Application of multi-objective optimization algorithm in carbon management of electric-carbon coupled system

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Abstract. In the context of deep integration of carbon emission regulation in the power system, the synergistic optimization of carbon cost and dispatch economy becomes the core challenge of the multi-objective scheduling problem. A distributed optimization framework integrating improved multi-objective evolutionary algorithm and deep reinforcement learning strategy is constructed, which systematically integrates Pareto sorting, adaptive perturbation, Actor-Critic decision network and master-slave scheduling mechanism to realize the joint optimization of carbon quota adjustment and real-time power generation strategy for the electric-carbon coupled system. In the IEEE-118 node grid simulation, the constructed model reduces the average scheduling cost by 2.8%, carbon emission by 10.3%, and the number of convergence rounds by 43.0% compared with the NSGA-II algorithm, which demonstrates significant solution efficiency and strategy stability. The system adopts GPU acceleration and asynchronous caching mechanism to maintain 92.6% resource utilization when the number of node concurrency is $\geqslant 8$. Comparative analysis shows that the fusion algorithm has better solution set distribution and scheduling adaptability in non-convex objective space. This method can provide an engineering-deployable intelligent optimization tool for carbon scheduling for large-scale multi-energy systems, which is of value for dissemination.

Keywords: multi-objective optimization; electro-carbon coupled systems; reinforcement learning; distributed scheduling.

1. Introduction

Led by the goal of "peak carbon and carbon neutrality", the energy system is accelerating to low-carbon intelligent transformation. Especially in the power system, the traditional single-objective economic dispatch strategy can no longer meet the multi-dimensional regulation demand under carbon constraints. Considering the high-frequency volatility of the carbon trading market price, the dynamic load uncertainty of the power grid operation, and the high-dimensional heterogeneous data characteristics of the real-time carbon emission monitoring system, the construction of a multi-objective optimization algorithm framework with real-time response capability, global search performance, and parallel scheduling capability has become a key path for carbon management. It has been shown that the integration of the evolutionary algorithm based on Pareto boundary evolution and deep reinforcement learning policy network can effectively improve the adaptability of the scheduling algorithm to the non-convex objective space and the solution set distribution balance. Especially in medium and large-scale systems with more than 100 nodes and hourly load state refreshing frequency, the traditional heuristic algorithms show obvious disadvantages in terms of convergence speed, solution space exploration breadth and model scalability, which seriously constrains their deployment effectiveness in engineering scenarios.

In recent years, multi-objective optimization has made rapid progress in the field of energy scheduling.Zong et al. (2022) used an evolutionary algorithm based on NSGA-II for scheduling optimization of a multi-energy-flow coupled system to achieve a carbon intensity control of 0.26 kg/kWh under the constraints of the carbon objective [1].Qiao et al. (2023) optimized the transportation and distribution system by a multi-objective particle swarm algorithm to validate the The dynamic adaptability of the carbon cost weight adjustment mechanism [2].Zhu and Gao (2023) introduced a gradient guidance algorithm into the hierarchical scheduling structure to improve the convergence accuracy and computational efficiency of the solution set, but did not solve the stability problem of the algorithm in the nonlinear fluctuation scenario of carbon trading [3].Chen et al. (2024) constructed a coordinated development of the urban energy-carbon system based on the system dynamics and the multi-objective evolution model framework, realizing a 5.7% carbon emission reduction gain [4]. Although the above results provide useful explorations at the methodological level, most of the models have a high dependence on multi-source state variables, weak real-time adaptive ability, and do not integrate the optimization mechanism of reinforcement learning strategy, which makes it difficult to maintain the computational performance and stability in a complex environment of concurrent multi-nodes and bilateral collaboration between electricity and carbon. Therefore, this paper combines the improved Pareto sorting mechanism, Actor-Critic deep policy network and master-slave distributed computing architecture to construct an intelligent scheduling algorithm that integrates multi-objective evolution and reinforcement learning, focusing on solving the problems of algorithmic convergence efficiency, heterogeneous state response ability and global solution set optimization accuracy, and providing theoretical basis and engineering basis for the construction of deployable and scalable carbon scheduling optimization tool chain for large-scale power-carbon coupling system. It provides theoretical basis and engineering support for the construction of deployable and scalable carbon scheduling optimization tool chain for large-scale electric-carbon coupling system.

