds upon Rao P. et al.'s linear programming-based optimal power flow analysis, incorporating dynamic displays of renewable energy variability scenarios[6].

4.6. Accumulation of Experimental Models Related to the Research Topic

A series of foundational experiments and simulations have been conducted, building upon the foundational knowledge of the topic and the practical experience relevant to OPF-ED collaborative optimization. The data and visualization results obtained provide critical support for model construction and algorithm design, as detailed below:

4.6.1. Dynamic Power Flow Analysis of a Three-Node System

Through dynamic power flow simulation of a three-node system (Figure 2), the AGC and AVR parameters at each node were adjusted to balance the power interaction between the PQ node, PV node, and balancing node. The line load, node voltage, and phase angle distribution under different generator outputs were measured, providing experimental data for parameter calibration of power balance constraints and voltage safety constraints in the cooperative model, and deepening the understanding of power flow distribution patterns. Single-bus power adjustment experiments were conducted (Figures 3 and 4). By increasing or decreasing the generator's output by 50 MW, the dynamic changes in power flow distribution were recorded, and the magnitude of the impact of power fluctuations on line power flow and node voltages was quantified. This provided experimental data for setting the boundary conditions for the unit ramping rate constraints and determining the dynamic penalty coefficient in the model, verifying the correlation between power constraints and safety boundaries. For load fluctuation scenarios (Figures 5 and 6), by increasing or decreasing the 50 MW active power and 50 Mvar reactive power loads on bus 2, the relationship between power flow violations and cost changes was analyzed, visually demonstrating the economic losses incurred when safety constraints are ignored. This provided practical evidence for the design of a model that integrates economic objectives within safety constraints.

