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A fully distributed algorithm for dynamic economic dispatch of cross regional power systems based on alternating direction multiplier method

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Abstract

In the present study, a novel approach to dynamic economic dispatch for power systems spanning multiple regions is introduced, utilizing the alternating direction multiplier method (ADMM) as its computational foundation. The proposed economic scheduling model is designed to optimize the operational costs of the system comprehensively, while adhering to a spectrum of operational constraints. Employing the ADMM, the study achieves a distributed resolution of the model by severing the inter-regional interconnections, thereby partitioning the overarching optimization challenge into manageable sub-problems specific to each region. This methodology facilitates the attainment of the system's global optimum through the iterative resolution of these regional sub-problems. Furthermore, the algorithm obviates the necessity for a centralized data repository for multiplier updates, thereby endorsing a fully distributed scheduling paradigm. Concurrently, the study incorporates a multi-period optimization technique within the economic scheduling model to accommodate the inherent temporal dependencies of the power system. The culmination of this research is the empirical analysis of a tri-regional interconnected system, predicated on the IEEE standard test system, which substantiates the efficacy of the proposed economic dispatch strategy.

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1. Introduction

Within the domain of power systems, Economic Dispatch (ED) is characterized as an optimization dilemma aimed at minimizing network losses or generation costs while conforming to the constraints of power flow and operational parameters [1-8]. The integration of renewable energy sources, notably photovoltaic and wind power, has introduced a heightened degree of intertemporal coupling in power systems. Such advancements have deemed static ED, reliant on single temporal analysis, insufficient for the complex scenarios of modern power systems, thereby necessitating a transition to dynamic ED. The burgeoning power market demands increased interconnectivity and more frequent power exchanges across regions, achievable through centralized dispatching by an authoritative cross-regional center or via coordination among regional centers. Nevertheless, centralized scheduling (CS), which requires a central entity to collect detailed data and centrally determine operational strategies, faces numerous challenges. Scholars globally have explored centralized dispatching, utilizing classical optimization algorithms like the interior point method [9], Lambda iteration method [10], and Lagrange method [11], which are intrinsically centralized. Centralized scheduling algorithms eliminate iterative processes, facilitating direct global optimization. However, this method is impractical for large-scale scheduling due to the exponential increase in variable volume and complexity. Moreover, research intensification on the global energy Internet and the development of transnational regional UHV power grids aim to enhance power complementarity, load peak shifting, and support. China has achieved some power interconnection with neighboring countries, including Russia, Mongolia, Vietnam, Laos, and Myanmar, totaling an interconnection capacity of roughly 2.6 million kilowatts. Nonetheless, the reluctance of nations to share detailed power system information, for strategic confidentiality reasons, limits the viability of higher-level dispatch centers with global authority.

In light of these challenges, the necessity for a distributed scheduling framework becomes critical, one that allocates scheduling responsibilities to regional dispatching centers. This paradigm shift paves the way for globally optimal power scheduling based on a distributed architecture that minimizes the need for extensive inter-regional information sharing. Consequently, Distributed Dynamic Scheduling (DDS) has attracted increasing academic attention, emerging from research on Distributed Optimal Power Flow (DOPF) optimization approaches.

In the scholarly discourse on power systems, the concept of virtual nodes has been introduced as a means to balance power flow post-decoupling within subregions, thus enabling the formulation of a multi-regional decomposition algorithm. Significantly, Kim and Baldick [12] endorse a parallel Distributed Optimal Power Flow (DOPF) model, designed for extensive regional interconnection systems, validated through simulations on systems of moderate size. Further, Kim and Baldick [13] mathematically implement the proposed distributed framework by amalgamating two distinct decomposition methods: the Predictor-Corrector Proximal

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Multiplier (PCPM) and the Alternating Direction Method (ADM). Additionally, Cheng et al. [14] addresse the distributed processing of the multi-objective reactive power optimization issue within large-scale power systems, effectively resolving the centralized reactive power optimization challenge.

Furthermore, Conejo and Aguado [15] incorporate network loss into the foundational DOPF model using cosine approximation. The Auxiliary Problem Principle (APP) is employed in literature [16-18] to manage regional coupling constraints, leading to the development of the DOPF algorithm. The Alternating Direction Multiplier Method (ADMM), thoroughly examined in literature [19-23], has been extensively refined for deployment within the Distributed Dynamic Scheduling (DDS) sphere. Notably, Dall'Anese et al. [19] convert the optimal power flow problem within microgrids into a convex issue via semi-definite programming relaxation techniques, thereafter seeking a distributed solution through the ADMM. Sulc et al. [20] utilize the ADMM, predicated on consistency, for the distributed optimal control of reactive power in power systems, demonstrating its superiority to the dual-ascent method.