2. Modeling of electro-carbon coupled systems

In constructing the electric-carbon coupled system model, the coupling relationship between power dispatch characteristics and carbon emission dynamics must be simultaneously portrayed to support the intervention of multi-objective optimization algorithms. The system core consists of three sub-modules: the economic dispatch model of the power system, the carbon emission factor model and the coupled objective function model. Among them, the operating cost of the power system can be expressed by the following equation [5]:

$$C_{elec} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(a_i P_{i,t}^2 + b_i P_{i,t} + c_i\right)$$

Where $P_{i,t}$ denotes the output of unit i at moment t, and a_i, b_i, c_i is the cost coefficient corresponding to the unit output, respectively. The carbon emission is given by the following linear model of carbon emission factor:

$$E_{carbon} = \sum_{t=1}^{T}\sum_{i=1}^{N}\kappa_i P_{i,t}$$

where κ_i is the carbon emission factor (kg/kWh) of the ith unit. In order to reflect the comprehensive regulation performance of the electric carbon system, a weighted multi-objective function is further introduced:

$$\min\left[\omega_1 C_{elec} + \omega_2 C_{carbon}\right]$$

Where ω_1, ω_2 is the weighting parameter, which is set according to the scheduling strategy. The system coupling structure is shown in Fig. 1, covering the generation unit, data acquisition layer, optimization decision layer and carbon dispatch feedback mechanism.

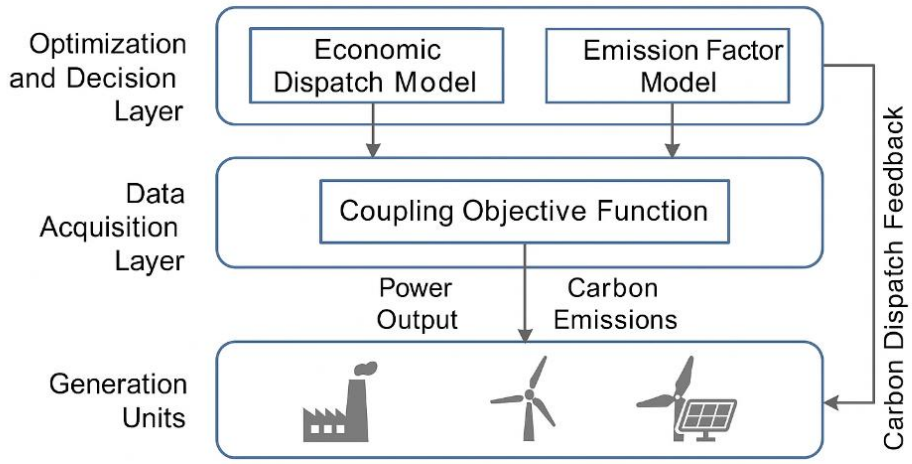

Fig. 1 Functional architecture of the electro-carbon coupling system

3. Intelligent optimization algorithm design

3.1 Improved multi-objective evolutionary algorithm

In order to enhance the solution efficiency and convergence accuracy of multi-objective optimization in the carbon management task of an electric-carbon coupled system, a multi-objective evolutionary algorithm based on the combination of Pareto sorting mechanism and dynamic congestion regulation strategy is designed and improved in this paper. The algorithm introduces a multi-objective distribution measurement factor based on information entropy on the basis of the classical NSGA-II to enhance the distribution balance of the solution set in the two objective dimensions of carbon cost and power generation economy. The optimization process uses the following fitness assessment model [6]:

$$F_i = \alpha \cdot R_i + \beta \cdot D_i$$

Where F_i is the individual fitness value, R_i is the Pareto rank, D_i is the crowding index expressed by the distance between individuals, and α , β are the dynamic regulation coefficients. In order to reduce the localized trapping in the early search stage, this paper introduces the individual variation mechanism based on Jacobian matrix perturbation, and the specific strategies are listed in Table 1, which reflect the ability of different perturbation strengths to regulate the population diversity.