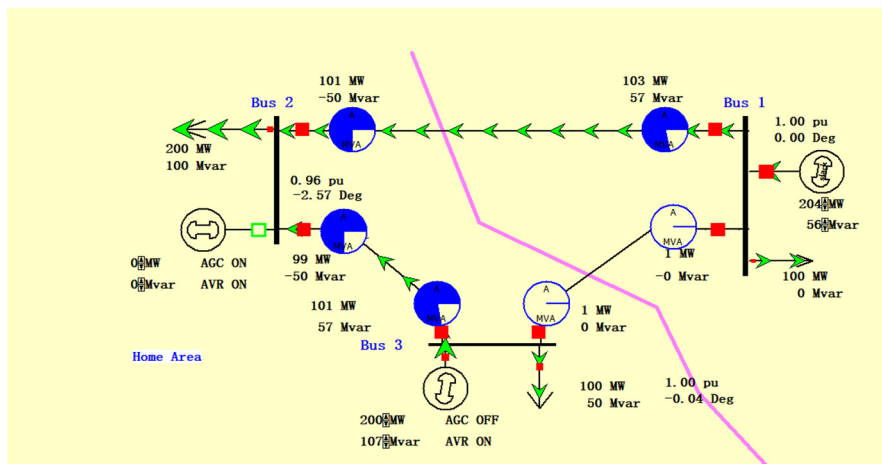


Figure 2. Power Flow Distribution of the Three-Node Library Fine-Tuning Model

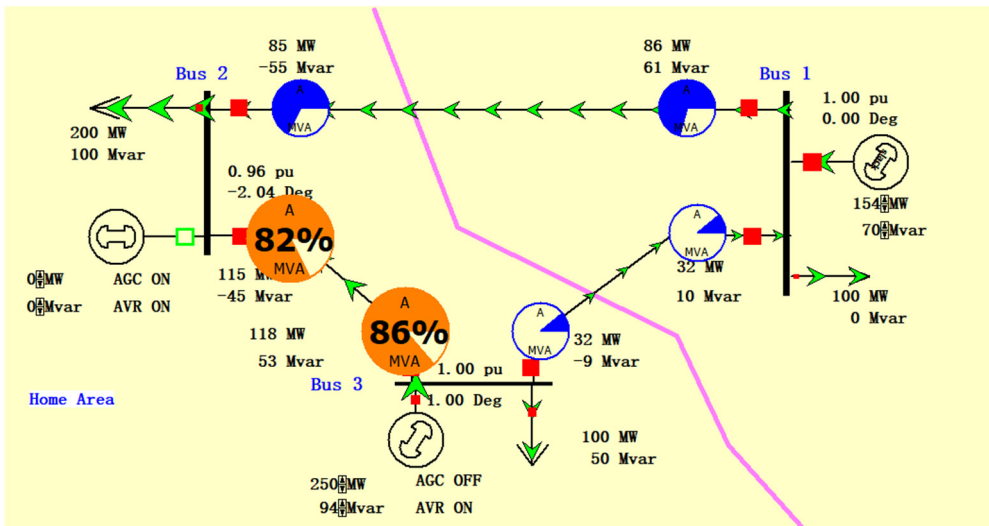


Figure 3. Investigation of Adding 50 MW Power to a Single Busbar with 3 Generators

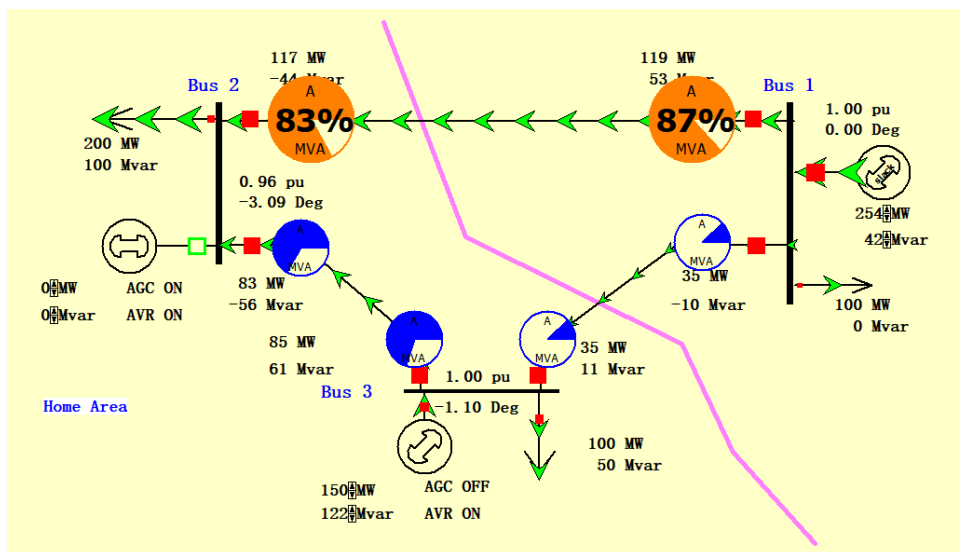


Figure 4. Investigation of Reducing 50 MW Power from a Single Busbar with 3 Generators