This research articulates a fully distributed algorithm to address the centralized dynamic scheduling issue within power systems featuring a multi-regional interconnection structure. Based on the inherent characteristics of power systems and employing the ADMM for the decoupling of inter-regional connections, this approach decomposes the central issue into individual sub-optimization tasks for each region. Simultaneously, the traditional role of the data center, responsible for multiplier updates, becomes redundant, resulting in a completely distributed scheduling framework. The achievement of an optimal system-wide solution is accomplished through the iterative resolution of economic scheduling sub-problems specific to each region. An illustrative analysis, utilizing a multi-regional interconnected system modeled on the IEEE standard test system, affirms the effectiveness and precision of the proposed model in managing the intricacies of multi-regional distributed dynamic scheduling in power systems.

2. Multi-region dynamic scheduling model

The multi-regional power scheduling model, as depicted in Figure 1, encapsulates the intricate scheduling dynamics extant among various regions within a power system. It is constituted by an array of generator sets and loads, each interlinked via transmission lines. The transfer of power and information is facilitated through contact lines bridging regions, thereby enabling their interconnectivity. Owing to the autonomous dispatching attributes inherent to each region, the real-time sharing of comprehensive power dispatching data presents a formidable challenge. Consequently, the adoption of a distributed scheduling approach is necessitated, one that eschews the traditional dispatching center, and through iterative processes, converges upon the globally optimal power scheduling, all while minimizing the exchange of information between regions.

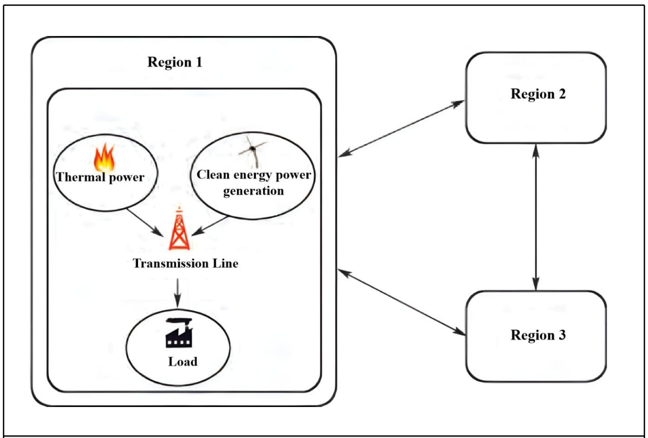

Figure 1. Multi-region economic dispatch model

2.1 Traditional centralized scheduling model

The traditional centralized power dispatching model can be established as follows:

1) Objective function

The objective function is to minimize the total operating cost of the system. Among them, the main consideration of the operating cost of the generator set. The expression of the objective function is as follows:

$$F=\sum_{t=1}^{T}\sum_{n=1}^{N}\left(a_n P_{n,t}^2+b_n P_{n,t}+c_n\right) \tag{1}$$

where F is the total operating cost of the system; t is the number of each scheduling period; T represents the total number of scheduling periods; n and n_{B} are the number of the generator set and the system node respectively; N and N_{B} are the total number of generator sets and system nodes respectively; $P_{n,t}$ represents the actual output of generator set n during the period t; a_n, b_n and c_n are the coefficient of output characteristic of generator set n.

2) Constraints

a) System power balance constraint, that is, the total generator output at any time is equal to the load demand:

$$\sum_{n=1}^{N}P_{n,t}=\sum_{n_{\mathrm{B}}=1}^{N_{\mathrm{B}}}D_{n_{\mathrm{B}},t} \tag{2}$$

where $D_{n_{\mathrm{B}},t}$ is the load demand of node n during the period t.

b) Constraints on the upper and lower limits of generator set output:

$$P_n^{\min}\leq P_{n,t}\leq P_n^{\max} \tag{3}$$

where $P_n^{\min}$ and $P_n^{\max}$ are, respectively, the lower limit and upper limit of output of generator set n in any period.

c) The upper and lower limits of the generator set climbing:

$$\Delta P_n^{\min}\leq P_{n,t}-P_{n,t-1}\leq \Delta P_n^{\max} \tag{4}$$

where $\Delta P_n^{\min}$ and $\Delta P_n^{\max}$ indicate the minimum climb rate (i.e. maximum downward climb rate) and maximum climb rate (i.e. maximum upward climb rate) of generator set n, respectively.

