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Graph-Theoretic Ant Colony Optimization for Dynamic Distribution Network Reconfiguration with High-Penetration Renewable Energy Sources and Battery Energy Storage Systems

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Abstract

High-penetration integration of Renewable Energy Sources (RESs) and Battery Energy Storage Systems (BESSs) has transformed Distribution Network Reconfiguration (DNR) from a static topology optimization task into a complex combinatorial problem with strong coupling between discrete switch decisions and dynamic power flow constraints. This evolution requires that optimization algorithms provide two capabilities: native adaptability to discrete decision variables without approximation, and real-time responsiveness to dynamic operating conditions. Ant Colony Optimization (ACO), as the most widely applied discrete-native Swarm Intelligence (SI) algorithm, faces three critical bottlenecks in DNR due to its Traveling Salesman Problem (TSP)-oriented design: framework incompatibility, ambiguous heuristic formulation, and ineffective pheromone strategies. To address these limitations, this study proposes a Graph-Theoretic Ant Colony Optimization (GTACO) algorithm. Multi-scenario experiments on IEEE 33-bus and PG&E 69-bus systems demonstrate that GTACO outperforms state-of-the-art algorithms in core metrics including loss reduction rate, voltage stability, convergence efficiency, and economic–environmental benefits. This research overcomes the TSP-centric limitations of conventional ACO, establishes a methodological foundation for extending the ACO framework to complex non-TSP discrete optimization tasks, and provides a practical solution for dynamic DNR under high-penetration RES and BESS integration.

Keywords: distribution network reconfiguration; renewable energy sources; graph theory; ant colony optimization; dynamic discrete optimization



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1. Introduction

Modern power systems consist of three core operational pillars: generation, transmission, and distribution [1]. As the terminal link between bulk power systems and end-users, the Distribution Network (DN) operates at lower voltage levels and higher line currents, resulting in significantly greater power losses and voltage deviations than transmission networks [2]. Statistical data show that distribution system losses account for up to 70% of total power system losses, and nearly 80% of customer-side power outages originate from DN faults [3]. Reducing DN losses through advanced optimization technologies is therefore a core priority for power system efficiency enhancement and global carbon emission reduction.

Distribution Network Reconfiguration (DNR) optimizes system performance by adjusting the open/closed states of sectionalizing (normally closed) and tie (normally open) switches to modify network topology, while satisfying all operational constraints of the DN [4]. Driven by global carbon neutrality goals, the penetration of Renewable Energy Sources (RESs) in the DN continues to grow rapidly [5]. Distributed Generation (DG), the primary carrier of RES integration, is classified into dispatchable types such as Biomass Generation (BG) and non-dispatchable types such as Photovoltaic (PV) and Wind Turbine (WT) systems [6]. The inherent intermittency and volatility of non-dispatchable RESs have transformed the traditional single-source radial DN into a multi-source active network, with frequent and dynamic changes in power flow direction and magnitude [7]. The Battery Energy Storage System (BESS) has emerged as a critical enabling technology to mitigate RES fluctuations, leveraging its rapid charge–discharge response to bridge the spatiotemporal mismatch between renewable generation and load demand [8]. However, the coupled integration of high-penetration RESs and BESSs has evolved DNR from a static topology optimization problem into a complex combinatorial optimization problem with strong coupling between discrete switch decisions and dynamic power flow constraints. This evolution imposes two essential requirements on optimization algorithms: native adaptability to discrete decision variables without approximation and real-time responsiveness to dynamic operating scenarios.

1.1. Literature Review

Optimizing DN operational performance through reconfiguration has been a focal point of power system research for nearly five decades, yet existing methods exhibit critical limitations in dynamic adaptability, computational efficiency, and uncertainty resilience, with no universally applicable solution established to date [9]. This section systematically examines the core characteristics and application limitations of existing methods, with a focus on establishing a rigorous logical chain to justify the selection of ACO for DNR optimization.

1.1.1. Traditional Methods

Traditional mathematical programming methods rely on precise mathematical modeling and deterministic optimization theory, dominating early DNR research. The branch-and-bound method proposed by Merlin and Back [10] marked the first systematic approach to large-scale DNR, establishing a theoretical foundation for accurate global optimization in small-scale networks. However, this method suffers from exponential efficiency degradation and the curse of dimensionality as network scale and constraint complexity increase. Subsequent linear programming approaches [11], Markov decision process frameworks [12], and mixed-integer second-order cone programming methods [13] have improved modeling accuracy for DG-integrated scenarios but remain dependent on fixed models and deterministic assumptions. These methods require complex mathematical transformations and high-performance solvers, with inadequate adaptability to the dynamic characteristics of RESs and BESSs. Their limitations become increasingly pronounced as DN scale and complexity expand, evidenced by prohibitively high computational complexity in 24 h optimization scenarios for large-scale networks [14] and frequent convergence failures or infeasible solutions in dynamic scenarios with high renewable penetration [15].

1.1.2. Heuristic Methods

Heuristic methods simplify the DNR problem through empirical rules and local optimization strategies, which offers the core advantage of high computational efficiency. Montoya et al. [16] proposed a constructive heuristic algorithm based on minimum current concepts and node ordering, which requires minimal computational effort but relies on

static load distribution rules, failing to adapt to complex dynamic constraints introduced by RESs and BESSs. Li et al. [17] integrated the Minimum Spanning Tree (MST) algorithm with enhanced heuristic rules to reduce reliance on initial network topology, but the resulting MST weights are calculated using fixed impedance matrices, limiting adaptability to high DG penetration scenarios. In summary, heuristic methods are susceptible to local optimality due to their static rule design and cannot adapt to dynamic constraint changes caused by RESs and BESSs, with their limitations becoming increasingly pronounced in high-penetration RES environments.

1.1.3. Metaheuristic Methods

Compared with traditional and heuristic approaches, metaheuristic algorithms simulate biological behaviors and natural phenomena, eliminating reliance on derivative information while demonstrating superior solution space exploration capabilities and multi-constraint adaptability. Over decades of development, these methods have become the mainstream solution for DNR in high-RES penetration scenarios, and they can be divided into continuous-native and discrete-native categories based on their design paradigms.

Continuous-native metaheuristic algorithms, including Particle Swarm Optimization (PSO) [18], Group Search Optimization (GSO) [19], and Salp Swarm Algorithm (SSA) [20], are inherently designed for continuous variable optimization. When applied to DNR's discrete binary switch states, they require discretization processing, which introduces mapping errors between the continuous search space and discrete solution space. This approximation leads to reduced accuracy, increased computational complexity, and a higher risk of entrapment in local optima [19,20]. Discretization alone cannot reconcile the fundamental mismatch between continuous algorithm frameworks and the discrete nature of DNR.

Discrete-native metaheuristic algorithms, represented by Genetic Algorithm (GA) [21], Harmony Search Algorithm (HSA) [22], and Ant Colony Optimization (ACO) [23], natively handle discrete variables without approximation. However, GA and HSA follow a static design paradigm, where their core optimization mechanisms rely on precalibrated parameters and fixed rules. For example, the improved GA filters radial initial solutions via topological matrices for efficiency, but its crossover and mutation parameters are manually set and runtime-invariant, causing significant performance degradation under dynamic load and RES fluctuations [21]. Similarly, HSA's harmony memory adjustment process heavily depends on empirical parameter configuration, and its search strategy cannot adapt to real-time power flow changes, making it prone to premature convergence under strong uncertainty from high-penetration RESs [22]. These static design limitations render them inherently incapable of adapting to the dynamic constraint changes introduced by RES and BESS coupling, leading to significant performance degradation in high-penetration scenarios and failure to meet the real-time requirements of dynamic DNR [24,25].

In contrast, ACO is recognized as the most promising discrete metaheuristic algorithm for DNR and has become the most widely applied in this field [26]. This prominence arises because its stigmergy-based distributed search mechanism inherently matches the discrete nature of switch state decisions [27], while also natively supporting adaptive adjustments in dynamic environments. Early studies by Su et al. [28] and Khoa and Phan [29] validated ACO's loss reduction potential in small-scale DNR scenarios, marking the first exploration of ACO in the DNR domain. Subsequent studies by Abdelaziz et al. [30] and Osama et al. [31] applied Hypercube Ant Colony Optimization (HC-ACO) to DNR, attempting to improve solution space exploration efficiency. However, a systematic review of existing ACO-related literature reveals that these studies have not addressed the core limitations of ACO when applied to the DNR problem [23,32]. ACO was originally

conceived for the TSP, a static discrete path optimization problem without dynamic operational constraints, which is fundamentally different from the dynamic, multi-constrained characteristics of DNR. This native design limitation restricts the practical effectiveness of ACO in DNR, with existing methods facing three critical, unresolved bottlenecks.

First, framework incompatibility. Existing studies directly apply the TSP-oriented ACO framework to DNR without targeted, mechanism-level modifications. Abdelaziz et al. [30] and Osama et al. [31] directly utilized the HC-ACO framework to solve DNR problems, and this unmodified adoption leads to two major defects: difficulty in defining suitable heuristic values aligned with DNR's electrical essence and limitation to encoding switch states via simple binary encoding, which severely restricts flexibility and adaptability to radial topology constraints. This unmodified framework leads to extremely low feasible solution screening efficiency and a high proportion of infeasible solutions, which is further exacerbated in dynamic RES-integrated scenarios.

Second, ambiguous heuristic definition. In the TSP, the heuristic value is typically defined as the inverse of physical distance between cities, which is static, precomputable, and directly aligned with the objective of minimizing path length. For DNR, however, heuristic values must dynamically reflect electrical characteristics and adapt to switching operations and power flow changes. Existing attempts exhibit three typical flaws. Guan and Fan [33] adopted node physical distance as the heuristic value, which is completely detached from the electrical essence of DNR. Xue et al. [34] and Li et al. [23] only used the reciprocal of line resistance, while existing graph-theoretic ACO adaptations ([32]) also rely on static indicators like voltage differences. These single static indicators cannot reflect the impact of dynamic power flow changes on network loss after switching operations. Kasaei and Norouzi [35] proposed a power loss difference-based heuristic design but failed to define the contribution of a single switching operation to loss reduction, violating the core self-organizing logic of ACO where individual ants accumulate experience from high-quality intermediate decisions. All existing designs fail to achieve direct alignment between heuristic values and the multi-objective optimization requirements of DNR, violating the core principle of ACO's pheromone–heuristic value collaborative guidance.

Third, ineffective pheromone strategies. The pheromone semantics of physical paths in the TSP are completely mismatched with DNR's cross-loop switch combination optimization requirements. In the TSP, pheromone intuitively accumulates on short physical paths, with clear and consistent semantics. However, for DNR, pheromone paths are defined by abstract power loss objectives, where performance indicators between any two network nodes change continuously with topology and operating conditions. Applying the unconstrained path search of the TSP easily generates infeasible solutions such as ring networks and islands, which contaminate pheromone trails. This leads to the failure of pheromone updates to converge to topologies with low network loss and high voltage stability, with more severe failure in dynamic RES- and BESS-integrated scenarios [36].

It is worth noting that most existing studies have attempted to alleviate these issues through parameter tuning or adding local search operators, which are merely patchwork improvements. They have not resolved the fundamental contradiction between ACO's TSP-oriented native design and the inherent characteristics of DNR at the framework level, which constitutes the core motivation of this study.

1.2. Research Gap

The preceding review identifies a critical research gap: no existing algorithm simultaneously satisfies the dual requirements of discrete decision precision and dynamic scenario adaptability for DNR under high-penetration RESs and BESSs. Even ACO, the most promising discrete-native algorithm, is fundamentally limited by its TSP-oriented native

framework. Specifically, existing research has not systematically resolved ACO's three core bottlenecks in DNR applications at the framework level: framework incompatibility, ambiguous heuristic definition, and ineffective pheromone strategies. This gap is the core obstacle restricting the effective application of ACO in dynamic DNR scenarios and constitutes the core problem addressed in this paper.

1.3. Main Contributions

Based on in-depth analysis of the ACO framework and DNR problem characteristics, this study proposes the GTACO algorithm, which deeply integrates graph theory with ACO core mechanisms to systematically address the three core bottlenecks of ACO in DNR applications at the framework level. The core contributions are outlined as follows:

First, a graph-theoretic reconstruction method for the ACO framework is proposed. The DN is mapped to an undirected graph, and infeasible solutions are eliminated at the source through loop membership rules, single-loop breakpoint rules, and connectivity maintenance rules. This innovation redefines the solution space of ACO from TSP's city traversal path sequence to the DN's radial feasible topology spanning tree and directly addresses the core bottleneck of framework incompatibility.