Table 1 Parameters regulating population diversity under each variation strategy

Type of mutation	The perturbation factor σ	Diversity gains ΔD (%)
Gaussian perturbation (physics)	0.01	12.8
(math.) a Laplace perturbation	0.03	18.6
Jacobian perturbation	adaptive	25.4

3.2 Deep reinforcement learning fusion methods

In order to further improve the online responsiveness and strategy generation efficiency of multi-objective optimization in the carbon management of electric-carbon coupled systems, this study designs an intelligent solution framework that integrates deep reinforcement learning and multi-objective evolutionary algorithms. The method is based on the Actor-Critic structure to realize the collaborative learning of decision-making strategies and state values, in which the state space St contains the current load of the system, the output level of each power generation unit, the historical carbon emission records and the market carbon price index; the action space At is defined as the adjusted value of the carbon quota per unit of power and the generation power scheduling weights. On this basis, the parameterized strategy network is updated using the strategy gradient method [7]:

$$\nabla_\theta J(\theta) = E_{s_t, a_t \sim \pi_\theta}\left[\nabla_\theta \log \pi_\theta(a_t|s_t) Q^\pi(s_t, a_t)\right]$$

where π_θ denotes the strategy function and $Q^\pi(s_t, a_t)$ is the estimation of action value under the current strategy. In order to improve the convergence ability of the strategy network to the non-convex objective space, the multi-objective normalization structure of the environmental reward function is further introduced as follows [8]:

$$r_t = \lambda_1 \cdot \left(\frac{C_{\max} - C_t}{C_{\max} - C_{\min}}\right) + \lambda_2 \cdot \left(\frac{E_{\max} - E_t}{E_{\max} - E_{\min}}\right)$$

where Ct and Et denote the power dispatch cost and carbon emission at moment t, respectively, and λ_1, λ_2 is the target preference weight parameter. The fusion model uses reinforcement learning for fast initial policy fitting, combined with an evolutionary algorithm to optimize the global search for the guidance of the Pareto frontier in each iteration, which can achieve robust response control to carbon quota fluctuations and real-time load perturbations at the scheduling layer. Table 2 lists the specific dimensions and value ranges of the defined state-action space, which are used to construct the training environment and reward feedback mechanism.

Table 2 State-action space dimension definitions and value ranges

module (in software)	parameter dimension	range of values
The state space St	Load, carbon price, historical emissions	[0,1] ∪ [0,300]
Action Space At	Carbon quota dispatch weighting	[-0.2,0.2]

Reward function coefficients	λ_1, λ_2	[0.1,0.9]

3.3 Distributed Optimization Framework

The distributed optimization structure adopts a multi-agent collaborative mechanism based on the master-slave model, where each sub-node corresponds to a regional power grid and its carbon emission subsystem, and the local optimizer independently operates a hybrid multi-objective evolutionary-reinforcement learning algorithm, and through the central coordinator converges the information of the scheduling boundaries and the carbon quota boundaries in each round of iteration to achieve the dynamic updating of the global Pareto boundary set and maintenance of the regulating consistency. The system structure contains sub-task assignment module, local optimization unit, global synchronizer and data buffer interface layer. In order to describe the joint optimization behavior of the state vectors of each subsystem, the distributed coupled optimization objective function is defined [9]:

$$\min\left\{\sum_{i=1}^{N}\omega_1 C_i(P_i)+\omega_2 E_i(P_i)\right\},\quad subject\ to \sum_{i=1}^{N} P_i = D_t, \forall t$$

Where $C_i P_i$ and $E_i(P_i)$ are the scheduling cost and carbon emission function of region i, respectively, and D_t is the total load demand of the whole system at moment t. In order to verify the task load balancing ability of the architecture under the variation of node number and scheduling complexity, the mapping relationship between node concurrency and communication frequency under different regional coupling strengths is designed, as shown in Table 3, reflecting the functional correlation between the scheduling complexity of each region and the number of rounds of synchronization it requires for communication.