d) The power constraint of the generator set contract, that is, the total power generation of the generator set within a given period of time must comply with the agreed contract:

$$\sum_{t=1}^{T}P_{n,t}=E_n, n\in\phi \tag{5}$$

where E_n is the contracted electricity quantity of generator set n in a given period of time; ϕ is the set of generator sets for which the contracted electricity quantity is agreed.

e) The contract unit can be decomposed value deviation constraint, that is, the contract electricity decomposed to the day needs to be within a certain deviation range:

$$E_n^{\text{day,min}} \leq E_{n,d}^{\text{day}} \leq E_n^{\text{day,max}} \tag{6}$$

where d is the number of the dispatch date; $E_{n,d}^{\text{day}}$ is the generation capacity of generator set n in date d; $E_n^{\text{day,min}}$ and $E_n^{\text{day,max}}$ are the planned allowable minimum and maximum of the energy decomposition value of the generator set n, respectively.

f) Transmission line maximum capacity constraints:

$$-P_l^{\max} \leq P_{l,t} \leq P_l^{\max} \tag{7}$$

where $P_{l,t}$ is the transmission power of line l in the time period t; $P_l^{\max}$ is the maximum transmission power of line l. The maximum capacity of the two-way transmission of the line is equal.

g) Maximum capacity constraint of regional liaison line:

$$-T_{ij}^{\max} \leq T_{ij,t} \leq T_{ij}^{\max} \tag{8}$$

Among them: $T_{ij,t}$ is a vector variable, representing the transmission power of each contact line between region i and region j in the time period t; $T_{ij}^{\max}$ is a vector constant that represents the maximum transmission power of the contact lines between region i and region j. This paper assumes that the maximum two-way transmission capacity of each link line is equal.

h) Constraint on the power of the regional contact line transaction, that is, the power of the contact line transaction within a given period must comply with the agreement between regions:

$$\sum_{t=1}^{T} 1^{\mathrm{T}} T_{ij,t} = E_{ij}, ij \in \Gamma \tag{9}$$

where $1 = (1 \cdots 1)^{\mathrm{T}}$; E_{ij} is the total amount of agreed transaction power between region i and region j in a given period of time; Γ is the set of region pairs for the agreed transaction of electricity.

i) Regional liaison line switching power plan constraints, that is, the regional liaison line switching power of each period should be within the allowable range of assessment deviation:

$$T_{ij}^{kh,\min} \leq 1^{\mathrm{T}} T_{ij,t} \leq T_{ij}^{kh,\max} \tag{10}$$

where $T_{ij}^{kh,\min}$ and $T_{ij}^{kh,\max}$ are the minimum and maximum value allowed by the switching power plan between region i and region j during the t period, respectively.

The power transmission distribution factor (PTDF) matrix can be used to obtain the power transmission lines. The PTDF matrix directly links the net injected power of each node to the power transmission of each branch, and its main advantage is that it avoids introducing redundant voltage phase angle variables, and only depends on the grid structure and line parameters, and is independent of the variation of the injected power of each node, that is, for a given network, only one PTDF matrix is needed to be reused. The basic format of its application is:

$$P_{\text{flow}} = HP_{\text{inj}} \tag{11}$$

where P_{flow} is the vector composed of the power of each branch; H is the corresponding *PTDF* matrix; P_{inj} is the vector composed of the net injected power of each node.

For this centralized scheduling problem:

$$P_{l,t} = H(CP_{n,t} + C_{\mathrm{W}} W_{n_{\mathrm{W}},t} + C_{\mathrm{S}} S_{n_{\mathrm{S}},t} - D_{n_{\mathrm{B}},t}) \tag{12}$$

where C is the sorting matrix, the generator sets are rearranged in the order of node numbers.

2.2 Distributed scheduling model

In the discourse of distributed scheduling (DS), the concept is predicated on the decoupling of inter-regional connections, thereby enabling the segmentation of the aggregate power scheduling optimization quandary into distinct regional sub-problems. These sub-problems are iteratively addressed until a pre-defined error threshold is attained. Within the mathematical frameworks employed for DS, Lagrange relaxation (LR) is commonly invoked. This method mitigates the constraints, amalgamates them into the objective function, and iteratively refines the Lagrange multipliers until the cessation criteria of the iteration are fulfilled. Nonetheless, the LR method grapples with the challenge of selecting an appropriate step size for updating the multipliers, which impinges upon convergence rates.