Second, an MST-driven dynamic power flow calculation method is designed. Real-time branch power loss is used as the weight to generate the MST and dynamically define the power flow direction, which provides accurate dynamic electrical data for heuristic value calculation and objective function evaluation. This method provides underlying support for resolving the bottlenecks of ambiguous heuristic definition and ineffective pheromone strategies.

Third, three ant colony behavior constraints for feasible solution optimization are defined based on graph-theory loop and spanning tree characteristics: single-loop switch constraint, adjacent loop migration constraint, and local topology awareness constraint. These constraints limit the ant colony search to an efficient feasible domain, significantly reduce invalid iterations, and further improve the adaptation of the ACO framework to DNR characteristics.

Fourth, a virtual pheromone update mechanism is proposed. Virtual paths are constructed through graph theory to connect cross-loop switch selections, and pheromone trails are directly correlated with core dynamic metrics such as power loss reduction and voltage stability improvement. This mechanism prevents the contamination of pheromones by infeasible solutions and systematically resolves the core bottleneck of ineffective pheromone strategies.

Fifth, a DNR-specific multi-dimensional dynamic heuristic function is constructed, which integrates three dimensions of information: normalized power loss reduction, voltage deviation improvement, and power flow fluctuation characteristics. This function overcomes the defects of traditional static and one-sided heuristic values and directly addresses the core bottleneck of ambiguous heuristic definition.

1.4. Paper Organization

The remainder of this paper is organized as follows. Section 2 presents the DNR problem description and mathematical model. Section 3 details the core principles and implementation process of the GTACO algorithm. Section 4 provides multi-scenario experimental verification and in-depth discussion. Section 5 concludes the study.

2. Problem Description and Mathematical Model

DNR optimizes system performance by adjusting switch states while satisfying operational constraints. Under high-penetration RES and BESS integration, DNR has evolved from a static problem into a discrete topology optimization under dynamic power flow constraints. Its discrete and dynamic characteristics are fundamentally incompatible with the TSP-oriented framework of traditional ACO.

2.1. Optimization Objective

The core objective of DNR is to minimize the system's total active power loss, while taking into account economic costs and environmental benefits. This requires real-time integration of RES and BESS output fluctuations and load dynamics, with core calculations based on the forward-backward sweep method for power flow solution.

The total active power loss of the system, which is the core optimization target of DNR, is aggregated from the losses of all line branches and calculated as:

$$P_{\text{loss}} = \sum_{i=1}^N \sum_{j=1, j \neq i}^N R_{ij} \frac{|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos\delta_{ij}}{|Z_{ij}|^2} \quad (1)$$

where N is the total number of buses in the DN; δ_{ij} is the voltage phase angle difference between bus i and bus j ; R_{ij} is the resistance of branch $i - j$; Z_{ij} is the impedance of branch $i - j$; V_i and V_j are the voltage magnitudes of bus i and bus j , respectively.

The active and reactive power of branch $i - j$, which form the basis for loss calculation, are defined as:

$$P_{ij} = \frac{|V_i||V_j|}{|Z_{ij}|} \cos(\theta_{ij} + \delta_j - \delta_i) - \frac{|V_j|^2}{|Z_{ij}|} \cos\theta_{ij} \quad (2)$$

$$Q_{ij} = \frac{|V_i||V_j|}{|Z_{ij}|} \sin(\theta_{ij} + \delta_j - \delta_i) - \frac{|V_j|^2}{|Z_{ij}|} \sin\theta_{ij} \quad (3)$$

where θ_{ij} is the phase angle of the branch admittance; δ_i and δ_j are the voltage phase angles of bus i and bus j , respectively.

To accurately characterize the impact of RESs and BESSs on system power balance, their output characteristics are modeled based on time-series probability distributions. PV output is described by the beta distribution to characterize the randomness of light intensity, calculated as:

$$P_{PV}^t = N_{PV} P_{PV}^{\text{rated}} \eta_{PV} \frac{G_{ir}^t}{G_{ir}^{\text{std}}} \left[1 + K_t (T_{ir}^t - T_{ir}^{\text{std}}) \right] \quad (4)$$

where t is the time step; N_{PV} is the number of PV modules; P_{PV}^{rated} is the rated power of a single PV module; η_{PV} is the PV conversion efficiency; G_{ir}^t and T_{ir}^t are the irradiance intensity and temperature at time t , respectively; G_{ir}^{std} and T_{ir}^{std} are the irradiance intensity and temperature under standard test conditions; K_t is the power temperature coefficient.

The stochastic nature of solar irradiance G_{ir}^t is modeled using a beta distribution to generate the time-series input profiles required for the dynamic scenarios. The shape parameters (α_{Beta} , β_{Beta}) of the distribution are derived from the mean (μ_{PV}) and standard deviation (σ_{PV}) of historical irradiance data, ensuring the generated profiles reflect real-world variability and preserve the statistical characteristics of the historical data.

WT output adopts the Weibull distribution to describe the random characteristics of wind speed, combined with cut-in, rated, and cut-out wind speed constraints, defined as:

$$P_{WT}^t = \begin{cases} 0, V_{WT}^t < V_{WT}^{in} \text{ or } V_{WT}^t > V_{WT}^{out} \\ \eta_{WT} P_{WT}^{rated} \frac{V_{WT}^t - V_{WT}^{in}}{V_{WT}^{rated} - V_{WT}^{in}}, V_{WT}^{in} \leq V_{WT}^t \leq V_{WT}^{rated} \\ \eta_{WT} P_{WT}^{rated}, V_{WT}^{rated} < V_{WT}^t \leq V_{WT}^{out} \end{cases} \quad (5)$$

where V_{WT}^t is the wind speed at time t ; V_{WT}^{in} , V_{WT}^{rated} , and V_{WT}^{out} are the cut-in, rated, and cut-out wind speeds, respectively; η_{WT} is the WT conversion efficiency; P_{WT}^{rated} is the rated power of the WT.

The stochastic nature of wind speed V_{WT}^t is modeled using a Weibull distribution to generate the time-series input profiles required for the dynamic scenarios. The shape (k_{WT}) and scale (λ_{WT}) parameters of the distribution are derived from the mean (μ_{WT}) and standard deviation (σ_{WT}) of historical wind speed data, ensuring the generated profiles reflect real-world turbulence and preserve the statistical characteristics of the historical data.

BG is a dispatchable RES, whose output is determined by biomass feedstock supply and gasification efficiency, subject to start–stop and minimum output constraints:

$$P_{BG}^t = F_{bf}^t H_{hv} \eta_{gg} \quad (6)$$

$$P_{BG}^{out} = \begin{cases} 0, P_{BG}^t < P_{BG}^{min} \\ P_{BG}^t, P_{BG}^{min} < P_{BG}^t < P_{BG}^{max} \\ P_{BG}^{max}, P_{BG}^t > P_{BG}^{max} \end{cases} \quad (7)$$

where F_{bf}^t is the biomass feedstock supply rate at time t ; H_{hv} is the calorific value of the biomass feedstock; η_{gg} is the gasifier efficiency; P_{BG}^{out} is the actual output of BG; P_{BG}^{min} and P_{BG}^{max} are the minimum and maximum output limits of BG, respectively.

The BESS balances RES fluctuations through charging and discharging operations, with its dynamic energy model considering the difference between charging and discharging efficiencies:

$$E_{BESS}^t = \begin{cases} E_{BESS}^{t-1} - \frac{P_{BESS}^t}{\eta_{BESS}^d} \Delta t, P_{BESS}^t > 0 (\text{discharging}) \\ E_{BESS}^{t-1} - P_{BESS}^t \eta_{BESS}^c \Delta t, P_{BESS}^t < 0 (\text{charging}) \end{cases} \quad (8)$$

where E_{BESS}^t is the energy storage capacity of the BESS at time t ; P_{BESS}^t is the charging and discharging power of the BESS at time t ; η_{BESS}^c and η_{BESS}^d are the charging and discharging efficiencies of the BESS, respectively; Δt is the time step.

To fully reflect the engineering value of DNR, economic and environmental benefits are quantified based on system power loss. The annual power loss cost is calculated as:

$$C_{loss} = 8760 C_{kwh} P_{loss} \quad (9)$$

where C_{kwh} is the cost per kilowatt-hour of electricity. Greenhouse gas emissions, including CO₂, NO_x, and SO₂, are calculated using the IPCC general emission factors [37] to quantify the environmental benefits of DNR.

2.2. Operational Constraints

To ensure the safe and stable operation of the DN, the optimization process must satisfy multi-dimensional operational constraints dynamically adapted to the output characteristics of RESs and BESSs.

First, the radial topology constraint, which is the primary hard constraint of DNR. The optimized DN topology must be an acyclic and fully connected radial structure, corresponding to a spanning tree of the DN undirected graph. This constraint ensures no looped power flow and continuous power supply to all loads.

Second, the power balance constraint, which requires real-time balance of the total active and reactive power of the system at each time step:

$$\sum_{i=1}^N P_{\text{load},i}^t = \sum_{i=1}^N P_{\text{DG},i}^t + P_{\text{grid}}^t \mp P_{\text{BESS}}^t + P_{\text{loss}}^t \quad (10)$$

$$\sum_{i=1}^N Q_{\text{load},i}^t = \sum_{i=1}^N Q_{\text{DG},i}^t + Q_{\text{grid}}^t \mp Q_{\text{BESS}}^t + Q_{\text{loss}}^t \quad (11)$$

where $P_{\text{load},i}^t$ and $Q_{\text{load},i}^t$ are the active and reactive loads at bus i at time t ; $P_{\text{DG},i}^t$ and $Q_{\text{DG},i}^t$ are the total active and reactive outputs of the RES at bus i at time t ; P_{grid}^t and Q_{grid}^t are the active and reactive powers injected by the main grid at time t ; P_{loss}^t and Q_{loss}^t are the total active and reactive losses of the system at time t ; the negative sign indicates BESS charging, while the positive sign denotes BESS discharging.

Third, the safe operation constraint, which requires that node voltage magnitudes and branch currents remain within the rated allowable range:

$$V_{\min} \leq |V_i| \leq V_{\max} \quad (12)$$

$$|I_{ij}| \leq |I_{ij}^{\max}| \quad (13)$$

where $V_{\min}$ and $V_{\max}$ are the minimum and maximum allowable voltage magnitudes of the system; I_{ij} is the current magnitude of branch $i - j$; $I_{ij}^{\max}$ is the rated current of branch $i - j$.

Fourth, the DG output constraint, which covers the capacity constraint and ramp rate constraint of the RES:

$$|P_{\text{DG}}^{\min}| \leq |P_{\text{DG},i}^t| \leq |P_{\text{DG}}^{\max}| \quad (14)$$

$$|Q_{\text{DG}}^{\min}| \leq |Q_{\text{DG},i}^t| \leq |Q_{\text{DG}}^{\max}| \quad (15)$$

$$-P_{\text{DG}}^{\text{rdown}} \leq (P_{\text{DG},i}^t - P_{\text{DG},i}^{t-1}) \leq P_{\text{DG}}^{\text{rup}} \quad (16)$$

$$-Q_{\text{DG}}^{\text{rdown}} \leq (Q_{\text{DG},i}^t - Q_{\text{DG},i}^{t-1}) \leq Q_{\text{DG}}^{\text{rup}} \quad (17)$$

where $P_{\text{DG}}^{\min}$ and $P_{\text{DG}}^{\max}$ are the active output limits of DG; $Q_{\text{DG}}^{\min}$ and $Q_{\text{DG}}^{\max}$ are the reactive adjustment ranges of the DG inverter; $P_{\text{DG}}^{\text{rup}}$ and $P_{\text{DG}}^{\text{rdown}}$ are the maximum upward and downward ramp rates of DG active power; $Q_{\text{DG}}^{\text{rup}}$ and $Q_{\text{DG}}^{\text{rdown}}$ are the maximum upward and downward ramp rates of DG reactive power.

Fifth, the BESS operational constraint, which includes charge–discharge power, capacity, and state switching constraints:

$$-P_{\text{BESS}}^{\text{rated}} \leq P_{\text{BESS}}^t \leq P_{\text{BESS}}^{\text{rated}} \quad (18)$$

$$E_{\text{BESS}}^{\min} \leq E_{\text{BESS}}^t \leq E_{\text{BESS}}^{\max} \quad (19)$$

$$P_{\text{BESS}}^t P_{\text{BESS}}^{t-1} \geq 0 \quad (20)$$

where $P_{\text{BESS}}^{\text{rated}}$ is the rated power of the BESS; $E_{\text{BESS}}^{\min}$ and $E_{\text{BESS}}^{\max}$ are the minimum and maximum allowable energy storage capacities; the final constraint prevents abrupt changes in BESS charging and discharging states between adjacent time steps to avoid battery damage.