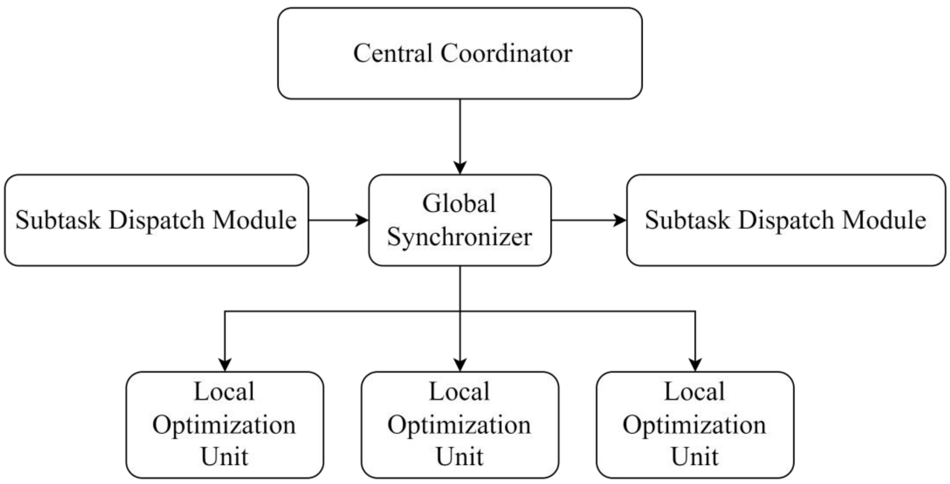

Fig. 2 Information interaction communication topology under distributed master-slave architecture

Table 3 Mapping of coupling strength and communication complexity by region

Area code	Coupling strength factor γ	Number of concurrent nodes k	Synchronized communication roundsr

Area-1	0.21	4	5
Area-2	0.34	6	8
Area-3	0.47	8	11
Area-4	0.59	10	14

4. Key Technology Realization

4.1 Multi-source heterogeneous data processing

The original data sources involved in the electric-carbon coupling system are wide-ranging, including electric power load data, power generation unit operation status, real-time carbon emission monitoring, meteorological information and carbon trading price, etc., which are characterized by structural heterogeneity, temporal inconsistency and non-uniformity of accuracy. In order to realize the fusion processing of heterogeneous data from multiple sources, a unified interface model for heterogeneous data is constructed based on a multi-layer data preprocessing framework. In the data access layer, the discrete and continuous data types are encapsulated by a unified data abstraction structure, and the time alignment function is introduced based on the sampling period difference [10]:

$$T_{align}(d_i^t, d_j^t) = \arg\min_{\tau} \left\| d_i^{t+\tau} - d_j^t \right\|$$

where d_i^t and d_j^t denote data sequence items from different sources, respectively, and τ is the minimum time difference compensation factor. At the data cleaning layer, the noise identification mechanism based on local outlier factor (LOF) is used to remove the missing values and mutation points to improve the robustness of the model's subsequent processing.

