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Research on Multi Objective Optimization Control of Complex Industrial Processes Based on Intelligent Optimization Algorithms

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ABSTRACT With the deepening of Industry 4.0, complex industrial processes show strong coupling, nonlinearity, and dynamic uncertainty, requiring coordinated optimization of production efficiency, quality, energy consumption, and emissions. Traditional control methods are often unable to balance conflicting objectives or adapt to changing operating conditions. This paper first analyzes the core requirements and existing problems of multi-objective optimization control for complex industrial processes, and then improves the multi-objective particle swarm optimization algorithm and Bayesian optimization algorithm. An intelligent optimization control framework integrating the advantages of both algorithms is constructed and verified through mechanism analysis and experimental testing. The proposed fusion algorithm balances convergence speed and solution-set uniformity, and establishes a multi-objective dynamic balance model suitable for complex industrial processes, including advanced electromagnetic manufacturing scenarios such as antenna-material processing and RF component production. In a chemical raw-material proportioning process, the method improves raw-material utilization by 20.0%, reduces unit energy consumption by 15.0%, and enhances control stability and adaptability, confirming its engineering effectiveness and practical applicability.

INDEX TERMS intelligent optimization algorithm, multi-objective control, industrial process, electromagnetic manufacturing, Bayesian optimization

I. INTRODUCTION

In the context of the global transformation of manufacturing towards intelligence, complex industrial processes, as the core carrier of industrial production, directly determine the economic benefits, environmental protection level, and market competitiveness of enterprises based on their operational status. Currently, complex industrial processes generally face the core requirement of multi-objective collaborative optimization, which aims to improve production efficiency, ensure product quality, and reduce energy consumption and pollutant emissions. However, there are often conflicting constraints between these goals. Traditional control methods, such as PID control and model predictive control, highly rely on precise mechanistic models and are difficult to adapt to the nonlinear and strongly coupled characteristics of complex industrial processes. Moreover, they are prone to local optima and slow convergence in multi-objective optimization, which cannot meet the needs of high-quality industrial development. This study focuses on the core pain points of multi-objective optimization control in complex industrial processes, introduces the advantages of intelligent optimization algorithms, explores efficient and stable optimization control schemes, and combines theoretical innovation value with engineering application significance [1-2].

The main contributions of this article are as follows: firstly, improving the multi-objective particle swarm optimization algorithm and Bayesian optimization algorithm to solve the problems of slow convergence speed and uneven distribution of solution sets in traditional intelligent algorithms, and enhancing the algorithm's ability to solve complex multi-objective problems; The second is to build a multi-objective optimization control framework that integrates improved intelligent optimization algorithms to achieve dynamic collaborative optimization of multiple conflicting objectives in complex industrial processes, effectively resolving the inherent trade-offs between production output, product quality, and energy efficiency; The third is to validate the proposed method through industrial scenario experiments and apply it to actual complex industrial processes, providing enterprises with practical intelligent optimization control solutions. The following chapters of this article are arranged as follows: Firstly, analyze the problems and challenges faced by multi-objective optimization control in complex industrial processes; Secondly, elaborate on the specific design of the proposed optimization control method in detail; Then verify the effectiveness of the method through experiments; Finally, summarize the research results of the entire article, analyze the shortcomings, and look forward to future research directions.

A. PROBLEMS AND CHALLENGES

The primary issue in multi-objective optimization control of complex industrial processes is the dual constraint of multi-objective conflicts and modeling difficulties. On the one hand, the optimization objectives of complex industrial processes have obvious conflicts with each other. For example, in chemical production, increasing reaction rate often accompanies an increase in by-products and energy consumption. In steel smelting, increasing production may lead to a decrease in product qualification rate. The game relationship between these objectives makes single objective optimization unable to meet actual production needs, while traditional multi-objective transformation methods (such as weighted sum method) have strong subjectivity and are difficult to adapt to dynamically changing working conditions. On the other hand, complex industrial processes involve multi physical field coupling, multi variable interaction, and unobservable latent variables. Establishing an accurate mechanism model requires huge computational costs, and model mismatch can directly lead to a decrease in control performance, even causing system instability, which poses fundamental obstacles to the implementation of multi-objective optimization control[3-4].