3. GTACO Algorithm Principle

This section systematically elaborates the core mechanism of the GTACO algorithm. To address the mechanism-level conflicts between traditional ACO and DNR, GTACO reconstructs the ACO framework from three core dimensions, each operationalizing the resolution of one bottleneck identified in Section 1.1.3: heuristic guidance redesign via a DNR-specific multi-dimensional dynamic heuristic function (Section 3.2); solution space reconstruction via graph-theoretic mapping to eliminate infeasible solutions (Section 3.3.1); and pheromone mechanism innovation via virtual pheromone paths to avoid contamination (Section 3.3.4). We first analyze the fundamental limitations of traditional ACO (Section 3.1), then detail these three innovations, followed by the MST-driven dynamic power flow calculation (Section 3.3.2) and ant behavior constraints (Section 3.3.3), and finally present the integrated application flow (Section 3.4).

3.1. Mechanism Limitations of Traditional ACO

While Section 1.1.3 identifies three fundamental bottlenecks through literature analysis, this section rederives them from ACO's own governing equations to justify the necessity of the framework-level reconstruction proposed in Sections 3.2–3.4. ACO is a metaheuristic algorithm inspired by the foraging behavior of real ants, which solves complex combinatorial optimization problems through the stigmergy mechanism mediated by pheromone trails [38].

The first ACO variant, Ant System (AS), was proposed by Dorigo [39], and its core design is inherently tailored to the TSP's core features: static topology, symmetric distance measurement, and the objective of minimizing path length. Despite numerous ACO variants proposed in subsequent research, including Ant Colony System (ACS), Elite Ant System (EAS), and Max–Min Ant System (MMAS), the framework remains deeply bound to TSP-type path optimization problems [40]. This creates a fundamental barrier for its application in non-TSP-type problems such as DNR, which is elaborated from the mathematical mechanism level below.

The core solution construction logic of traditional ACO is defined by the state transition probability formula:

$$P(a_i^j | s_e) = \frac{\tau_{ij}^\alpha [\eta(a_i^j)]^\beta}{\sum_{a_i^k \in N(s_e)} \tau_{ik}^\alpha [\eta(a_i^k)]^\beta} \quad \forall a_i^j \in N(s_e) \quad (21)$$

Here, τ_{ij} denotes the pheromone concentration between decision units i and j , $\eta(a_i^j)$ represents the heuristic information of decision unit a_i^j , and α and β regulate the weights of historical pheromone and current heuristic information, respectively. $N(s_e)$ is the feasible decision unit set for the current ant.

After all ants complete one round of solution construction, pheromones are updated via evaporation and deposition:

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \sum_{s \in S_{upd} | a_i^j \in s} \omega(s) \quad (22)$$

In this equation, $\rho \in (0, 1)$ is the pheromone evaporation rate; S_{upd} is the set of solutions contributing to pheromone deposition; $\omega(s)$ is the quality evaluation function for solution s . Pheromone deposition on τ_{ij} occurs only when a_i^j belongs to solution s and $s \in S_{upd}$. However, these native mechanisms are primarily designed for path length optimization and fail to account for the electrical constraints and dynamic characteristics of DNR, resulting in optimization failure when directly applied.

From the mathematical mechanism level, the three core bottlenecks of traditional ACO in DNR applications are fundamentally derived from the mismatch between its TSP-native design and DNR characteristics, which cannot be resolved by mere parameter tuning or local search modifications.

First, structural incompatibility: the TSP's solution space is defined by sequential city traversal Hamiltonian cycles, while DNR's solution space is defined by radial spanning trees that dynamically evolve with RES and BESS states. The TSP framework lacks inherent mechanisms to enforce radial topology and connectivity constraints, leading to a high proportion of infeasible solutions.

Second, heuristic value conflict: in the TSP, heuristic values are static precomputed physical distances directly aligned with the optimization objective. For DNR, heuristic values must reflect the real-time impact of switch operations on power loss and voltage stability, which require dynamic power flow calculations. Static heuristic values based on fixed parameters disconnect heuristic guidance from actual optimization objectives.

Third, pheromone semantic mismatch: in the TSP, pheromones are deposited on physical edges with clear path length semantics. For DNR, the optimization objective depends on cross-loop switch combinations, not individual physical edges. Pheromones on physical edges cannot reflect the combined effect of multiple switches and are easily contaminated by infeasible solutions, leading to convergence failure.

To address these mechanism-level core conflicts, this paper reconstructs the ACO framework from three dimensions: solution space, search behavior, and pheromone mechanism, through graph theory, and proposes the GTACO algorithm.

3.2. DNR-Specific Multi-Dimensional Dynamic Heuristic Function

As identified in Section 3.1, ambiguous heuristic definition is one of the three core bottlenecks of traditional ACO in DNR applications. To resolve this issue, this study proposes a DNR-specific multi-dimensional dynamic heuristic function, which directly aligns with the core optimization objectives of DNR, and its expression is:

$$\eta(a_i^j) = \omega_1 \cdot \frac{\Delta P_{\text{loss},ij}}{\max(\Delta P_{\text{loss}})} + \omega_2 \cdot \frac{V_{\text{rated}} - |V_i - V_{\text{rated}}|}{V_{\text{rated}}} \quad (23)$$

$$\Delta P_{\text{loss},ij} = P_{\text{loss},\text{initial}} - P_{\text{loss},\text{after}(ij)} \quad (24)$$

Here, $\Delta P_{\text{loss},ij}$ represents the power loss reduction after opening branch $i - j$, normalized by the maximum possible loss reduction in the current iteration to prioritize switches with significant local optimization effects. V_{rated} represents the rated voltage of the system, and $|V_i - V_{\text{rated}}|$ quantifies node voltage deviation. ω_1 and ω_2 denote the weight coefficients of power loss reduction and voltage stability, respectively, ensuring a balance between economic efficiency and operational safety. This absolute deviation metric is specifically chosen to guarantee the strict non-negativity required by the ACO state transition probability (Equation (21)) and to maintain linear numerical scaling for effective weight adjustment. This design dynamically responds to switch operations and power flow changes, overcoming the limitations of traditional static heuristics.

In essence, this function translates the global electrical objectives of DNR into localized, real-time guidance for each ant's decision-making step. The two terms correspond to the two core priorities of distribution system operation: economic efficiency (power loss reduction) and operational safety (voltage stability).

This heuristic function has three core advantages over traditional designs. First, it is dynamically updated after each topology change and power flow calculation, which fully adapts to the dynamic characteristics of DNR and overcomes the defect of static heuristic values that cannot reflect real-time operating conditions. Second, it integrates the two

core optimization objectives of network loss reduction and voltage stability, avoiding the one-sidedness of traditional single-parameter heuristic designs, and directly aligns the ants' local optimization behavior with DNR's global optimization objectives. Third, it quantifies the contribution of a single switch operation to the global optimization objective, which conforms to the core self-organizing logic of ACO where individual ants accumulate experience from high-quality intermediate decisions. This function systematically resolves the core bottleneck of ambiguous heuristic definition in traditional ACO and also provides an accurate value basis for the effective update of pheromones.

3.3. Core Mechanisms of GTACO

3.3.1. Graph-Theoretic Reconstruction of the ACO Framework

DNR's primary hard constraint, the radial topology requirement (defined in Section 2.2), aligns naturally with spanning tree properties in graph theory. GTACO maps the DN to an undirected graph $G = (V, E)$, where the vertex set $V = \{v_1, v_2, \dots, v_N\}$ corresponds to the buses of the DN, with N denoting the total number of buses. The edge set $E = \{e_{12}, e_{13}, \dots, e_{(N-1)N}\}$ corresponds to the distribution lines, with each edge's attributes including branch resistance, real-time power loss, and other electrical parameters.

To ensure the feasibility of the solution, three graph-theoretic topology rules are defined for the graph G , which eliminate infeasible solutions such as ring networks and islands at the source. First, the loop membership rule, which requires that selected switches must belong to the candidate edge set of their respective loops, and invalid switches outside the loops are prohibited. Second, the single loop single breakpoint rule, which allows only one edge to be opened per loop to avoid power supply interruption caused by multiple breakpoints in a single loop. Third, the connectivity maintenance rule, which prohibits the simultaneous opening of switch combinations that cause islands, to ensure continuous power supply to all buses.

Based on these rules, the core topological parameters of the graph G are calculated, which provide a quantitative basis for reducing ACO's search space. The number of potential feasible topologies is calculated using the cofactor of the Laplacian matrix:

$$N_t = |\det(\mathcal{L}')| \quad (25)$$

where $\mathcal{L}$ is the Laplacian matrix of the graph G and $\mathcal{L}'$ is the submatrix of $\mathcal{L}$ with one row and one column removed. Additionally, the number of switches to be opened L is derived from the number of edges $|E|$ and vertices N :

$$L = |E| - (N - 1) \quad (26)$$

Through this graph-theoretic mapping, the search space of ACO is reduced from $2^{|E|}$ level full switch combination to $\prod_{l=1}^L |E_l|$, where E_l is the edge set of the l -th loop. This greatly reduces the search dimension and the number of invalid iterations. More importantly, this mapping redefines the search object of ACO from the city traversal path sequence in the TSP to the radial feasible topology spanning tree of the DN. Each feasible ACO solution corresponds to a spanning tree of G , which requires $N - 1$ edges to connect all vertices and matches the radial topology requirements of the DN. This constitutes a framework-level reconstruction of ACO's solution space semantics, distinguishing GTACO from prior graph-theoretic ACO adaptations such as Swarnkar et al. [32]. In [32], graph theory serves as a feasibility-control layer around the conventional TSP-native search paradigm. In GTACO, the graph-theoretic rules define the construction law itself—ants build spanning trees from the first step, redefining the search space from arbitrary switch combinations to radial feasible topologies by construction. This redefinition, together with the dynamic heuristic defined in Equation (23) and Section 3.2 and the virtual-path

pheromone defined in Equations (27)–(31) and Section 3.3.4, constitutes a mechanism-level re-embedding of ACO's solution space, heuristic, and pheromone semantics rather than a graph-theoretic addition to the existing TSP-native framework. This eliminates the structural incompatibility between the traditional ACO framework and DNR's topology constraints and resolves the core bottleneck of framework incompatibility.

3.3.2. MST-Driven Dynamic Power Flow Calculation

DNR's optimization objective is inherently dependent on real-time power flow calculation, but the integration of RESs and BESSs causes dynamic changes in power flow direction and magnitude, making traditional ACO's static evaluation methods produce calculation bias. GTACO couples the MST algorithm with the ACO solution construction process in real time, using line real-time power loss $\omega_{ij} = P_{\text{loss},ij}$ as the weight to dynamically determine power flow direction through MST.

The MST generation process consists of three core steps. First, vertex group initialization divides all vertices into two sets, V_{MST} and $V_{non-MST}$, where V_{MST} initially contains only the power supply bus. Second, constrained edge selection traverses all edges connecting V_{MST} and $V_{non-MST}$, screens candidate edges that meet the operational constraints, and selects the edge e_{ij} with the minimum weight ω_{ij} . Third, MST expansion and power flow direction definition adds the selected edge e_{ij} to the MST, incorporates the corresponding vertex into V_{MST} , and repeats until V_{MST} includes all vertices. This process defines the edge direction from V_{MST} to $V_{non-MST}$, which is the dynamic power flow direction of the system.

Crucially, MST is not an independent module but tightly coupled with the ACO search process in real time. After each ant selects an edge, the MST is recalculated immediately based on the updated topology, and the weights ω_{ij} of the remaining edges are updated through the power flow equations. These weights serve as real-time inputs for the multi-dimensional dynamic heuristic value in Equation (23), preventing disconnection between the heuristic value and actual power flow. The total active power loss of the spanning tree is the sum of ω_{ij} for all edges in the tree. This value is calibrated by MST to ensure consistency with actual power flow. It replaces the static estimation of traditional ACO, enabling the objective function to accurately reflect the network's dynamic state. This mechanism resolves the problem of disconnection between static parameters and dynamic power flow in traditional ACO and provides an accurate electrical basis for heuristic value calculation and pheromone update.