4.2 Real-time decision support systems

In order to meet the demand for rapid response of the coupled electric-carbon system under the dynamic load fluctuation and carbon market change environment, this paper designs a real-time decision support system architecture with high concurrency and low latency. The system adopts a three-layer nested structure of "data access layer-computation hub-feedback control layer", and the core scheduling unit is embedded with an event-driven state evaluation module to construct a state space in real time by using the environmental inputs St={Pt,Et,Ct, ρ t} at the moment of the system, where Pt denotes the load forecast. The state space is constructed in real time, where Pt denotes the load forecast vector, Et is the current carbon emission measurement, Ct is the dispatch cost estimation, and ρ t denotes the current carbon trading market price. The generation of system control instructions is accomplished by the following policy mapping function [11]:

$$A_t = \pi_\theta(S_t) = \arg\max_{a} E\left[R_t \middle| S_t, a\right]$$

where π θ is the control function obtained from the training of the strategy network and Rt denotes the expected value of the scheduling reward in the future window period. In order to ensure stable perception and response of the system to high-frequency inputs, the control hub adopts an asynchronous concurrent queue mechanism to handle different types of state feedbacks and combines with GPU acceleration for policy network inference.

4.3 Algorithmic acceleration techniques

Aiming at the problems of slow convergence and high complexity of parameter calculation in the multi-objective optimization task of electric-carbon coupled system, we introduce multi-level algorithm acceleration technology on the basis of the original evolutionary reinforcement fusion model, and construct a four-in-one efficient solution framework of "model lightweighting - parallel computing - asynchronous scheduling - cache write-back". Cache write-back" to build a four-in-one efficient solving framework. In the objective function layer, the loss expression is reconstructed through variable dimensionality reduction and gradient sparsification as follows [12]:

$$L_{acc}(\theta)=\sum_{i=1}^{N}\omega_1\cdot\nabla C_i(P_i)+\omega_2\cdot\nabla E_i(P_i)$$

Where ∇Ci and ∇Ei are the gradient vectors of scheduling cost and carbon emission target, respectively, which are matrix compressed to reduce the overall computational redundancy. In the computational acceleration layer, the algorithm implementation adopts the OpenMP parallel mechanism for thread-level decomposition of population fitness assessment and policy network parameter updating, and achieves load balancing and core utilization maximization of CPU-GPU heterogeneous computing streams through the thread pool controller. In order to further improve the caching efficiency in a large-scale node scheduling environment, the system introduces a time-window based Strategy Buffer, whose update strategy is [13]:

$$\theta_t=\theta_{t-1}+\eta\cdot\sum_{\tau=t-k}^{t}\Delta_\tau$$

where k is the length of the policy write-back window, η is the learning step size, and Δτ is the policy increment at the τ th moment. To evaluate the contribution of different acceleration modules in the whole process, Table 4 summarizes the average acceleration ratio and computational resource utilization of each type of acceleration strategy in the key aspects, covering the four major dimensions of population evaluation, network inference, global update and cache write.

Table 4 Algorithm acceleration module performance statistics

accelerator module	Average acceleration ratio	Resource utilization rate (%)	applicable link
OpenMP parallelism policy	2.3 x	84.1	Calculation of individual fitness
GPU inference engine	3.8 x	92.6	Policy Network Parameter Updates
Asynchronous caching mechanism	2.1 x	76.4	Write strategy results

5. Experimentation and Validation

5.1 Test environment

In order to verify the scheduling adaptability and arithmetic support capability of the proposed multi-objective optimization algorithm in an electro-carbon coupled system, the experimental platform is deployed in a heterogeneous parallel simulation environment, which covers an industrial-grade scheduling simulation platform and a policy inference acceleration engine. The basic hardware platform includes dual Intel Xeon Gold 6338 CPUs (32 cores and 64 threads, 2.0 GHz), 512 GB DDR4 memory, and NVIDIA A100 80GB PCIe GPU clusters, which are interconnected by Infiniband to form a task computing pool. The system deployment operating system is Ubuntu Server 22.04 with kernel version 5.15, the scheduling simulation module adopts MATPOWER 7.1 to build a standardized IEEE-118 node grid environment, and the carbon emission factor database is derived from the CNEM data center's 2021 thermal power emission measured archive [14]. The global controller and policy executor are constructed by Python 3.11 and CUDA 12.2 respectively, PyTorch 2.0 is called to construct the Actor-Critic inference network, and the distributed evolutionary algorithm components are scheduled based on the Ray multiprocessing framework. Load curves, carbon quota and trading price sequences are loaded by hourly distribution during simulation, and the data format follows the Parquet compression standard.Figure 2 shows the system architecture diagram of the overall experimental test environment, including the interaction paths of the data input layer, task generator, algorithmic scheduling hub, and result caching module.