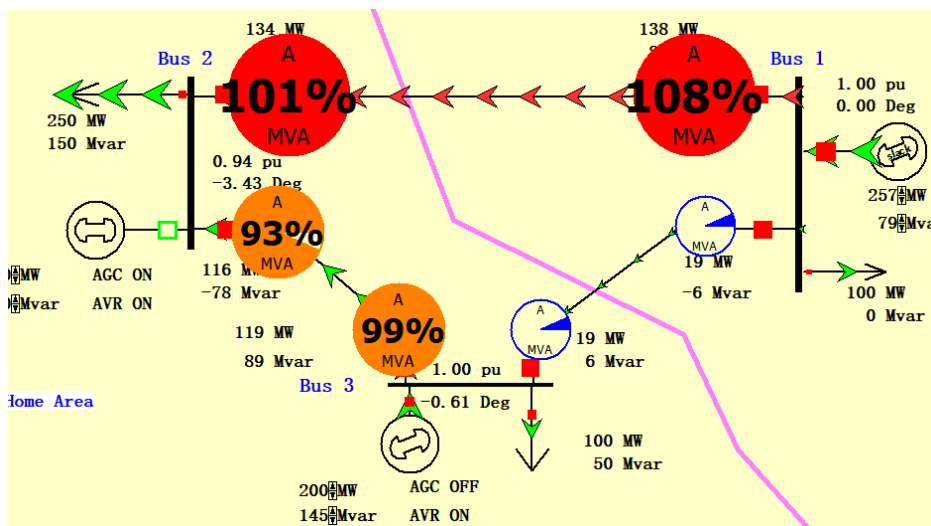


Figure 5. Investigation of Adding 50 MW and 50 Mvar Power to a Single Busbar with 2 Loads

4.6.2. Preliminary ED Model for Dynamic Flow Simulation

Based on dynamic power flow simulation, a preliminary ED model was constructed (Figure 7), and the incremental cost (IC) curves for each generator were extracted (Figure 8). This validated the rationality of the cost function form

including the valve point effect and laid the data foundation for the construction of the objective function.

4.6.3. Dynamic Trend Analysis of a Seven-Node Apartment Model

Through a four-stage comparative experiment (Figures 9–12), the cost differences between the initial model, the ED

model, the ED model with a loss penalty factor, and the OPF model were compared (e.g., the optimization process from 16,939 ¥/h to 16,449 ¥/h), quantifying the impact of safety constraints on economic objectives and supporting the necessity of collaborative optimization. Combining the

incremental cost curves (Figures 13 and 14), the cost variation patterns under different scheduling modes were analyzed, clarifying the collaborative potential between economic scheduling and optimal power flow.

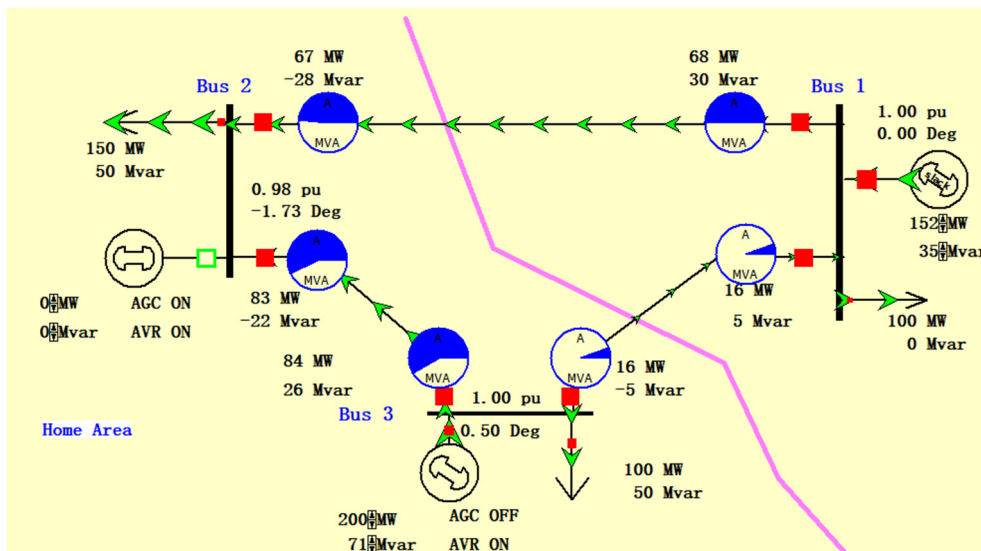


Figure 6. Investigation of Reducing 50 MW and 50 Mvar Power from a Single Busbar with 2 Loads