3.3.3. Ant Behavior Constraints for Feasible Solution Optimization

The random search behavior of ants in traditional ACO often generates a large number of invalid iterations in the complex solution space of DNR. To address this issue, GTACO defines three core behavior constraints based on the topological characteristics of graph theory to guide ants to focus on high-quality feasible regions.

First, the single-loop switch constraint, which requires each ant to select only one edge per loop. Once an edge is selected from a loop, all other edges in that loop are marked as unselectable to avoid islands caused by multiple switch openings in the same loop. Second, the adjacent loop migration constraint, which requires ants to migrate only between adjacent loops, guided by the edge connection relationship of MST, to reduce iteration redundancy caused by discrete search. Third, the local topology perception constraint, which requires ants to make decisions only based on the topological information of the current loop and its adjacent loops, to focus the search on regions directly related to the current solution construction and reduce exploration of invalid edges.

To maintain continuity of information across loop switch selections, virtual paths are constructed to connect the edges selected by ants in different loops. A virtual path is an

abstract path connecting the selected edges across different loops. Conceptually, it serves as a bridge that links switch decisions made in separate loops into a coherent solution, while also providing a dedicated carrier for pheromone deposition that reflects the collective quality of the entire switch combination. In the initialization phase, an ant selects edge e_1 in loop L_1 and initializes the virtual path $P_v = \{e_1\}$. When the ant migrates to the adjacent loop L_2 and selects edge e_2 , the virtual path expands to $P_v = \{e_1, e_2\}$, and pheromones are deposited on the virtual path segment connecting e_1 and e_2 . When $P_v = \{e_1, e_2, \dots, e_L\}$ covers all L loops, the ant returns to the initially selected edge e_1 to form a closed loop, ensuring the connectivity of the spanning tree. These behavior constraints strictly limit the ant colony search within the efficient feasible domain, significantly reduce invalid iterations and the generation of infeasible solutions, and further improve the adaptation of the ACO framework to DNR characteristics.

3.3.4. Virtual Pheromone Update Mechanism

To resolve the core bottleneck of ineffective pheromone strategies in traditional ACO, this paper proposes a virtual pheromone update mechanism based on virtual paths. Unlike traditional ACO, which deposits pheromones on physical edges, virtual pheromones are deposited on the virtual path connecting the selected edges, and their increment is directly determined by the optimization benefits, such as network loss reduction and voltage improvement, resulting from the corresponding switch combination. Virtual pheromone τ_{ik} represents the contribution of the path segment, formed by edge e_{ik} selected by ant i at step k and edge e_{ik-1} selected at step $k-1$, to the reduction in power loss. The update process is divided into four core stages, which fully adapt to the dynamic characteristics of DNR.

First, the local update stage. After ant i selects edge e_{ik} to expand the virtual path, the pheromone of the corresponding virtual path segment is updated immediately based on the network loss reduction brought by the operation:

$$\tau_{ik} = (1 - \rho)\tau_{ik} + \rho\Delta P_{\text{loss},ik} \quad (27)$$

Here, $\Delta P_{\text{loss},ik}$ denotes the power loss reduction subsequent to selecting edge e_{ik} and ρ represents the pheromone evaporation rate. This stage strengthens the local efficient decision making of ants and ensures that pheromones directly reflect the contribution of each switch operation to the optimization objective.

Second, the pheromone evaluation stage. The total pheromone increment of a single ant i along the complete virtual path is calculated to assess the overall quality of its solution:

$$\omega(i) = \sum_{k=1}^L \tau_{ik} \quad (28)$$

where L is the total number of loops that the ant needs to select.

Third, the incremental calculation stage. After all ants complete the construction of the spanning tree, additional pheromone increment is calculated exclusively for the ant with the optimal fitness i_{best} :

$$\Delta\omega(i_{\text{best}}) = \rho \frac{Q}{V_{\text{fit}}^{i_{\text{best}}}} \quad (29)$$

where Q is the pheromone constant and $V_{\text{fit}}^{i_{\text{best}}}$ is the fitness value of the optimal ant. This stage strengthens the positive feedback mechanism of the algorithm and guides the ant colony to converge to the global optimal solution.

Fourth, the global update and convergence control stage. Additional pheromones are added only to the virtual path corresponding to the current iteration's optimal solution, and

the pheromone concentration is limited by upper and lower bounds to avoid premature convergence and search stagnation:

$$\tau_{ik}(t+1) = \begin{cases} \min[\tau_{\max}, (1 - \rho)\tau_{ik}(t) + \omega(i_{\text{best}}) + \Delta\omega(i_{\text{best}})] & \text{if } \sum_{k=1}^L \eta(a_{\text{best}}^k) \text{ is optimal} \\ \max[\tau_{\min}, (1 - \rho)\tau_{ik}(t)] & \text{otherwise} \end{cases} \quad (30)$$

$$\tau_{\max} = \frac{1}{\rho \sum_{k=1}^L \eta(a_{\text{best}}^k)}, \tau_{\min} = \frac{\tau_{\max}}{2L} \quad (31)$$

where $\eta(a_{\text{best}}^k)$ represents the heuristic value of the decision unit at step k for the optimal ant; $\tau_{\max}$ and $\tau_{\min}$ denote the upper and lower bounds of pheromone concentration, respectively, with initial values set to $\tau_{\max}$.

This virtual pheromone mechanism transforms the pheromone from an abstract path trace on physical edges into a dynamic indicator on virtual paths that directly reflects the improvement degree of DNR's core optimization objectives. It prevents the contamination of pheromones by infeasible solutions, realizes the tight coupling between ACO's pheromone positive feedback mechanism and DNR's optimization objectives, and systematically resolves the core bottleneck of ineffective pheromone strategies in traditional ACO.

In essence, this mechanism ensures that only switch combinations that actually improve system performance can accumulate pheromones, guiding the ant colony to converge to globally optimal topologies rather than locally optimal physical edges. From a stochastic process viewpoint, the admissible construction space is finite, bounded by the product form in Equation (26) derived from Equation (25). The update mechanism in Equations (27)–(31) maintains a strictly positive pheromone floor, as established by Equation (31), while reinforcing only when local increments are positive, as defined by Equation (27). Consequently, the algorithm satisfies the standard regularity conditions, including finite state space, non-extinction with $\tau_{\min}$ strictly greater than zero, and monotonic reinforcement, on which ACO-class convergence theory is built. This ensures the mechanism is mathematically well-defined rather than a simulation-only construct.

3.4. Application Flow of GTACO in DNR

The complete application flow of GTACO in DNR consists of three core closed-loop stages that strictly align with the core mechanisms described above. In brief, the algorithm first constructs the graph-theoretic search space, then iteratively searches for the optimal spanning tree within this constrained space, and finally updates the virtual pheromone to guide future search. The full flow is shown in Figure 1.

First, the initialization stage. The DN is mapped to an undirected graph, and core topological parameters such as the number of loops and the number of switches to be opened are calculated via Equations (25) and (26).

The algorithm's core parameters are set, including the number of ants m , pheromone weight α , heuristic value weight β , evaporation rate ρ , maximum iteration number $T_{\max}$, and convergence threshold ϵ . Ants are randomly allocated to each loop, the initial virtual pheromone concentration is set to $\tau_{\max}$, and the initial state of the iteration is completed. The key algorithm parameters (α , β , ρ) are calibrated based on classic ACO theory and the graph-theoretic mechanism of GTACO. Specifically, setting $\beta > \alpha$ ensures that the DNR-specific dynamic heuristic information dominates over historical pheromones, preventing premature convergence, while ρ is calibrated to balance pheromone accumulation with evaporation under dynamic topological updates. This mechanism-driven calibration, combined with the graph-theoretic feasibility constraints that confine the search to

a well-structured feasible manifold, ensures that the algorithm is not sensitive to small perturbations around the chosen configuration.

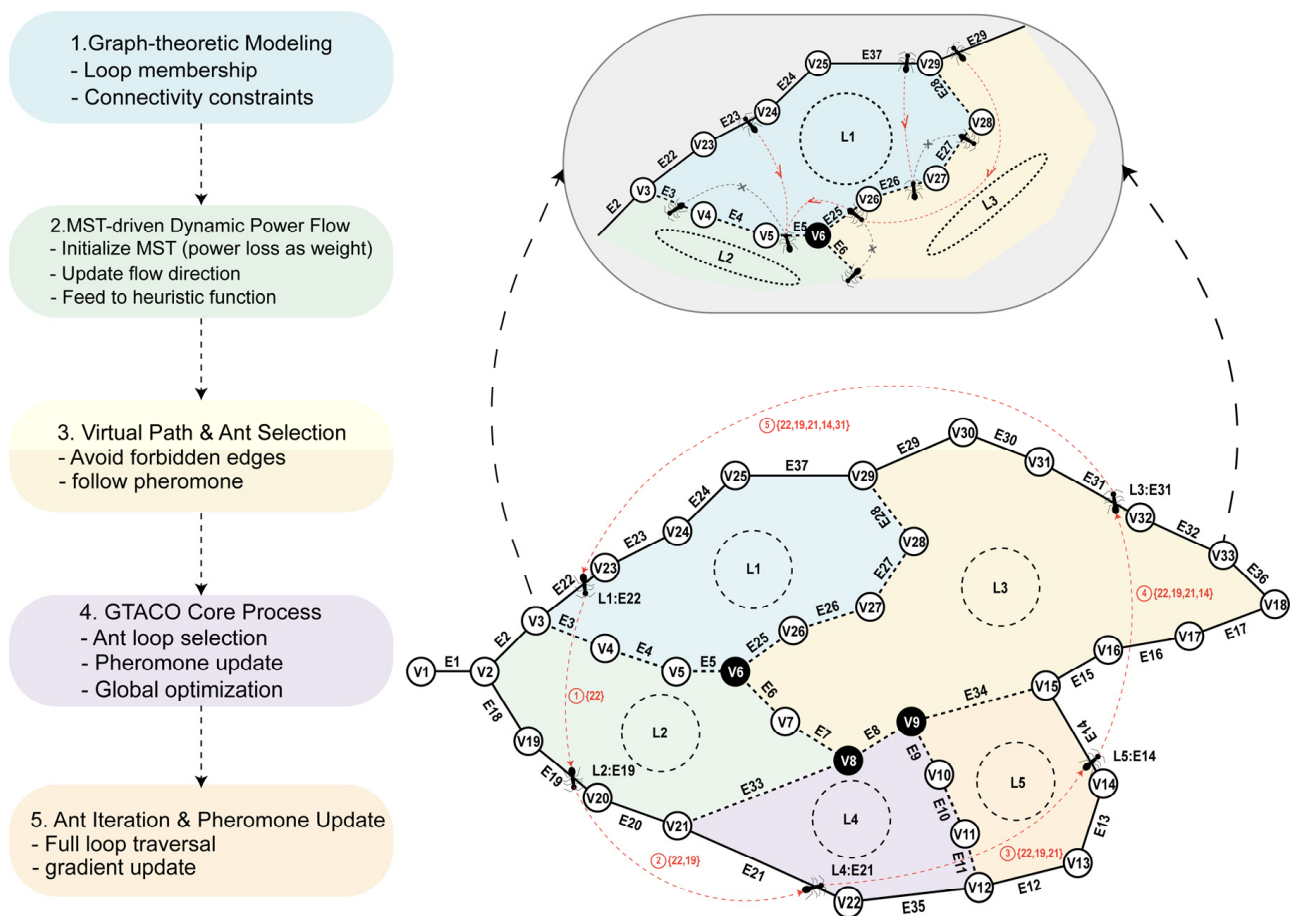


Figure 1. Complete application flow of the GTACO algorithm for DNR. Colored regions correspond to independent loops; dashed lines represent virtual pheromone paths; arrows indicate algorithm execution flow and ant search direction. (Note: The numbers in braces denote branch numbers selected by ants.).

Second, the iterative search stage. Each ant, following the three behavior constraints defined in Section 3.3.3, selects switches using the state transition probability Formula (21) and constructs a virtual path. After each switch selection, the dynamic power flow is calculated immediately through the MST algorithm described in Section 3.3.2 to update the heuristic value and local pheromone via Equation (27). When all ants complete the construction of the complete virtual path, the objective function value of all solutions is calculated via Equation (1), and the optimal solution of the current iteration is screened.

Third, the pheromone update and termination judgment stage. The virtual pheromone global update is performed based on the current iteration's optimal solution via Equations (28)–(31). It is judged whether the termination condition is met, that is, the maximum iteration number $T_{\max}$ is reached, or the change of the optimal solution in consecutive iterations is less than the convergence threshold ϵ . If the condition is met, the global optimal switch combination and corresponding optimization results are output; otherwise, the process returns to the iterative search stage to start a new round of iteration.