To surmount this impediment, the present study introduces the augmented Lagrangian relaxation method (ALR), which incorporates a quadratic penalty term for the relaxed constraints within the objective function and adheres to a fixed step length for multiplier updates, thereby enhancing convergence. However, this incorporation of a quadratic penalty term compromises the factorability of the optimization problem, representing a significant limitation of the ALR approach. Two prevalent resolutions are the auxiliary problem principle method (APP) [24-27] and the alternating direction multiplier method (ADMM) [28-32]. Each methodology exhibits its own merits and demerits: the APP method facilitates parallel solutions albeit with moderate convergence velocity, whereas the ADMM approach necessitates serial resolution but boasts rapid convergence rates. Given the relatively modest number of regions within the extant power system architecture, the ADMM method is selected for resolving the multi-regional distributed power dispatching conundrum.

1) Traditional ADMM method

Consider the following optimization problems:

$$\min f(x) + g(x) \tag{13}$$

$$\text{s.t.} Ax + Bz = c \tag{14}$$

Applying augmented Lagrange relaxation to equality constraints, the unconstrained optimization problem is

$$\min f(x) + g(z) + \lambda^{\mathrm{T}}(Ax + Bz - c) + \frac{\rho}{2}\|Ax + Bz - c\|_2^2 \tag{15}$$

where λ is the Lagrange multiplier and ρ is the positive quadratic penalty term coefficient.

The quintessence of the Alternating Direction Method of Multipliers (ADMM) approach resides in the premise that, during the resolution of a variable, concomitant variables are held constant, utilizing the outcomes from the antecedent iteration. This stratagem effectively “decouples” the inter-variable nexus, thereby adroitly circumventing the complexities associated with the quadratic penalty term. The fundamental iterative schema of ADMM unfolds in the ensuing manner:

$$x^{k+1} := arg\ \min_x L_\rho(x, z^k, \lambda^k) \quad (16)$$

$$z^{k+1} := arg\ \min_z L_\rho(x^{k+1}, z, \lambda^k) \quad (17)$$

$$\lambda^{k+1} = \lambda^k + \rho(Ax^{k+1} + Bz^{k+1} - c) \quad (18)$$

This iterates over and over again until the iteration termination condition is met.

2) Multi-region distributed power scheduling based on traditional ADMM method

A multi-region distributed power dispatching model is derived from the centralized dispatching model by applying the conventional ADMM method. The main process is as follows: The centralized scheduling model reveals that the coupling constraint between regions is manifested in the constraint related to the liaison line, that is, the maximum capacity constraint of the regional liaison line $-T_{ij}^{max} \le T_{ij,t} \le T_{ij}^{max}$. However, the $T_{ij,t}$ variable is correlated with both region i and region j. If the constraint is directly relaxed, the decoupling in the true sense cannot be achieved. Therefore, the constraint should be first rewritten as follows:

$$T_{ij,t}^i = T_{ij,t}^j \quad (19)$$

$$-T_{ij}^{\max} \le T_{ij,t}^i \le T_{ij}^{\max} \quad (20)$$

$$-T_{ij}^{\max} \le T_{ij,t}^j \le T_{ij}^{\max} \quad (21)$$

Among them: $T_{ij,t}^i$ represents the transmission power of the contact lines between region i and region j in the time period t when solving the sub-problem of region i; $T_{ij,t}^j$ represents the transmission power of the contact lines between region i and region j in the time period t when solving the subproblem of region j. Figure 2 illustrates this process by treating the contact lines between region i and region j as two, each belonging to its own region and satisfying the same maximum capacity constraint, and finally ensuring that the power of the two contact lines is equal at all times. After processing, the relationship between the two regions is clearly reflected in the constraint $T_{ij,t}^i = T_{ij,t}^j$.