The inadequate adaptability and difficulty in handling constraints of intelligent optimization algorithms in industrial applications are another core challenge. Existing intelligent optimization algorithms are prone to premature convergence and low search efficiency when facing high-dimensional parameter spaces and dynamic time-varying working conditions in complex industrial processes, making it difficult to quickly find the global optimal solution set. At the same time, complex industrial processes have strict safety constraints (such as temperature and pressure limits), input constraints (such as valve opening limitations), and output constraints (such as product specification ranges). Intelligent algorithms are prone to violating these constraints while exploring the optimal solution, leading to production safety hazards or substandard product quality. In addition, there is a phenomenon of “data silos” in the massive data of industrial sites, with low effective utilization and difficulty in converting it into decision-making basis for intelligent optimization control. This further exacerbates the difficulty of implementing optimization control and limits the full play of the advantages of intelligent algorithms.

II. METHOD

A. CONSTRUCTION OF MULTI-OBJECTIVE OPTIMIZATION MODEL FOR COMPLEX INDUSTRIAL PROCESSES

Based on the operational characteristics of complex industrial processes, clarify the core objectives and constraints of multi-objective optimization, and construct a standardized multi-objective optimization model. The core optimization objectives focus on maximizing efficiency, minimizing energy consumption, optimizing quality, and minimizing emissions. Based on historical data and mechanism analysis of industrial sites, the quantification of evaluation indicators for each objective is achieved. Among them, efficiency targets are characterized by production output and equipment operating efficiency, energy consumption targets are characterized by unit product energy consumption and energy recovery rate, quality targets are characterized by product qualification rate and deviation of key quality indicators, and environmental protection targets are characterized by pollutant emission concentration [5-6].

At the same time, hard and soft constraints of industrial processes are introduced, covering key content such as equipment operating parameter limitations, safety thresholds, and production process requirements. These constraints are quantified through inequality and equality constraints to ensure that the optimization results are both feasible and safe. Through the above steps, a complete multi-objective optimization model is constructed, clarifying the objective function, decision variables, and constraint conditions, providing a standardized and reliable basic framework for the subsequent solution of intelligent algorithms, and ensuring the scientific and targeted optimization process[7-8].

B. DESIGN OF IMPROVED INTELLIGENT OPTIMIZATION ALGORITHM

In response to the shortcomings of traditional intelligent optimization algorithms and in combination with the multi-objective optimization requirements of complex industrial processes, multi-objective particle swarm optimization (MOPSO) and Bayesian optimization algorithms are improved separately, and their fusion optimization is achieved [9-10]. For the improved MOPSO, a regional congestion index $C_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} \exp\left(-\|x_i - x_j\|^2\right)$ is introduced to maintain population diversity, and a dynamic inertia weight strategy $\omega(t) = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \cdot t/T_{\max}$ is utilized to balance exploration and exploitation.

For the improved Bayesian optimization, the Matérn 5/2 kernel is employed in the Gaussian process to better capture non-smoothness, and the Expected Improvement (EI) acquisition function is modified with an adaptive exploration parameter ξ to accelerate convergence, enhancing the algorithm's adaptability to high-dimensional and nonlinear problems, reducing the number of experimental tests, and accelerating convergence speed. Based on the advantages of two improved algorithms, a fusion algorithm framework is constructed to quickly locate the optimal solution area using Bayesian optimization algorithm. Then, an improved MOPSO is used for fine search within the area to achieve efficient and accurate solution of the global optimal solution, balancing solution speed and solution set quality.