4. Simulation Analysis and Discussion

This section verifies the effectiveness, superiority and engineering practicability of the GTACO algorithm through multi-scale and multi-scenario experiments.

4.1. Experimental Systems and Comparative Algorithms

Simulation Design Framework

To systematically verify the effectiveness and superiority of the proposed GTACO algorithm, a three-layer progressive experimental design framework is adopted in this study. This framework is strictly aligned with the mechanism innovations resolving the three core bottlenecks of traditional ACO analyzed in the literature review:

Fundamental Effectiveness Validation Layer: Verifies whether GTACO effectively resolves the core bottlenecks of traditional ACO in static DNR scenarios, establishing the basic validity of the algorithm framework.

Theoretical Superiority Validation Layer: Analyzes the internal working mechanism of GTACO through pheromone evolution analysis, revealing the theoretical reasons behind its superior performance.

Engineering Practicability Validation Layer: Evaluates the dynamic adaptability and practical application value of GTACO in complex scenarios with high-penetration RES and BESS integration.

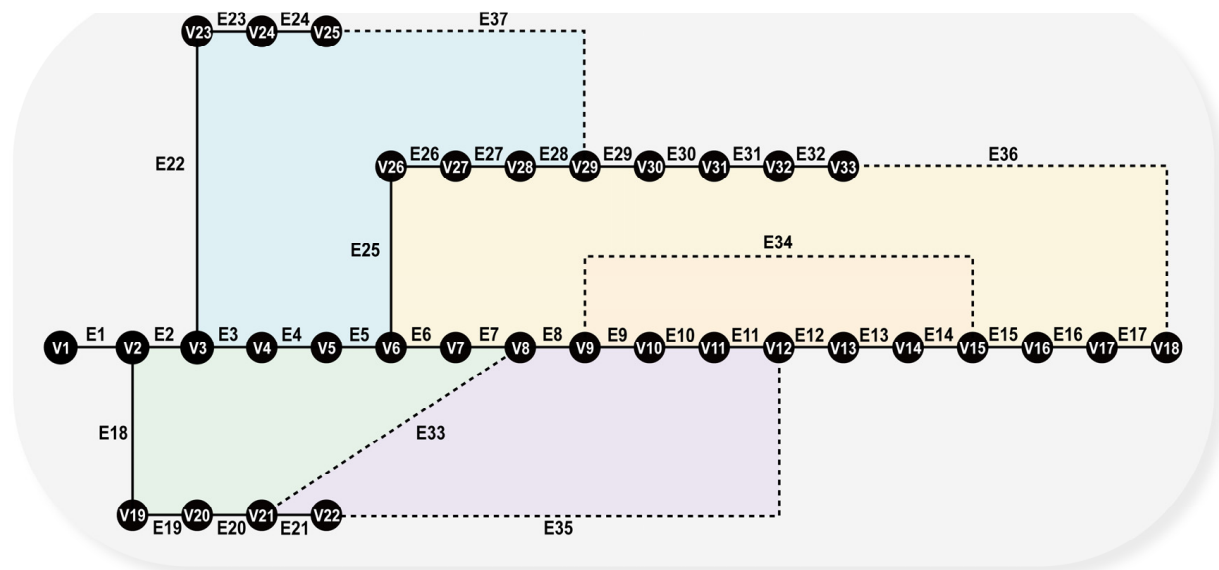
Based on this framework, two internationally recognized standard test systems (IEEE 33-bus and PG&E 69-bus) are selected, which are the most widely used benchmark systems in the DNR field and provide a unified comparison basis. Three categories of representative algorithms are selected for comparison, corresponding to the three types of algorithm defects analyzed in the literature review. A comprehensive evaluation metric system is designed to measure algorithm performance from three complementary dimensions: optimization accuracy (LRR, FMV), convergence efficiency (MIC), and engineering value (PLC, NS, GGR).

Two international standard test systems are used for experimental verification, namely the IEEE 33-bus system and the PG&E 69-bus system [41], with annual load growth rates of 7.5% and 8% respectively. The topology of the two test systems is shown in Figure 2.

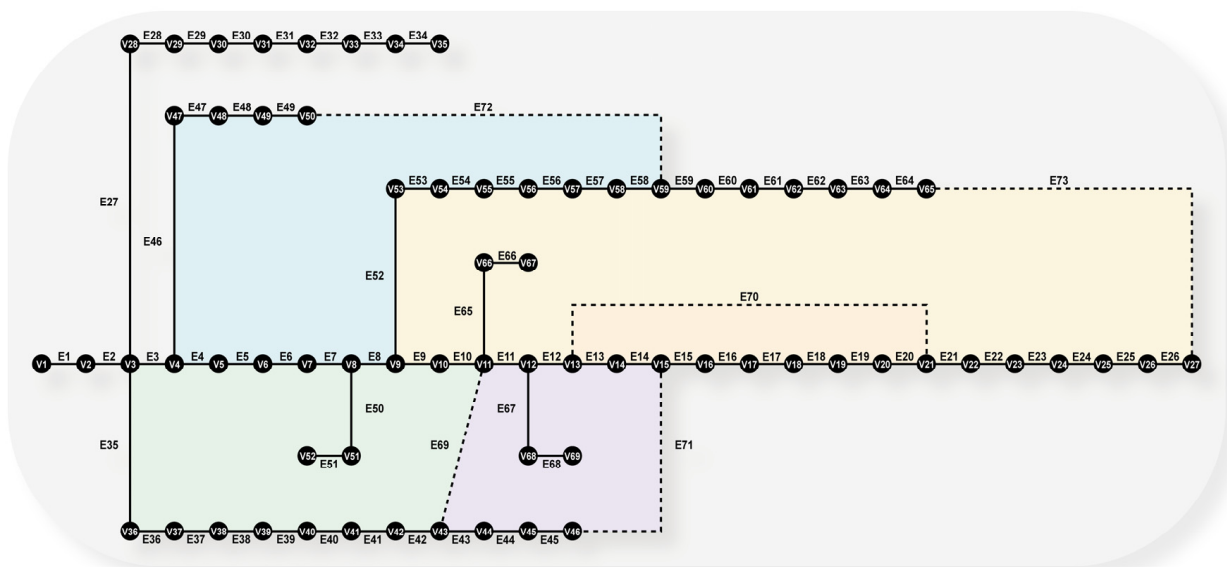
The IEEE 33-bus system features 32 normally closed sectionalizing switches and five normally open tie switches, with an initial active load of 3.72 MW, reactive load of 2.30 MVAR, and initial power loss of 202.68 kW. The PG&E 69-bus system has 68 normally closed sectionalizing switches and five normally open tie switches, with an initial active load of 3.80 MW, reactive load of 2.69 MVAR, and initial power loss of 224.89 kW.

To comprehensively evaluate algorithm performance, three categories of advanced algorithms are selected for comparison, which completely correspond to the algorithm defects analyzed in the literature review. The first category is discretization-improved continuous optimization algorithms, including 3D-GSO [19] and ISSA [20]. The second category is classic discrete optimization algorithms, including GA [42] and HSA [22]. The third category is traditional ACO variants, including basic ACO [23] and HC-ACO [43]. All comparison algorithms were tested under identical experimental conditions, with population size and maximum iterations set consistently to ensure fairness.

Key evaluation metrics include Loss Reduction Rate (LRR), Final Minimum Voltage (FMV), Open Switches (OS), Mean Iteration Count (MIC), Power Loss Cost (PLC), Net Savings (NS), and Greenhouse Gas Reduction (GGR). To eliminate the influence of random initial solutions on metaheuristic algorithm performance, all algorithms were executed for 50 independent runs under identical experimental conditions. MIC is defined as the average number of iterations required to converge to a final solution, while the optimal power loss value across all runs is reported as the final result.



(a) The 33-bus system



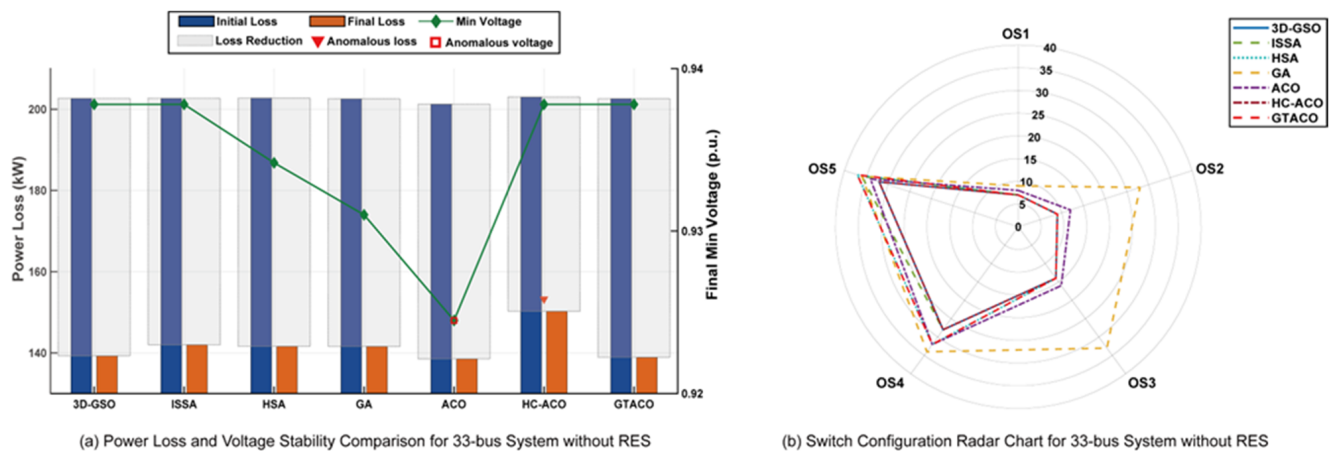


Figure 3. Power loss, voltage stability and switch configuration comparison for 33-bus systems without RES.

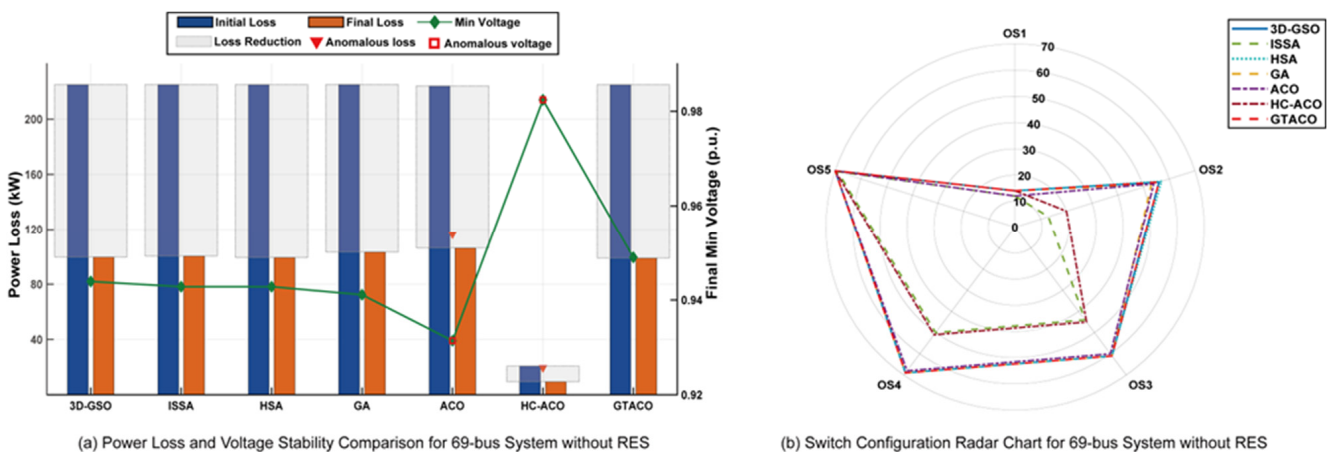


Figure 4. Power loss, voltage stability and switch configuration comparison for 69-bus systems without RES.

In the IEEE 33-bus system, GTACO achieves the highest LRR of 31.43% and the highest FMV of 0.9378 p.u., outperforming all comparison algorithms. The basic ACO achieves an LRR of 31.16% and an FMV of 0.9245 p.u., while HC-ACO achieves an LRR of only 25.99%, significantly underperforming other algorithms. The optimal switch combination obtained by basic ACO violates the radial topology constraint of the DN (specifically causing ring formation and islanding), while GTACO's optimal switch combination (7–9–14–32–37) strictly satisfies all graph-theoretic topology rules, generating 100% feasible solutions.