For constraint $T_{ij,t}^i = T_{ij,t}^j$, applying augmented Lagrange relaxation, the objective function is:

$$F_{\mathrm{L}} = \sum_{t=1}^{T}\sum_{n=1}^{N}(a_n P_{n,t}^2 + b_n P_{n,t} + c_n) + \sum_{j\in i, j\neq i} \lambda_{ij,t}^{\mathrm{T}}(T_{ij,t}^i - T_{ij,t}^j) + \sum_{j\in i, j\neq i} \rho \parallel T_{ij,t}^i - T_{ij,t}^j \parallel_2^2 \quad (22)$$

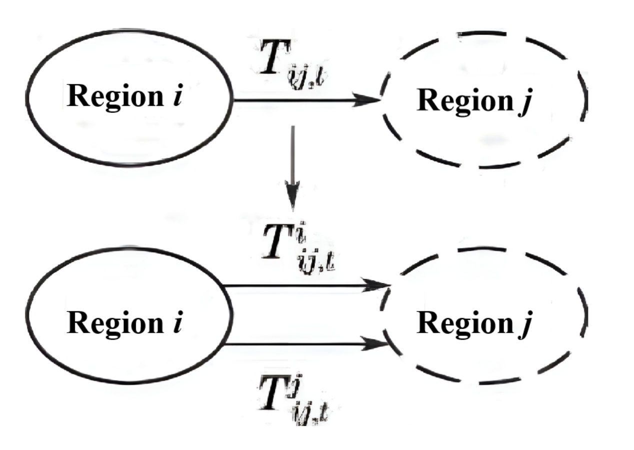

Figure 2. Schematic diagram of constraint rewriting of the contact line

where $\lambda_{ij,t}^{\mathrm{T}}$ is the Lagrangian vector multiplier of the relaxed constraint $T_{ij,t}^i = T_{ij,t}^j$; ρ is the positive coefficient of the corresponding quadratic penalty term. Notice that the quadratic penalty term $\sum_{j\in i, j\neq i}\rho \parallel T_{ij,t}^i - T_{ij,t}^j \parallel_2^2$ destroyed the decomposability of the problem, so the ADMM method was applied for distributed solution, that is, each region was solved separately, and the variables of other regions were regarded as constants in each solution, and the latest iteration results were used. The *k-th* iteration optimization problem for region i can be given as follows:

$$\min F_{\mathrm{L}}^{i(k)} = \sum_{t=1}^{T}\sum_{n\in A^i}(a_n P_{n,t}^2 + b_n P_{n,t} + c_n) + \sum_{j\in i, j\neq i}\lambda_{ij,t}^{(k-1)T} T_{ij,t}^i + \sum_{j\in i, j\neq i}\rho \parallel T_{ij,t}^i - T_{ij,t}^{j(\mathrm{newest})} \parallel_2^2 \quad (23)$$

$$\mathrm{s.t.} \sum_{n\in A^i} P_{n,t} + \sum_{j\in i, j\neq i} 1^{\mathrm{T}} T_{ij,t}^i = \sum_{n_{\mathrm{B}}\in A^i} D_{n_{\mathrm{B}},t} \quad (24)$$

$$P_n^{\min} \le P_{n,t} \le P_n^{\max}, n \in A^i \quad (25)$$

$$\Delta P_n^{\min} \le P_{n,t} - P_{n,t-1} \le \Delta P_n^{\max}, n \in A^i \quad (26)$$

$$\sum_{t=1}^{T} P_{n,t} = E_n, n \in \Phi, n \in A^i \quad (27)$$

$$-P_l^{\max} \le P_{l,t} \le P_l^{\max}, l \in A^i \quad (28)$$

$$-T_{ij}^{\max} \le T_{ij,t} \le T_{ij}^{\max}, j \in i, j \neq i \quad (29)$$

$$\sum_{t=1}^{T} x 1^{\mathrm{T}} T_{ij,t} = E_{ij}, ij \in \Gamma, j \in i, j \neq i \quad (30)$$

where A^i represents the set of all elements in region i; $T_{ij,t}^{j(\mathrm{newest})}$ is the value of the latest iteration of $T_{ij,t}^j$:

$$T_{ij,t}^{j\,(\text{newest})} = \begin{cases} T_{ij,t}^{j\,(k)}, & j < i \\ T_{ij,t}^{j\,(k-1)}, & j > i \end{cases} \quad (31)$$

After each iteration, the update process of the multiplier is:

$$\lambda_{ij,t}^{(k)} = \lambda_{ij,t}^{(k-1)} + \rho\left(T_{ij,t}^{i\,(k)} - T_{ij,t}^{j\,(k)}\right) \quad (32)$$

The PTDF matrix can still be used to calculate the power transmission of the lines in region i. However, the whole network PTDF matrix derived from the centralized scheduling requires the information of all nodes, which obviously cannot be directly applied to the problem solving of region i. Therefore, the corresponding PTDF matrix needs to be found, which can utilize the information of region i and the information of the contact lines between region i and other regions to obtain the power transmission of the lines in region i.