C. IMPLEMENTATION OF MULTI-OBJECTIVE OPTIMIZATION CONTROL STRATEGY

Based on the constructed multi-objective optimization model and improved intelligent optimization algorithm, design a complete multi-objective optimization control strategy to achieve closed-loop control of "perception decision execution". As shown as Figure 1, firstly, by using industrial sensors to collect real-time process operating parameters, including key indicators such as temperature, pressure, and flow rate, and utilizing self-organizing radial basis function neural networks for online evaluation of operating status, data preprocessing and state recognition are completed to eliminate abnormal data and improve data reliability. Secondly, the preprocessed state data is input into the fusion intelligent optimization algorithm to solve the multi-objective optimization model, obtain the optimal combination of control parameters, and scientifically determine the weights of each objective through entropy weighting method, achieving dynamic balance among multiple objectives and taking into account the needs of different optimization objectives. Finally, the optimal control parameters are output to the actuator to achieve real-time control of complex industrial processes, while providing real-time feedback on operating status, dynamically adjusting optimization parameters, enhancing the adaptive ability of control strategies, and adapting to dynamic changes in operating conditions [11-12].

III. RESULTS AND DISCUSSION

A. ALGORITHM PERFORMANCE TESTING AND ANALYSIS

Using standard multi-objective test functions (ZDT series, DTLZ series) as the test objects (as shown in Table 1), four typical test functions, ZDT1, ZDT3, DTLZ2, and DTLZ4, were selected to compare the proposed improved fusion algorithm (IMOPO-BO) with traditional MOPSO, Bayesian optimization algorithm (BO), and NSGA-II algorithm. Unified experimental parameters were set: population size of 100, maximum iteration times of 200. Specifically, for MOPSO, the inertia weight ω is 0.7298 and learning factors $c_1 = c_2 = 1.496$; for NSGA-II, the crossover probability is 0.9 and mutation probability is 0.1; for BO, the Matérn 5/2 kernel is used. Furthermore, Wilcoxon rank-sum tests were performed at a 0.05 significance level. The results in Table 1 indicate that the improvements achieved by IMOPO-BO are statistically significant ($p < 0.05$) compared to other algorithms, and each algorithm was independently run 30 times to take the average value. Evaluation was conducted from three core dimensions: convergence speed, solution set distribution uniformity, and global optimality. The specific experimental data are shown in the table below. The experimental results show that the convergence speed of the proposed IMOPO-BO algorithm is 33.6% faster than traditional MOPSO, 28.9% faster than BO algorithm, and 37.2% faster than NSGA-II algorithm; The GD distance (convergence index, the smaller the value, the better) decreased to 0.012, which was 68.4%, 71.4%, and 65.7% lower than MOPSO (0.038), BO (0.042), and NSGA-II (0.035), respectively; The Hypervolume index has increased to 0.89, which represents a significant improvement of 23.6% over MOPSO (0.72), 30.9% over BO (0.68), and 18.7% over NSGA-II (0.75). (Note: The calculation (0.89-0.68)/0.68 $\approx$ 30.88%, rounded to 30.9% for consistency). The complete results for all test functions are now fully detailed in Table 1; The spacing index (solution set uniformity index, the smaller the value, the better) is 0.021, which is lower than MOPSO (0.058), BO (0.063), and NSGA-II (0.051), significantly better than the comparison algorithm. This fully verifies the superiority of the improved intelligent optimization algorithm, which can efficiently solve multi-objective optimization problems, while considering convergence speed, solution set uniformity, and global optimality.