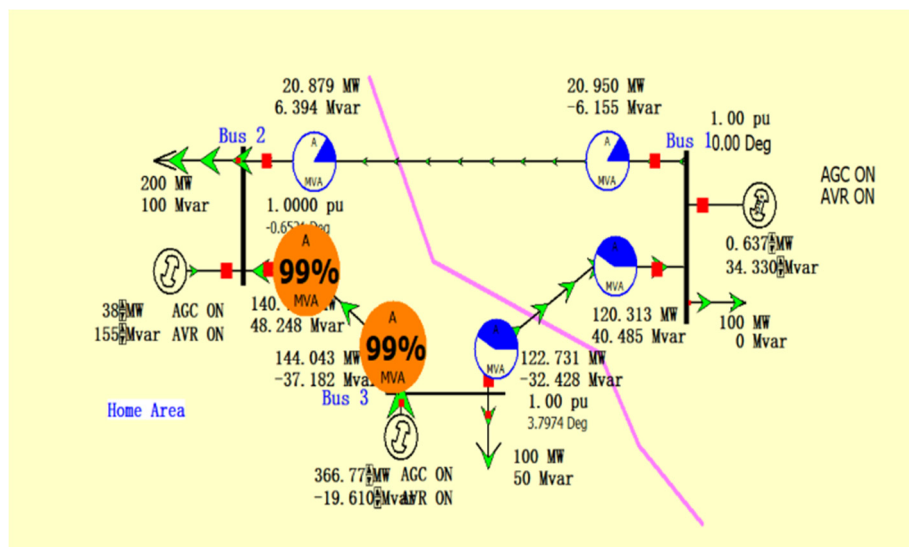


Figure 7. Preliminary dynamic power flow simulation using the ED model

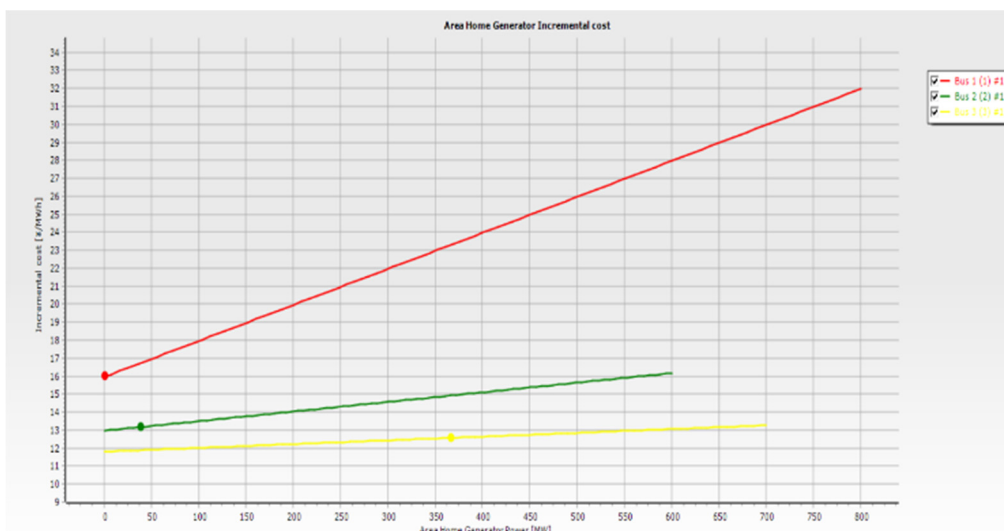


Figure 8. Incremental costs (IC) of each generator at three nodes