Figure 3 illustrates the solution method of the target PTDF matrix. First, all regions connected to region i (i.e., regions j_1 and j_2 in the figure) are equivalent to nodes outside region i, whose injected power is the corresponding power transmitted by the liaison line. Then, the PTDF matrix is computed for this equivalent network. Using the PTDF matrix, the power transmission of the lines in region i can be acquired by using the information of region i and the information of the contact lines between region i and other regions. Its formula is as follows (all variables belong to region i):

$$P_{l,t} = H_i \cdot [(CP_{n,t} + C_W W_{n_W,t} + C_S S_{n_S,t} - D_{n_B,t}), T_{ij,t}^{i}, T_{i-j+1,t}^{i}] \quad (33)$$

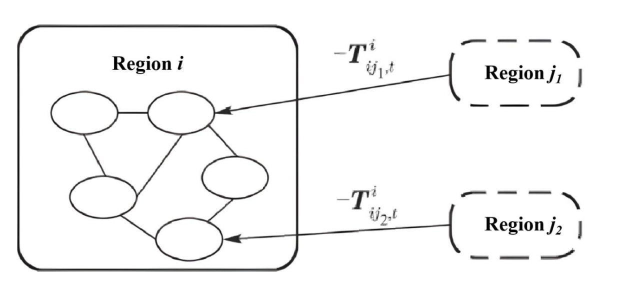

Figure 3. Schematic diagram of PTDF matrix construction corresponding to region i

Similarly, the corresponding PTDF matrix can be solved for other regions. The PTDF for all regions still only needs to be solved once and can be used in all iterations with great convenience.

3) Multi-region distributed power dispatching with fully distributed ADMM method

A limitation of traditional ADMM is that it still requires an upper level data center to collect data from each contact line, and perform the calculation and distribution of multipliers. Although each region does not need to share its own key power information, such upper-level data centers still have a certain authority in practical applications, which is hard to achieve. As shown in Table 1, the only relaxed constraint in the whole iteration process of the traditional ADMM method is the contact line constraint, and the information on each contact line is only generated and used by the two areas of the contact, and is irrelevant to other areas.

Hence, by exploiting the feature that the contact line is not a global constraint, the update process of the corresponding multiplier for each contact line can be completed between the two interconnection areas, without uploading to the data center. Thus, the multiplier calculation and assignment of each contact line can be done by the relevant subareas, and the upper data center can be eliminated, resulting in a fully distributed ADMM method. It should be noted that the mathematical formulas for solving subproblems and updating multipliers for each region are unchanged, so the method has the same mathematical properties as the traditional ADMM method.

Table 1. Comparison of relaxation constraints in ADMM methods

Relax constraints	Global constraints	Contact line constraints
Multiplier update features	Information for all regions is required	Only contact area information is required
Multiplier assignment features	Assignment to all regions is required	Only need to be assigned to the contact area
Upper-tier data center	Need	No, the corresponding work can be transferred to the liaison area

Figure 4 illustrates the transformation from traditional ADMM method to fully distributed ADMM method. The solid line denotes the power connection line, and the dashed line denotes the information connection line. The traditional ADMM method performs power transmission between regions, and each region transmits information to the upper data center. The fully distributed ADMM method eliminates the upper layer data center, and accomplishes the transmission of power and information directly between regions. The specific process is as follows: in the k-th iteration, the problem of region i is solved sequentially, and the corresponding power result of the tie line is obtained. Region i sends this result to region $i+1$ and participates in the problem solving of region $i+1$, as the latest iteration result. After solving the problem for region $i+1$, region $i+1$ already has the necessary information to update the line multiplier between region i and region $i+1$, namely $T_{i-j+1,t}^{i\,(k)}$ and $T_{i-j+1,t}^{i+1(k)}$, so the update of the corresponding multiplier can be done directly in the region $i+1$. Before the $k+1$ iteration, region $i+1$ passes the updated multiplier back to region i, starting the next iteration. Similarly, region $i+2$ can update the multipliers of region i with region $i+2$ and region $i+1$ with region $i+2$. Ultimately, all multiplier updates are done by the regions, without the involvement of the upper data center. In addition, the stop condition of the iteration can also be determined by each region. The region responsible for updating the multiplier can further calculate the corresponding relaxed constrained error and compare it with the given error tolerance.