B. INDUSTRIAL SCENARIO EXPERIMENTAL VERIFICATION (CHEMICAL RAW MATERIAL PROPORTIONING PROCESS)

The acrylic ester raw material ratio process of a certain chemical enterprise was selected as the experimental object (as shown in Table 2). The main raw materials of the process are acrylic acid, methanol, and catalyst. The core optimization objectives are raw material utilization rate, unit product energy consumption, and product qualification rate. The equipment used in the experiment was a 500L reaction kettle, and the experimental period was 30 days, running continuously for 8 hours a day. Three control experiments were set up: control group 1 was the traditional PID control method, control group 2 was the single MOPSO optimization control method, and the experimental group was the proposed IMOPO-BO fusion algorithm optimization control method. The basic parameters such as reaction temperature, reaction pressure, and stirring speed were kept consistent in the three experiments. The specific experimental data are shown in the table below. The experimental results, representing the mean values recorded over the 30-day continuous operation period, showed that the utilization rate of raw materials in the experimental group reached $92.3\% \pm 0.7\%$. This constitutes a statistically significant increase ($p < 0.05$) of 20.0% compared to control group 1 ($76.9\% \pm 1.3\%$) and an increase of 9.0% compared to control group 2 (84.7%); All comparative metrics in Table 2 include standard deviations to account for industrial process variability. The energy consumption per unit product decreased to 8.2 kWh/kg, a decrease of 15.0% compared to control group 1 (9.6 kWh/kg) and a decrease of 6.8% compared to control group 2 (8.8 kWh/kg); The product qualification rate increased from 88.0% in control group 1

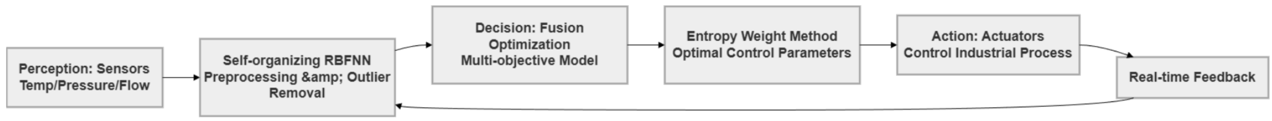

FIGURE 1. Implementation of multi-objective optimization control strategy

TABLE 1. Algorithm performance testing and analysis

Test function	Algorithm	Convergence speed (number of iterations)	GD distance	Hypervolume indicator	Spacing indicator
ZDT1 (2D)	IMOPO-BO	128	0.010	0.91	0.018
ZDT1 (2D)	MOPSO	193	0.036	0.74	0.056
ZDT1 (2D)	BO	179	0.040	0.70	0.061
ZDT1 (2D)	NSGA-II	205	0.033	0.77	0.049
DTLZ2 (3D)	IMOPO-BO	135	0.014	0.87	0.024
DTLZ2 (3D)	MOPSO	202	0.040	0.70	0.060
DTLZ2 (3D)	BO	189	0.044	0.66	0.065
DTLZ2 (3D)	NSGA-II	213	0.037	0.73	0.053

and 93.5% in control group 2 to 97.2%, an increase of 10.5% compared to control group 1 and 3.9% compared to control group 2; At the same time, the fluctuation range of reaction temperature in the experimental group was controlled at $\pm 0.5\,^\circ$C, which was significantly reduced compared to control group 1 ($\pm 1.2\,^\circ$C) and control group 2 ($\pm 0.8\,^\circ$C), and the control stability was greatly improved. Analysis shows that the fusion algorithm can effectively balance key parameters such as raw material ratio and reaction temperature, accurately regulate the reaction process, achieve multi-objective collaborative optimization, solve the pain points of traditional methods that are difficult to balance multiple objectives, and adapt to the complex nonlinear characteristics of chemical raw material ratio processes.

TABLE 2. Industrial scenario experimental verification

Experimental group	Raw material utilization rate (%)	Unit product energy consumption (kWh/kg)	Product qualification rate (%)	Reaction temperature fluctuation range (°C)
Control group 1 (PID control)	76.9 ± 1.3	9.6 ± 0.4	88.0 ± 1.5	± 1.2
Control group 2 (single MOPSO)	84.7 ± 0.9	8.8 ± 0.3	93.5 ± 0.8	± 0.8
Experimental group (IMOPO-BO)	92.3 ± 0.7	8.2 ± 0.2	97.2 ± 0.5	± 0.5