In the PG&E 69-bus system, GTACO achieves a leading LRR and the highest FMV of 0.9490 p.u., surpassing 3D-GSO's 0.9439 p.u. and ISSA's 0.9428 p.u. The basic ACO achieves an LRR of 52.57% and an FMV of 0.9314 p.u., while HC-ACO's initial and final loss values exhibit a marked discrepancy from those of other algorithms. GTACO's optimal switch combination (14–56–61–69–70) not only satisfies the radial topology constraint but also achieves an optimal balance between power loss and voltage stability.

The voltage profiles of the two systems before and after GTACO optimization under 5-year load growth are shown in Figure 5.

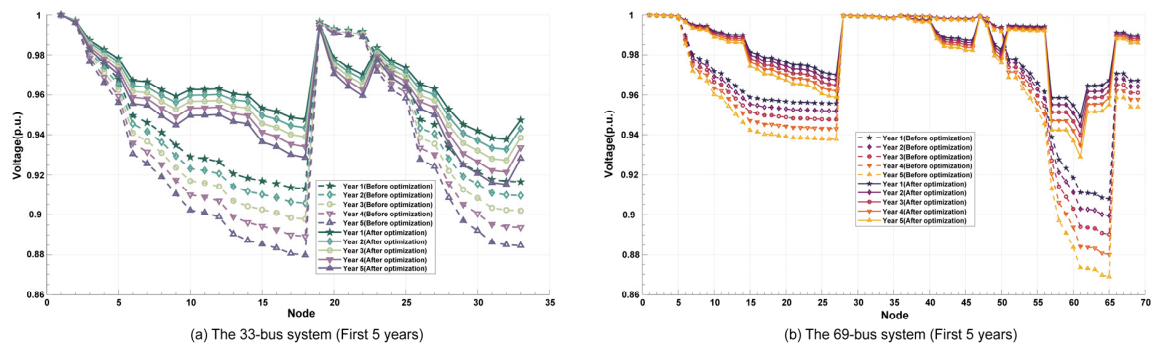


Figure 5. Comparison of system voltage profiles before and after GTACO optimization under load growth.

Analysis of the initial topology indicated that the 33-bus system experienced voltage violations in the 3rd year of load growth, and the 69-bus system in the 2nd year. After GTACO optimization, the minimum voltage of the 33-bus system in the 5th year of load growth was maintained at 0.9151 p.u., and that of the 69-bus system at 0.9291 p.u. Both values meet safe operation thresholds. This confirmed the delaying effect of topology adjustment on the voltage collapse point and demonstrated GTACO's robustness in long-term load growth scenarios.

These results confirm that GTACO effectively resolves the core bottlenecks of framework incompatibility and heuristic ambiguity in traditional ACO for static topology optimization. Its graph-theoretic framework eliminates infeasible solutions from the source, and the multi-dimensional dynamic heuristic function enables coordinated optimization of loss reduction and voltage stability.

4.2.2. Theoretical Superiority Validation: Pheromone Evolution Analysis

This layer of experiments verifies the theoretical effectiveness of the algorithm's framework-level innovation through convergence characteristics and pheromone evolution analysis, based on the baseline scenario experimental results. The pheromone evolution heatmaps of GTACO for the two test systems are shown in Figures 6 and 7.

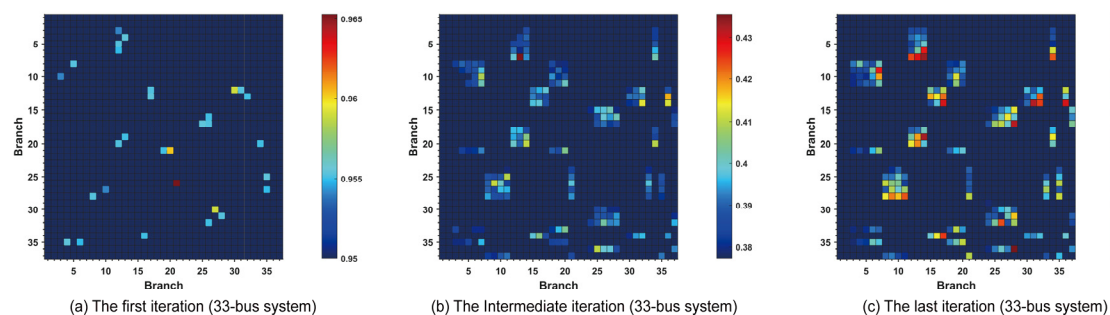


Figure 6. Pheromone evolution heatmaps of GTACO for the IEEE 33-bus system.

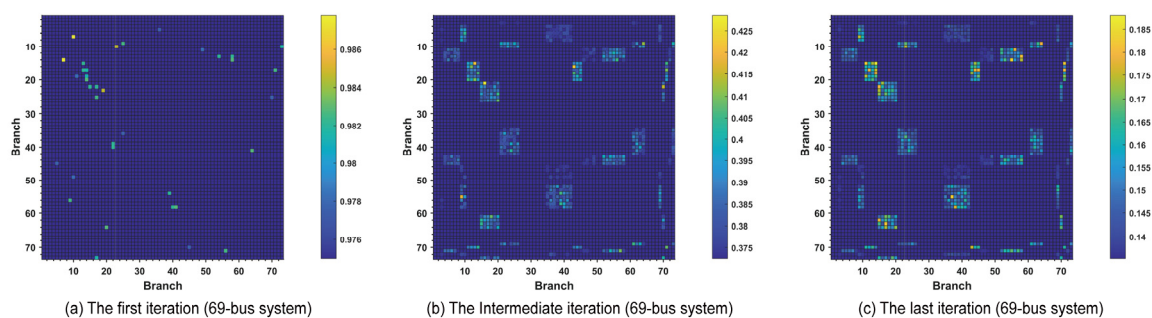


Figure 7. Pheromone evolution heatmaps of GTACO for the PG&E 69-bus system.

The pheromone evolution exhibits a clear three-stage characteristic: random exploration, neighborhood expansion, and global focus. In initial iterations, pheromones are randomly distributed across network branches, reflecting the colony's initial random exploration. Dynamic pheromone evaporation rapidly weakens initial path dependence, enabling the population to escape the influence of initial solutions and avoid local optima. In intermediate iterations, high-concentration pheromone regions diffuse toward adjacent branches, forming a core–periphery gradient distribution. The core region corresponds to locally optimal topologies, while the peripheral gradient distribution reflects the algorithm's exploration of adjacent branches, and together they achieve dynamic balance between exploration and exploitation mechanisms. In final iterations, pheromones become highly concentrated on the critical branches of the optimal topology, confirming the lock-in of the global optimal solution. Continuous pheromone deposition enhances the stability of the optimal path and preserves a small number of low-concentration regions to maintain local exploration capability.

These results empirically validate that the graph-theoretic framework reconstruction and virtual pheromone mechanism enhance the search efficiency and global optimization capability of ACO in the discrete DNR solution space at the theoretical level and verify the theoretical superiority of the framework-level innovation proposed in this paper. This three-stage pheromone evolution pattern empirically validates the rationality of the parameter settings (α, β, ρ) , as it demonstrates that the algorithm can effectively balance exploration and exploitation and converge to the global optimal solution without premature convergence or search stagnation.

Crucially, this three-stage evolution is not driven by pheromones alone but by the synergistic interaction between the multi-dimensional dynamic heuristic function and the virtual pheromone update mechanism. In the initial exploration stage, the heuristic function provides the primary directional signal against the uniform pheromone background, preventing ants from making completely random decisions and accelerating the identification of promising regions. In the neighborhood expansion stage, the heuristic function continuously updates based on real-time power flow changes, directing pheromone deposition toward branches that contribute to both loss reduction and voltage stability. In the global convergence stage, the accumulated pheromones reinforce the heuristic guidance, forming a positive feedback loop that rapidly locks in the global optimal topology. This synergistic mechanism systematically resolves the conflict between exploration and exploitation in traditional ACO, where static heuristics fail to adapt to dynamic power flow changes.

4.2.3. Engineering Practicability Validation: Dynamic Scenarios with RES and BESS

This layer of experiments verifies the dynamic adaptability and engineering application value of the algorithm in complex scenarios with RES and BESS access and long-term load growth. The RES and BESS normalized output profiles for different scenarios are shown in Figure 8.

Two sets of scenarios are constructed: the IEEE 33-bus system with single WT integration and PV-WT hybrid integration and the PG&E 69-bus system with BESS-WT, BESS-BG, and PV-WT-BESS coordinated operation scenarios.

The comparative results of the 33-bus system with RES integration are shown in Figures 9 and 10.

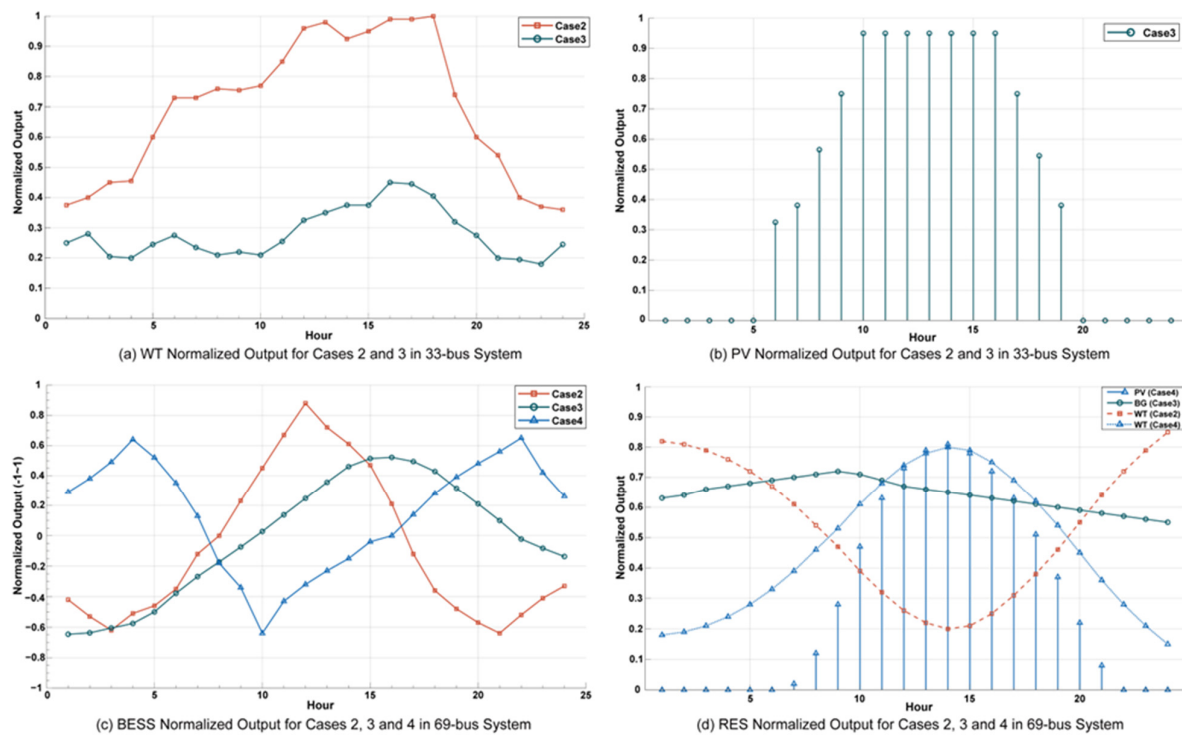


Figure 8. RES and BESS normalized output profiles for different dynamic scenarios.

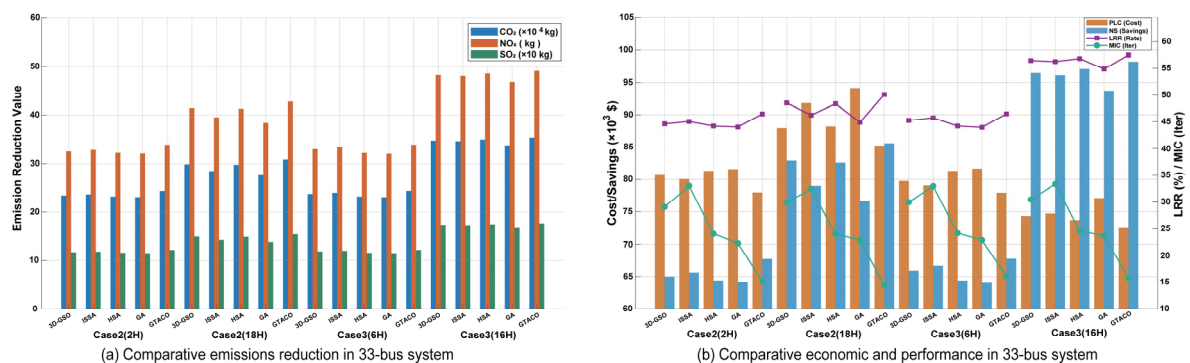


Figure 9. Comparative emissions reduction and economic performance in 33-bus system with RES.