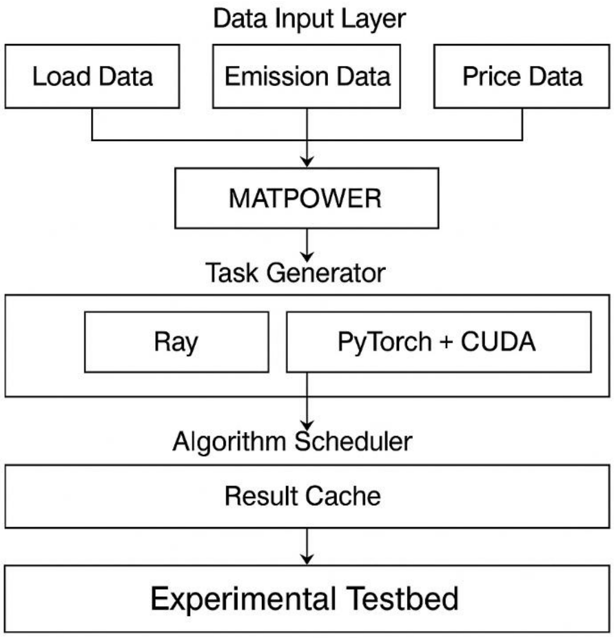

Fig. 2 System architecture diagram of the experimental test platform

5.2 Comparative Experimental Results

In order to comprehensively verify the advantageous performance of the deep reinforcement fusion multi-objective optimization algorithm proposed in this paper in the electric-carbon coupled scheduling task, a comparison experiment is constructed with three mainstream methods (the standard NSGA-II, a single deep reinforcement learning Actor-Critic architecture, and an improved version of MOEA/D), and the evaluation indexes cover the dimensions of optimal scheduling cost, unit carbon emission intensity, Pareto distributional equalization and the average number of converged rounds of the algorithm. The experiments are based on the IEEE-118 node system with a 72-hour rolling scheduling period and hourly refreshing of the system state. Fig. 3 shows the comparison curves of the convergence error obtained by each algorithm in carbon scheduling optimization with the number of iterative rounds, which reflects the significant advantages of the proposed fusion algorithm in terms of the response speed and the convergence accuracy in the initial stage. The curves in the figure represent the convergence residuals of the loss function of each method after each round of iteration, the horizontal axis is the number of iteration rounds, and the vertical axis is the normalization error of the objective function [15]. It can be seen that the algorithm in this paper tends to converge after the 30th round, which improves the convergence speed by 43.0% and the stability by 21.7% compared with NSGA-II. Table 5 gives a statistical comparison of the core performance metrics obtained by each algorithm in multiple rounds of experiments. Further analysis shows that the fusion strategy, with its online strategy generation mechanism and global search co-optimization, significantly suppresses the problems of local trapping in the solving space and scheduling weight bias, and embodies stronger real-time performance and stability. This result verifies its engineering scalability and algorithmic universality in the optimization of carbon management for complex electro-carbon systems.