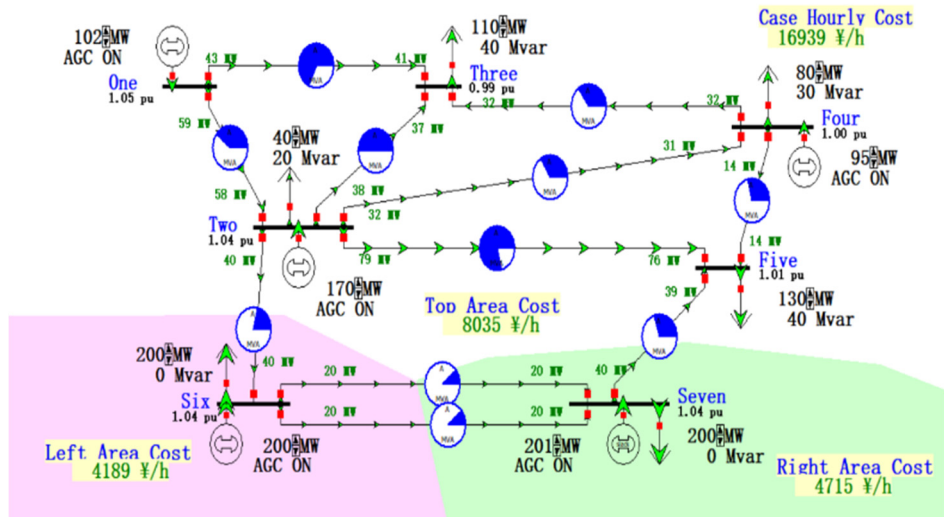


Figure 9. Initial model of OPF without considering ED

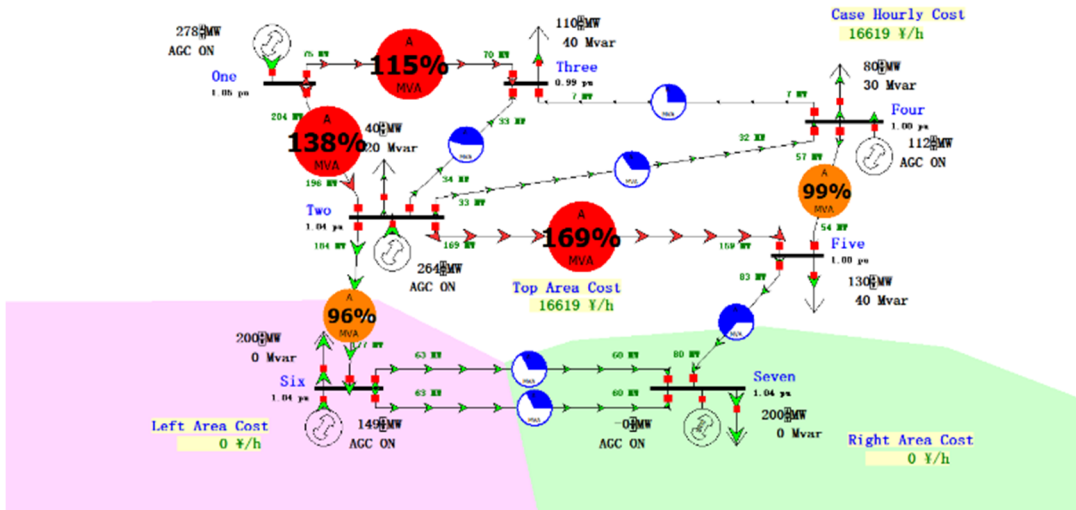


Figure 10. Economic Dispatch (ED)