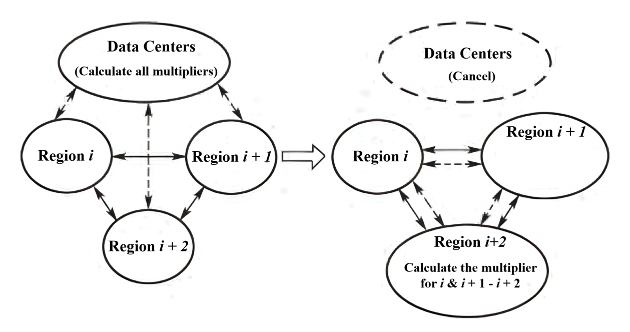

Figure 4. Schematic diagram of transformation from traditional ADMM method to fully distributed ADMM method

If the conditions are not met, this signal can be transmitted to each area through the entire information network, and the iteration continues. The solution steps of multi-region distributed power scheduling with fully distributed ADMM method are as follows:

Step 1: Give the initial values of all variables and parameters (number of iterations k = 0, area number i = 1).

Step 2: Solve the subproblem of region i based on the ADMM method.

Step 3: Compare the number of area i and the interconnection area. If i is greater than the number of any interconnect zone, zone i is responsible for updating the corresponding multiplier and transmitting the result to the corresponding interconnect zone.

Step 4: i = i + 1. If i is greater than the maximum area number, go to Step 5. Otherwise, go to Step 2.

Step 5: Compare the maximum error bound by the tie line with the specified allowable error. If the error requirement is met, the iteration ends and the result is output. Otherwise, k = k + 1, i = 1, go to Step 2.

3. Simulation result analysis

In this investigation, the efficacy of the proposed methodology was substantiated through the development of a tripartite interconnection test case, predicated on the IEEE 30-node, 39-node, and 57-node benchmark test systems. The schematic representation of the interconnected system's architecture is illustrated in Figure 5. Pertaining to each subsystem, the network's topology and ancillary parameters were preserved in congruence with the original configuration, with modifications confined solely to the corresponding numerals to fulfill the prerequisites of the interconnected framework. In alignment with the archetypal diurnal load fluctuation pattern, characterized by "two peaks and one trough" [33], a 24-hour load dataset was synthesized. Subsequently, generators situated at nodes 13, 23, 61, 68, 72, and 81 were designated as contractual power entities, with the stipulated power being allocated at a quantum equating to half of the maximal power output. The tie line's maximal capacity threshold was established at 500 MW, while the transactional power interlinking the 30-node and 39-node systems was ascertained at 2 GWh, and the exchange power schedule was constrained within a bandwidth spanning from −50 MW to 400 MW. Employing a parameterization of ρ = 0.1 and a maximal tie line constraint deviation of 0.1 MW, the model underwent resolution via both the centralized approach and the fully distributed ADMM technique, with the outcomes delineated in Table 2.

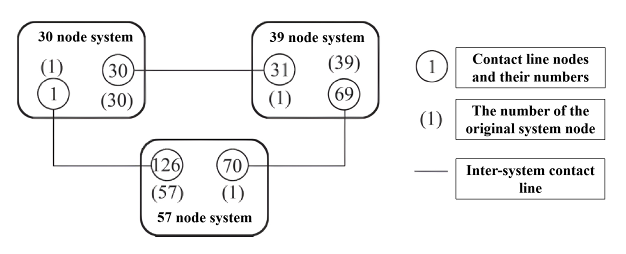

Figure 5. Schematic diagram of the three-system interconnection example

As delineated in Table 2, the methodology articulated herein is corroborated to engender precise solution outcomes, with the iteration count remaining well within an acceptable ambit. In pragmatic deployment, this approach is adept at navigating the complexities of inter-regional interconnected power dispatching quandaries, particularly in scenarios where centralized coordination proves to be infeasible.

Table 2. Comparison of solution results between centralized method and distributed method model

Scheduling method	$P_{21,1}$/MW	$1^T T_{30-39,1}$/ MW	$F/10^6$ yuan	Number of iterations
Centralized	314.8780	−131.0152	1.8167	—
Distributed	314.9792	−130.8220	1.8167	23

The exhibit delineates the fluctuation in the iteration count consequent to the selection of disparate regional iteration sequences within the distributed modality, given the parameter ρ = 0.1. It is discernible that the sequential order of iterations across the various regions exerts a negligible influence on the iteration quantity (Table 3). This implies that, within the distributed resolution framework, the iteration of each region may proceed in an arbitrary sequence, yet still achieve expeditious convergence. The determination of the parameter ρ is subjected to additional scrutiny in the ensuing discourse.