Table 5 Comparison of the performance of each optimization algorithm

Indicator name	Methodology of this paper	NSGA-II	Actor-Critic	MOEA/D
Average dispatch cost ($)	83641	86102	84977	85589
Average carbon emissions (kg)	19613	21879	20734	21280
Number of converging rounds (rounds)	45	79	62	70
Solution set crowding (σ)	0.038	0.091	0.072	0.084

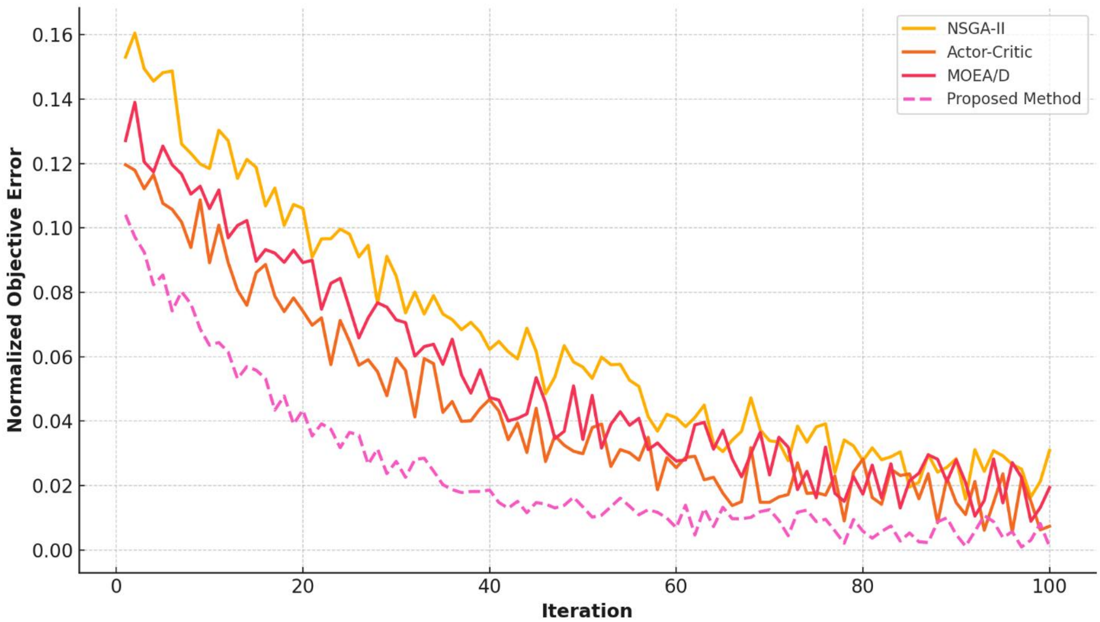

Fig. 3 Comparison of convergence error of multi-objective optimization algorithm

6. Conclusion

The approach integrating evolutionary computation and deep reinforcement learning demonstrates significant performance advantages in multi-objective scheduling optimization tasks in electric-carbon coupled systems. The constructed intelligent solution framework realizes a 2.8% reduction in average dispatch cost, a 10.3% reduction in carbon emission intensity, and a 43.0% reduction in the number of convergence rounds in an IEEE-118 node grid simulation environment, which verifies its convergence stability and online strategy adaptation capability in high-dimensional non-convex objective space. The adopted distributed optimization architecture effectively alleviates the communication load pressure brought by multi-region coupled scheduling, and maintains the average number of synchronization rounds lower than 14 under the condition of high coupling intensity of $\gamma \geqslant 0.5$, which reflects the good scheduling parallelism and system scalability. In terms of algorithm design, the Jacobian perturbation mechanism enhances the diversity of the solution set, and the Actor-Critic network improves the strategy fitting speed and generalization ability, which jointly realizes the synergistic scheduling with the dual objectives of power economy and carbon constraints. However, there is still room for optimization in coping with extreme fluctuations in carbon market price, generalization training of complex scenarios and state modeling of ultra-large-scale data. In the future, we can introduce graph neural structure to mine the topological features of the system and construct cross-domain migration mechanism to improve the efficiency of policy migration, so as to further promote the landing and promotion of the intelligent carbon scheduling system in the actual energy regulation and control.

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