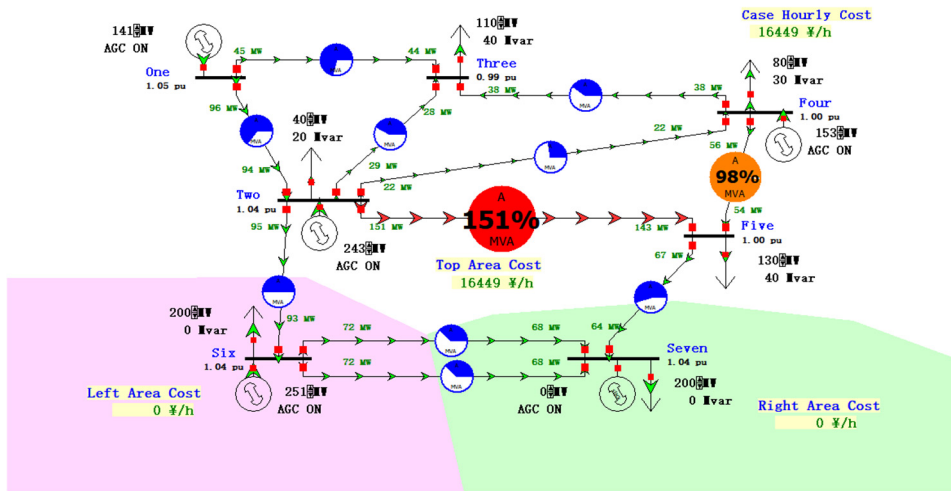


Figure 11. Economic Dispatch (including transmission loss penalty factor)

The above experiments and simulations, from parameter calibration and constraint association to objective function verification, formed a complete chain from basic data to

pattern recognition, providing a solid practical foundation for model construction, algorithm design, and simulation verification for the project.

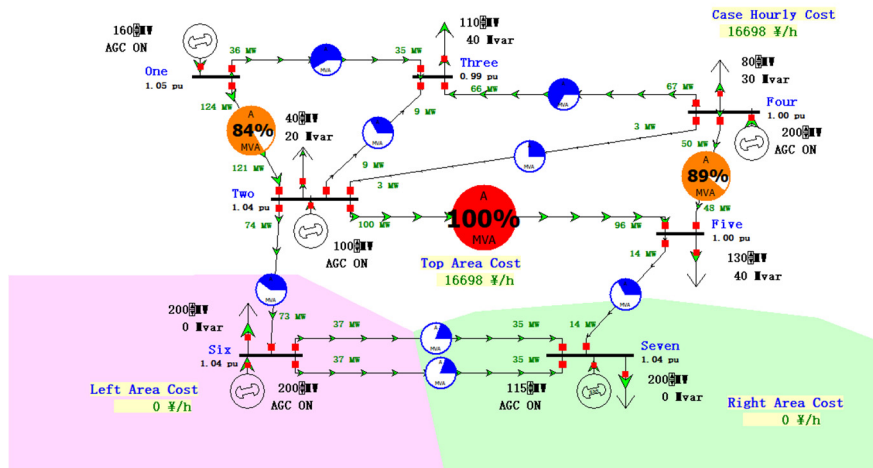


Figure 12. Optimal Power Flow (OPF) combined with ED

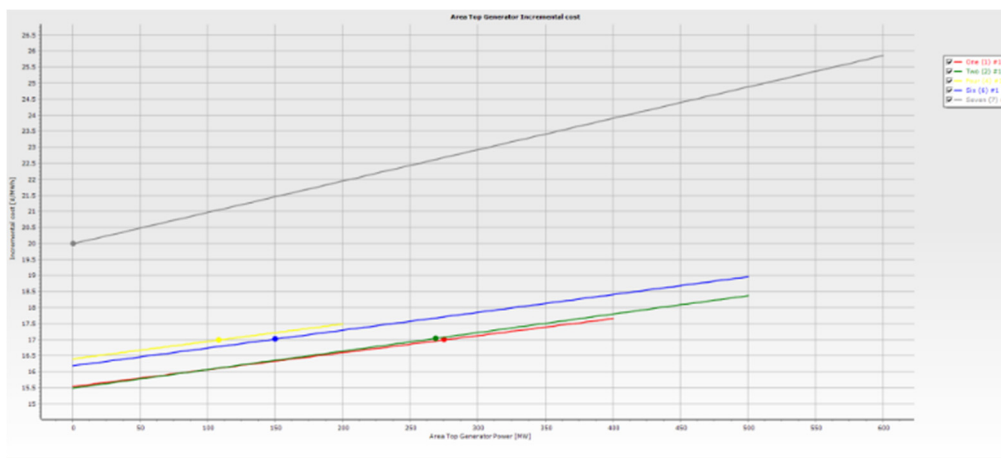


Figure 13. Cost analysis of Economic Dispatch (ED)