Table 3. Influences of regional iteration order on iteration times

Region iteration sequence	30–39–57	30–57–39	39–30–57
Number of iterations	23	24	21
Region iteration sequence	39–57–30	57–30–39	57–39–30
Number of iterations	20	23	24

Table 4 elucidates the variability of solution outcomes contingent upon the selection of divergent values for the parameter ρ. It is observed that the objective function's value, derived from varying ρ parameters, manifests with commendable precision. However, the iteration frequency exhibits discernible disparities: an excessively augmented or diminished ρ value precipitates an escalation in iteration quantity. Additionally, the error trajectory corresponding to ρ = 0.01 and ρ = 2 is graphically represented in Figures 6 and 7, respectively.

Table 4. Influence of the selection of parameter ρ on the solution results

ρ	0.01	0.05	0.1	0.5	2
$F/10^6$ **yuan**	1.8168	1.8166	1.8167	1.8167	1.8172
Number of iterations	79	21	23	24	34

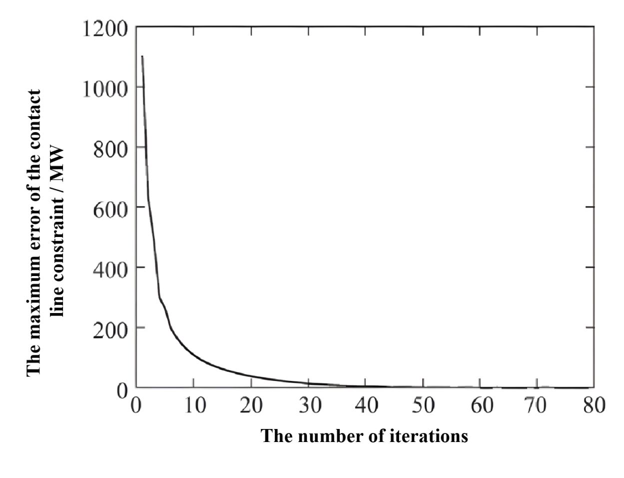

Figure 6. Iterative error curve of parameter ρ =0.01

Figures 6 and 7 elucidate the trajectory of iterative errors, revealing that with ρ = 0.01, the error curve is characterized by

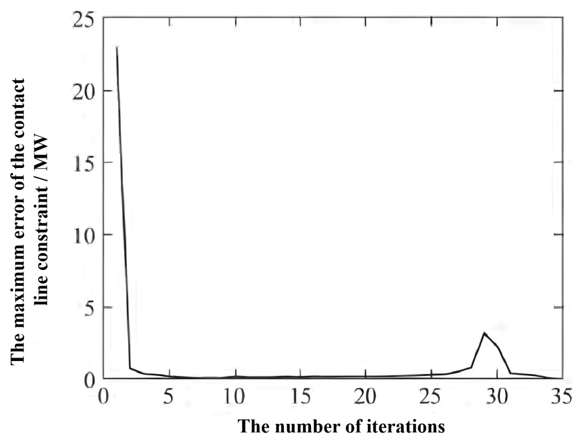

Figure 7. Iterative error curve of parameter ρ =2

a smooth yet gradual decline, necessitating an increased number of iterations. Conversely, when ρ = 2 is employed, the error curve exhibits a precipitous descent accompanied by notable fluctuations, resulting in a heightened iteration count. Consequently, the parameter ρ serves a dual function: it not only modulates the multiplier correction step within the iterative sequence but also impacts the oscillatory nature of the process. These dual roles exert antithetical effects on the rate of convergence. In practical scenarios, the optimal relative value of ρ can be ascertained through empirical experimentation.

4. Conclusion

The current investigation addresses the dynamic economic dispatch (DED) dilemma within a trans-regional power system context, advancing a model that leverages the alternating direction multiplier method (ADMM). This model innovatively obviates the traditional requirement for a superior data center to perform multiplier updates, thus fostering a fully distributed dynamic economic scheduling (DDES) framework. The model's validation was conducted through simulation tests on a set of interconnected systems, based on the IEEE standard test system. The results from these simulations substantiate the model's ability to generate highly precise solutions across a prudent range of iterations. The valuation strategy for the parameter ρ was scrutinized, revealing its significant impact on the iteration count. It was observed that an overly large or small ρ value could either amplify fluctuations in the iteration process or slow down the multiplier's update speed, both of which are counterproductive to rapid iterative convergence. In practical scenarios, optimizing the parameter ρ can be achieved through iterative experimental adjustments.

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