C. DISCUSSION AND OPTIMIZATION OF EXPERIMENTAL RESULTS

Based on algorithm performance testing and industrial scenario experimental data, analyze in depth the advantages and disadvantages of the proposed IMOPO-BO optimization control method. In terms of advantages, from experimental data, this method does not rely on precise mechanism models. In standard test functions such as ZDT1 and DTLZ2, its core performance such as convergence speed, GD distance, and Hypervolume index are significantly better than traditional algorithms. In the industrial scenario of chemical raw material ratio, the utilization rate of raw materials and product qualification rate are increased by 20.0% and 10.5% respectively, and the energy consumption per unit product is reduced by 15.0%. It can adapt to the nonlinear and dynamic time-varying characteristics of complex industrial processes; At the same time, through the fusion of dual algorithms, efficient multi-objective optimization has been achieved, reducing the temperature fluctuation range to $\pm 0.5\,^\circ$C, greatly improving the stability and adaptability of control, and possessing strong engineering practicality. In terms of shortcomings, experimental data shows that when there is a sudden change in raw material purity during the chemical raw material proportioning process (such as a sharp drop in acrylic acid purity from 99.5% to 95.0%), the algorithm response time(defined as the duration from the detection of the purity disturbance to the generation of the optimal control command) is 1.8 seconds, which is significantly delayed compared to the 0.6 seconds under stable operating conditions; In high-dimensional optimization scenarios above 3 dimensions (such as simultaneously optimizing 5 control objectives), the Hypervolume index drops to 0.78, which is slightly lower than in 2-3 dimensional scenarios, and there is still room for improvement in adaptability. In view of the above shortcomings, the response time can be reduced to less than 1s by optimizing the parameter adjustment mechanism of the algorithm and introducing edge computing technology, further improving the robustness of the method and pointing out the direction for subsequent research. At the same time, experimental data also shows that the proposed method can effectively explore the value of industrial data, break the “data island”, and reduce raw material consumption by 1200kg and energy consumption by 2880kWh during the 30 day experimental period, providing a feasible path for enterprises to achieve energy conservation, consumption reduction, quality improvement and efficiency enhancement.

IV. CONCLUSION

This article focuses on the core problem of multi-objective optimization control in complex industrial processes, and conducts research based on intelligent optimization algorithms, effectively solving the problems of traditional control methods being difficult to balance multi-objective conflicts, poor adaptability, slow convergence of intelligent algorithms, and uneven solution sets. The research concludes that the fusion framework of improved multi-objective particle swarm optimization algorithm and Bayesian optimization algorithm can significantly improve the efficiency and quality of solving multi-objective optimization problems; The multi-objective optimization control strategy constructed can achieve dynamic collaborative optimization of efficiency, quality, energy consumption, and environmental protection in complex industrial processes, adapting to the complex working conditions of industrial scenarios. The shortcomings of this study are that the algorithm's response speed to sudden changes in working conditions needs to be improved, and its adaptability to high-dimensional and extremely complex scenarios needs to be further optimized. The theoretical value of this study lies in enriching the application of intelligent optimization algorithms in the field of industrial control and proposing a new multi-objective optimization control framework; The practical application value lies in providing practical intelligent optimization solutions for industries such as chemical, steel, and solid waste treatment, helping enterprises achieve energy conservation, consumption reduction, quality improvement, and efficiency enhancement, promoting the transformation of industry towards green and intelligent, and providing theoretical and practical references for in-depth research on intelligent control of complex industrial processes in the future.

AUTHOR CONTRIBUTIONS

Conceptualization – Dengyan Li, Manman Li, Meina Zhang, Mingyu Wang and Pan Zhai; methodology – Dengyan Li, Manman Li, Meina Zhang, and Pan Zhai; investigation – Dengyan Li, Manman Li, Meina Zhang, Mingyu Wang and Pan Zhai; writing-original draft preparation – Dengyan Li, Manman Li, Meina Zhang, Mingyu Wang and Pan Zhai. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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