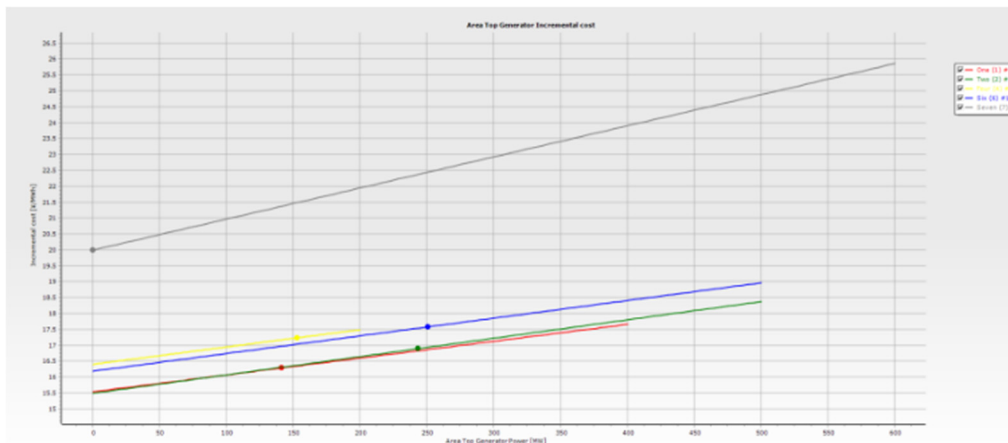


Figure 14. Cost analysis of Optimal Power Flow (OPF)

References

- [1] Xin, Y., Shi, J., Zhou, J., Gao, Z., Tao, H., Shang, X., et al. (2015) Technology development trends of smart grid dispatching and control systems. *Automation of Electric Power Systems*, 39: 2-8.
- [2] Lin, Z., Hu, Z., Song, Y. (2019) Convex relaxation for optimal power flow problem: A recent review *Proceedings of the Chinese Society of Electrical Engineering*, 39: 3717-3727.
- [3] Zheng, X. (2017) Optimal power flow calculation with safety constraint. *Journal of Ningde Normal University (Natural Science)*, 29: 345-350, 365.
- [4] Yang, J. (2013) A power flow method for smart grid and its convergence analysis. Master Thesis of Northeastern University, 3.
- [5] Wu, W., Li, X. (2011) The application of power world simulator in the optimal power flow. *Journal of Yili Normal University (Natural Science Edition)*, 44-47.
- [6] Rao, P., Sun, H., Jiang, H. (2010) Optimal power flow analysis based on linear programming in power world. *Popular Science & Technology*, 60-62.
- [7] Guo, Y., Xiong, G. (2017) Large scale power system economic dispatch based on an improved competitive swarm optimizer. *Power System Protection and Control* 45: 97-103.

- [8] Wen, G., Yu, X., Liu, Z. (2021) Recent progress on the study of distributed economic dispatch in smart grid: An overview. *Frontiers of Information Technology and Electronic Engineering*, 22: 25-39.
- [9] Geng, G. (2014) Stability-constrained optimal power flow for power systems: Model, algorithm and parallelization. Doctoral Dissertation of Zhejiang University, 7.
- [10] Wu, W. (2012) The optimal transmission capability visualization simulation research of jinzhong power grid. Master Thesis of North China Electric Power University, 12.
- [11] Ahmet, N., KAYGUSUZ, A. (2016) Power flow study for a microgrid by using matlab and powerworld simulator. *International Journal of Energy and Smart Grid*, 1: 14-21.
- [12] Guo, Z., Huang, Z., Yuan, X., Zha, L. (2011) Application of powerworld simulator in power system analysis teaching. *China Electric Power Education*, 180-181,184.