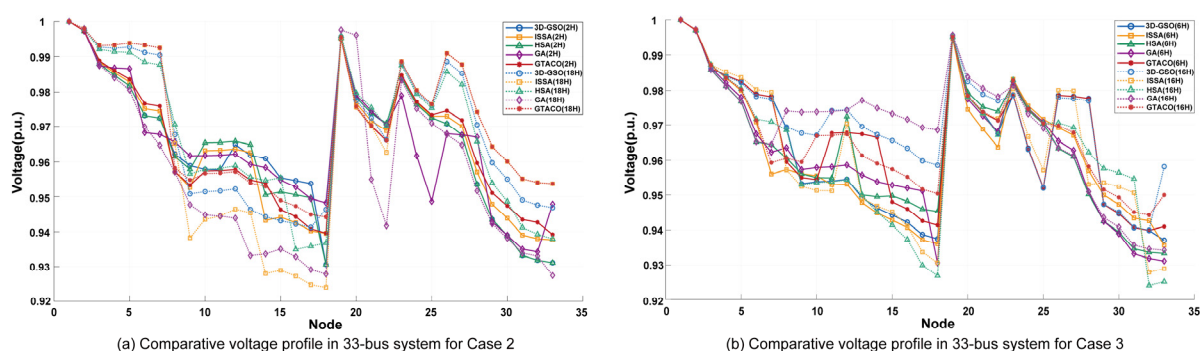


Figure 10. Comparative voltage profile in 33-bus system with RES.

In the 33-bus system with single WT integration, GTACO achieves an LRR of 46.47% at 2H (early morning low load + low WT output) and 50.11% at 18H (evening high load + high WT output), both exceeding the suboptimal 3D-GSO (44.61% and 48.54%, respectively). The MIC (average of 50 independent runs) is only 15.168 and 14.112 iterations, representing a convergence speedup of 38.85% and 43.84% over GA in terms of search efficiency. Power

loss fluctuation is limited to 9.3%, lower than GA's 15.4% and ISSA's 14.7%. Regarding economic and environmental benefits, CDR reached 243,727.24 kg (at 2H) and 308,132.58 kg (at 18H), while NS attained 67,702.01 USD per year and 85,592.38 USD per year, respectively, all being optimal. This validated its rapid dynamic response capability to the fluctuations of a single RES.

In the PV-WT hybrid integration scenario, GTACO's LRR was 46.49% at 6H (morning low load + low RES output) and 57.49% at 16H (afternoon high load + high RES output), representing an improvement of up to 7.38% compared to the single WT scenario. The FMV was maintained at 0.940 p.u. and 0.944 p.u., indicating no significant voltage stability degradation. PLC at 16H decreased to 72,615.84 USD, a 6.8% reduction from 6H, both being optimal. The OS combination dynamically adjusted to 7–11–32–34–37 (at 6H) and 7–11–28–31–34 (at 16H), precisely adapting to PV-WT output changes. In contrast, the OS configurations of HSA and GA failed to balance loss reduction and voltage constraints under multi-source fluctuations. The experimental data indicated that GTACO exhibited robust time-varying adaptability in complex, multi-variable coupled environments.

The comparative results of the 69-bus system with BESS integration are shown in Figures 11 and 12.

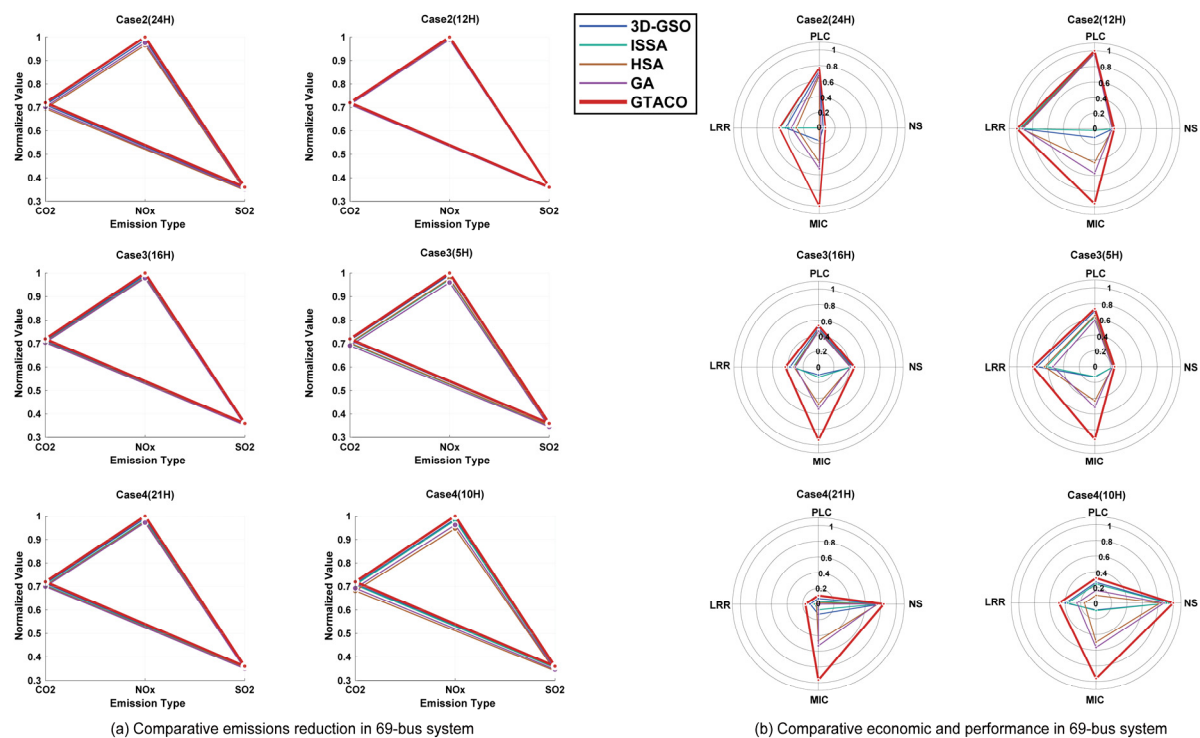


Figure 11. Comparative emissions reduction and economic performance in 69-bus system with RES/BESS.

In the BESS-WT coordinated operation scenario, GTACO achieved significant smoothing effects by coordinating BESS charging and discharging states with WT fluctuations. The LRR at 12H (midday high load + BESS discharging) and 24H (early morning low load + BESS charging) reached 79.53% and 73.77%, while FMV reached 0.974 p.u. and 0.960 p.u., respectively, all being optimal. Furthermore, the power loss fluctuation of 28.1% was lower than the suboptimal solution HSA, highlighting the economic advantage of bidirectional energy storage regulation.

In the BESS-BG coordination scenario, GTACO demonstrated coordinated peak shaving and valley filling using a controllable power source and energy storage. The LRR at 5H (morning low load + BESS charging) and 16H (afternoon high load + BESS discharging)

stabilized at approximately 72.80%, both being optimal. The PLC was 4.32% lower than the suboptimal solution ISSA (at 5H), and NS was 1.04% higher than the suboptimal solution 3D-GSO (at 16H). This verified robustness in managing dynamic energy storage regulation and base load from a controllable power source.

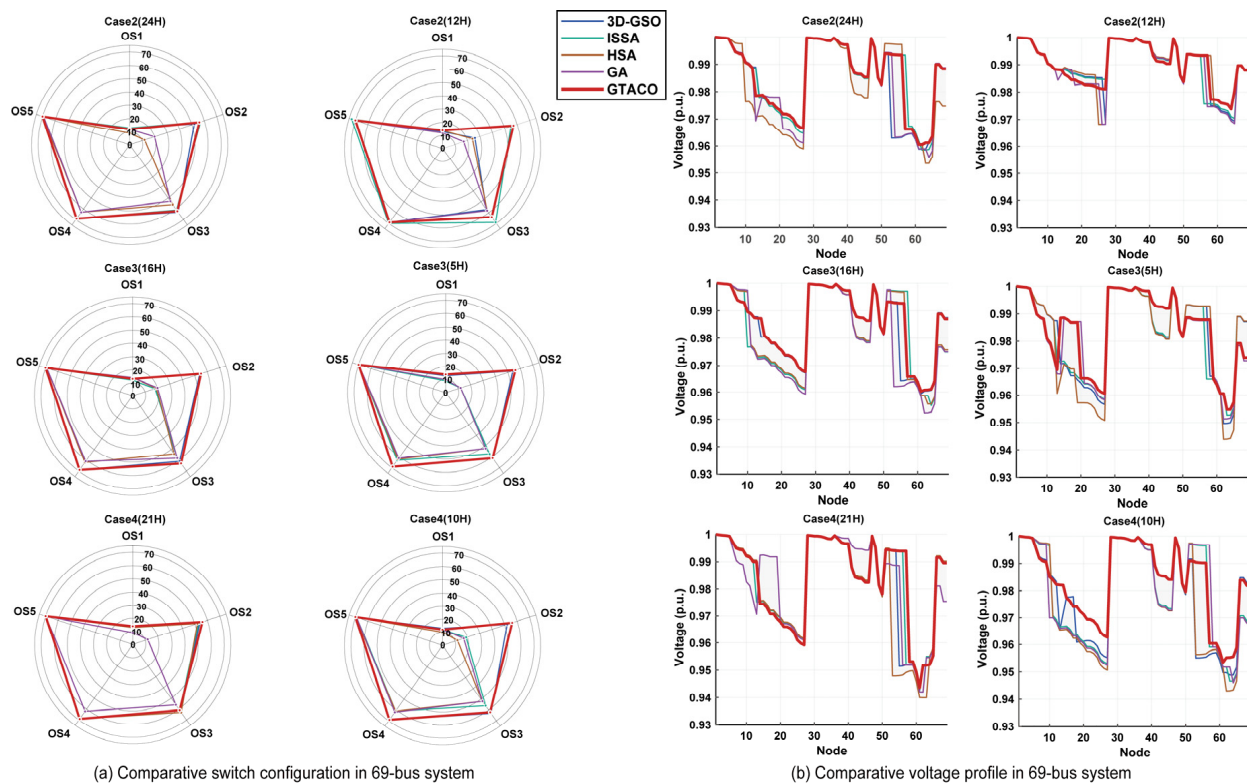


Figure 12. Comparative switch configuration and voltage profile in 69-bus system with RES/BESS.

In the PV-WT-BESS hybrid scenario with the most pronounced multi-energy complementarity, GTACO's advantage in handling strong multi-source coupling constraints was most significant. The LRR at 10H (morning high load + BESS charging) and 21H (night low load + BESS discharging) reached 73.38% and 69.64%, and CDR reached 620,798.77 kg and 589,158.07 kg, respectively, all being optimal. The MIC (average of 50 independent runs) was 25.119 and 25.898 iterations, 37.7% and 37.6% faster than the suboptimal GA in terms of search efficiency. The FMV was maintained at 0.944 p.u., effectively mitigating voltage fluctuations induced by energy storage discharge.

Across all dynamic scenarios, GTACO consistently leads in LRR, FMV, NS, and GGR, with the lowest power loss fluctuation and fastest convergence speed. Its dynamically adjusted switch combinations to adapt to real-time RES and BESS fluctuations, demonstrating effective dynamic response. These results validate that the MST-driven dynamic power flow calculation and virtual pheromone mechanism endow GTACO with both effective dynamic responsiveness and long-term operational robustness in high-penetration RES/BESS integration scenarios.

4.3. Formal Computational Complexity and Scalability Analysis

This section provides a rigorous analysis of the time and space complexity of GTACO, compared with the six comparative algorithms, to quantify its computational efficiency advantages. Furthermore, the structural properties of GTACO, derived from its graph-theoretic reconstruction, inherently support its scalability to larger-scale problems, which is discussed alongside the complexity analysis.

The time complexity of GTACO is determined by four core components: the maximum number of iterations T_{max} , the number of ants m , the average number of loops each ant traverses (equal to the number of switches to be opened L), and the number of nodes N . The computational burden per iteration includes two core parts. First, each ant's solution construction, dominated by the MST-based power flow calculation, with complexity $O(N)$ for each selection step, totaling $O(L \cdot N)$ per ant. Second, pheromone update operations, which are linear with respect to L . Thus, the total time complexity of GTACO is:

$$O(\text{GTACO}) = O(T_{max} \cdot m \cdot L \cdot N) \quad (32)$$

The basic ACO has the same asymptotic time complexity as GTACO, $O(T_{max} \cdot m \cdot N^2)$, but lacks the graph-theoretic constraints to reduce the search space, resulting in a much larger required number of iterations and ants in practice. HC-ACO has a time complexity of $O(T_{max} \cdot m \cdot N^2)$, with additional computational overhead from the hypercube framework. GA has a time complexity of $O(T_{max} \cdot m \cdot N^2)$, with higher computational overhead from crossover and mutation operations. HSA has a time complexity of $O(T_{max} \cdot m \cdot N)$, but its convergence speed is significantly slower than that of GTACO, requiring more iterations. 3D-GSO and ISSA, as discretized continuous algorithms, have a time complexity of $O(T_{max} \cdot m \cdot D \cdot N)$, where D is the dimension of the continuous search space, resulting in higher computational overhead than GTACO in practice.

In terms of space complexity, GTACO requires storage of the graph adjacency matrix, pheromone matrix on virtual paths, and ant solution sets, with an overall space complexity of $O(N^2 + L^2 + m \cdot L)$, which is on the same order as traditional ACO, but with significantly improved search efficiency, imposing no additional computational burden in practical engineering applications.

Beyond the asymptotic complexity, the structural design of GTACO provides intrinsic advantages for scalability. The time complexity in Equation (32) depends on the number of loops L and nodes N , not directly on the total number of switches. For a radial network with N nodes, L is typically $O(N)$, making the theoretical time complexity $O(T_{max} \cdot m \cdot N^2)$. This scales polynomially with network size, a crucial property for large-scale applications. More importantly, the graph-theoretic reconstruction in Section 3.3.1 systematically compresses the solution space from an exponential level $2^{|E|}$ to a manageable level $\prod_{l=1}^L |E_l|$. This compression, driven by network topology rules, is a structural property of the algorithm, not a parameter tuning. As network scale grows, the relative efficiency of this compression becomes more pronounced, as the invalid search space eliminated by graph rules grows super-exponentially. Therefore, the core mechanism of GTACO, which maps switch combinations to spanning trees via loop rules, scales effectively, ensuring that the fundamental advantages of framework reconstruction and virtual pheromones persist in larger networks. This graph-theoretic reconstruction paradigm is not limited to DNR problems; it can be generalized to other discrete combinatorial optimization tasks with topological constraints, such as communication network resource scheduling.

4.4. Statistical Validation and Real-Time Feasibility Analysis

To rigorously validate the robustness and engineering feasibility of the proposed GTACO, comprehensive statistical analyses based on 50 independent runs were conducted across all 10 dynamic scenarios. The results, summarized in Figure 13, quantify convergence stability, global optimality reliability, and computational time requirements.

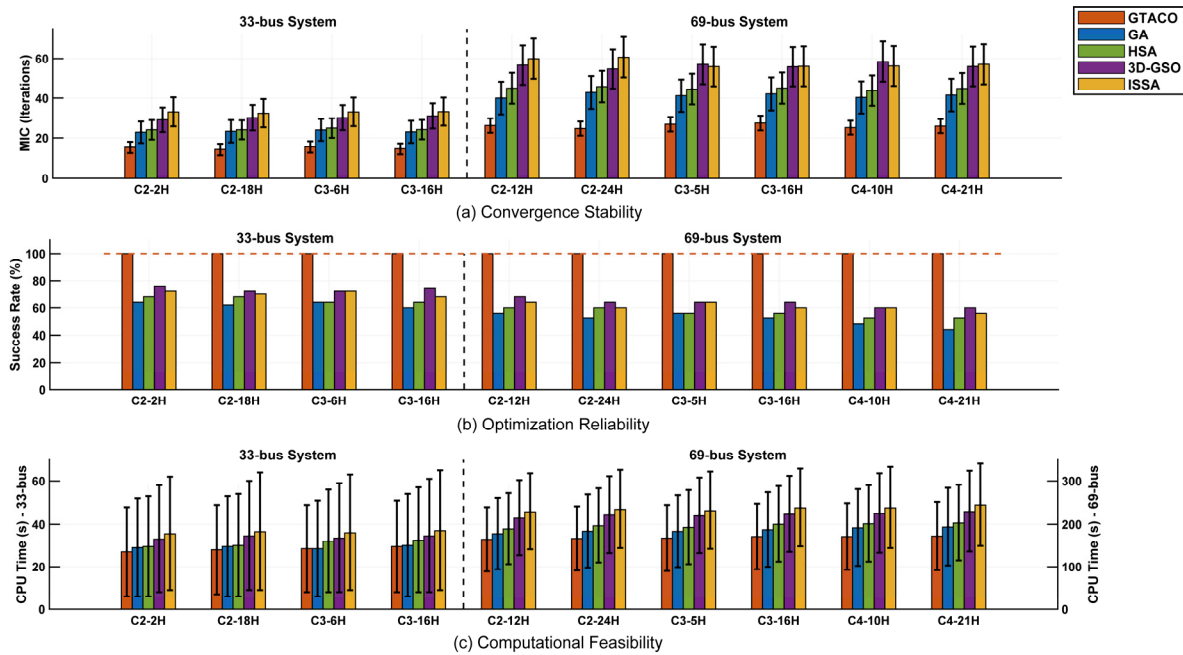


Figure 13. Statistical validation and real-time feasibility analysis of the GTACO algorithm. The dashed line serves as a visual separator to distinguish the results of the 33-bus system (**left**) and the 69-bus system (**right**); success rate is defined as the percentage of runs that converge to the known global optimal solution of the test system.

Regarding global optimality reliability (Figure 13a), GTACO consistently achieves a 100% success rate of converging to the identical global optimal topology across all 50 runs in all 10 scenarios. This deterministic convergence, where all runs converge to the identical optimal topology with negligible variance in the objective function value, is a direct result of the graph-theoretic framework eliminating infeasible solutions at the source. The repeatability reflects the combined effect of confining the search to the graph-theoretic feasible manifold defined in Section 3.3.1 and the objective aligned reinforcement in Section 3.3.4, not a lucky stochastic fluke. In contrast, comparative algorithms frequently fall into local optima due to the lack of such constraints, exhibiting success rates ranging from merely 44% to 76%. The complete separation between GTACO's deterministic performance and the stochastic distributions of comparative algorithms, where one group converges to a single optimal topology while the other spreads widely, renders standard two-sample tests such as the independent t-test and rank-based tests degenerate. The homoscedasticity condition fails when one group variance is near zero and the other is substantial, and rank statistics collapse when distributions do not overlap. The appropriate evidence in this context is therefore not a p -value from a misspecified test but the observed 50 out of 50 replication itself, which constitutes definitive statistical evidence for this problem structure.

Regarding convergence stability (Figure 13b), the standard deviation of MIC for GTACO is remarkably small (2.76~3.72), demonstrating high convergence stability. Comparative algorithms show significantly larger standard deviations (4.76~10.22), indicating inconsistent performance heavily dependent on initial conditions.

Regarding engineering feasibility (Figure 13c), while GTACO's sophisticated heuristic calculation introduces a marginal increase in per-iteration time, its significant reduction in MIC ensures highly competitive total CPU execution times. As documented in Figure 13, CPU times range from 6 s to 48 s for the 33-bus system and 89 s to 252 s for the 69-bus system, depending on hardware configurations ranging from high-performance workstations to entry-level computers. These durations are negligible relative to the hourly decision-making window of practical DNR operations. This window is dictated by the mechanical

lifespan and operational safety constraints of distribution switches, typically limited to one operation per hour, thereby confirming its real-time responsiveness.

4.5. Discussion

Comprehensive comparison across basic and complex scenarios validates GTACO's consistently superior performance in loss reduction and voltage stability. Traditional ACO variants failed due to TSP-centric constraints, discretized continuous algorithms suffered from inherent mapping errors, and classic discrete algorithms lacked dynamic adaptability. In contrast, GTACO achieved consistent superiority by leveraging virtual pheromone paths and graph-theoretic topological optimization. In dynamic RES/BESS scenarios, GTACO's MST-driven real-time power flow calculation enables rapid adaptation to fluctuating operating conditions.

The superior performance of GTACO originates from the deep synergistic integration of its three core innovations: graph-theoretic framework reconstruction, multi-dimensional dynamic heuristic function, and virtual pheromone update mechanism. The graph-theoretic framework eliminates infeasible solutions at the source, ensuring that all search efforts are directed toward valid radial topologies. This creates a clean search space where the heuristic function and pheromone mechanism can operate effectively without contamination.

Within this constrained search space, the heuristic function and pheromone mechanism form a closed-loop positive feedback system. The multi-dimensional dynamic heuristic function provides real-time, physics-based guidance for each ant's local decision making, prioritizing switches that offer significant improvements in both power loss and voltage stability. This high-quality local guidance ensures that pheromones are only deposited on paths that contribute to the global optimization objective. In turn, the virtual pheromone mechanism aggregates the experience of all ants, amplifying the guidance effect of high-quality decisions and suppressing low-quality ones.

This synergistic interaction is clearly reflected in the three-stage pheromone evolution pattern observed in Figure 5. In the initial exploration stage, the heuristic function dominates, providing a strong directional signal that prevents random wandering. In the neighborhood expansion stage, the balance between heuristic guidance and pheromone accumulation enables the algorithm to explore promising regions while avoiding local optima. In the global convergence stage, pheromone accumulation becomes dominant, rapidly converging the entire ant colony to the global optimal solution. This mechanism systematically breaks the dependence on initial solutions that plagues traditional metaheuristic algorithms, ensuring consistent and reliable performance across all scenarios.

GTACO's performance boundaries are constrained by metaheuristic characteristics and complex engineering demands. First, graph mapping currently relies on manual topology rules; future work could develop adaptive frameworks to reduce domain knowledge dependence. Second, heuristic indicators prioritize loss and voltage stability; weight recalibration may be needed for hybrid objectives that include reliability and resilience metrics. Third, dynamic virtual pheromone updates in ultra-large-scale networks may face computational bottlenecks, requiring lightweight management strategies. However, as analyzed in Section 4.3, the polynomial time complexity and structural solution space compression of GTACO provide a solid theoretical foundation for addressing this challenge in future work. Additionally, the employed IEEE 33-bus and PG&E 69-bus systems are canonical benchmark platforms derived from actual utility topologies, and extending validation to larger-scale utility-owned networks will further substantiate the practical engineering applicability of the GTACO framework as data-sharing agreements permit. Despite these limitations, GTACO provides a robust solution for complex decision making under dynamic constraints.

5. Conclusions

The integration of high-penetration RESs and BESSs has transformed DNR into a complex discrete optimization problem governed by dynamic power flow constraints. Existing algorithms struggle to balance discrete decision precision with dynamic scenario adaptability. This research proposes the GTACO algorithm, which deeply integrates graph theory with ACO core mechanisms to systematically resolve the three core bottlenecks of traditional ACO in DNR applications: framework incompatibility, heuristic ambiguity, and ineffective pheromone strategies. Multi-scale, multi-scenario experiments demonstrate that GTACO outperforms state-of-the-art algorithms in core metrics including loss reduction, voltage stability, and economic–environmental benefits. It exhibits robust cross-scale adaptability and strong resilience in dynamic scenarios characterized by load growth coupled with RES and BESS fluctuations.

The core academic contribution lies in providing a novel approach for non-TSP-type complex discrete optimization that achieves deep integration of physical constraints, algorithmic mechanisms, and optimization objectives. Its engineering significance is reflected in the provision of a practical solution for optimizing complex energy systems under high dynamic constraints. This solution requires no extensive training data, features clear constraints, and ensures real-time responsiveness. It also expands the cross-domain application scope of the ACO framework. Despite challenges including domain-knowledge-dependent graph mapping and limited heuristic generality, future enhancements are promising. Adaptive graph modeling frameworks, multi-source heuristic fusion systems, and lightweight pheromone management strategies are expected to further improve real-time performance in ultra-large-scale systems and extend applicability to multi-energy coupling optimization.

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