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An Ecological Efficiency–Based Framework for Environmental Risk Assessment in Manufacturing

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Abstract: With the accelerating global transition toward green manufacturing and ecological sustainability, establishing an efficient environmental risk assessment framework has become a critical requirement for sustainable industrial transformation. The study develops an environmental risk assessment system for the manufacturing industry based on ecological efficiency. By combining the Analytic Hierarchy Process (AHP)and the Fuzzy Comprehensive Evaluation (FCE) method. Additionally, the Particle Swarm Optimization (PSO) algorithm with the Genetic Algorithm (GA) were integrated into a unified multi-objective optimization framework, enabling the coordinated enhancement of both economic and environmental performance. Experimental results demonstrate that the proposed system achieves the shortest running time under small-scale enterprise conditions, approximately 9 seconds initially and under 20 seconds at 30 enterprises, with stable growth across larger scales. For a scale of 90-enterprises, the runtime remains about 42 seconds. It also exhibited the fewest convergence iterations across industries at around 30 for electronics and new energy sectors, with as few as 28 for new energy manufacturing, and the highest risk classification accuracy, exceeding 0.95. These findings emphasize the novelty of integrating multiple decision-making and optimization techniques into a cohesive eco-efficiency optimization framework, demonstrating significant potential for green decision-making, environmental risk control, and sustainable industrial development.

Keywords: Ecological efficiency, environmental risk assessment, manufacturing industry, multi-objective optimization, AHP, FCA.

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1. Introduction

The accelerating process of global industrialization has made the manufacturing industry both a driver of economic growth and a major source of resource consumption and pollution emissions. According to statistics, the manufacturing industry accounts for over 30% of global energy consumption, and its carbon emissions continue to rise, especially in high energy consuming industries such as steel, chemicals, and electronics, where environmental load issues are particularly prominent (Peng et al., 2024; Venugopal et al., 2024). Driven by the "dual carbon" strategies and green transformation policies, enterprises face an urgent need to take action. They must establish a scientific and efficient environmental management mechanism to realize the harmonious advancement of economic benefits and ecological protection. (Huang et al., 2023).

The ecological environment issues within the manufacturing industry have been extensively and deeply discussed. These discussions primarily focus on the application of resource consumption assessment, pollutant emission monitoring, and multi-criteria decision-making methods in environmental management. Nie et al. (2025) proposed a research and analysis method for the emission characteristics and impacts of volatile organic compounds (VOCs) from typical plastic enterprises. The research results indicated that the VOC emission concentration of hot melt extrusion was higher than that from injection molding, and the main contributing substances to non-carcinogenic risks varied among different processes. Lynch et al. (2023) introduced a research framework that combines methodological review and comparison of alternative models to evaluate the scientific validity of the occupational skin exposure assessment method used by the US

Environmental Protection Agency under the Toxic Substances Control Act. The research results indicated that the skin absorption doses of chlorinated organic compounds estimated by the existing model were 2 to 20 times higher than those calculated by the method proposed in their study. Tian et al. (2023) used a super-efficiency slack-based measure model to measure transformation efficiency to promote the green transformation of the manufacturing industry and achieve carbon peak and carbon neutrality under the dual-carbon target. The results indicated that the efficiency of green transformation in the manufacturing industry showed a fluctuating upward trend, with an imbalance between watersheds.

Particle Swarm Optimization (PSO) is a swarm intelligence optimization method that simulates the foraging behavior of a flock of birds and is commonly used for solving multi-objective functions and modeling complex systems (Sun et al., 2024). Genetic Algorithm (GA) draws inspiration from biological evolution mechanisms and possesses strong global optimization capabilities and robustness (Feng et al., 2025; Lin et al., 2025). In environmental risk assessment for the manufacturing industry, enterprises often face comprehensive optimization problems with multiple objectives and constraints, such as pollution control, energy efficiency improvement, and resource allocation. PSO and GA process remarkable global search capabilities and adaptability, making them highly effective in various tasks. They can proficiently handle tasks such as weight optimization, indicator selection, and risk level ranking in environmental performance evaluation, thereby offering robust technical support for green manufacturing and environmental decision-making. (Ren and Ma, 2024; Zhang et al., 2024). Previous studies have widely applied PSO and GA to improve resource allocation efficiency and optimize environmental performance. Fang et al. (2024) proposed a fuzzy C-means algorithm based on adaptive switching random perturbation PSO to improve the precision of industrial data anomaly detection. The results indicated that this algorithm outperformed five existing PSO algorithms in optimizing the initial clustering center and demonstrated significantly better performance in actual industrial data anomaly detection. Zhang et al. (2024) proposed a tree-like support structure generation algorithm that combines hierarchical clustering and an improved GA to solve the problem of collapse in high-angle suspended areas in additive manufacturing. The research results showed that this algorithm could save 20% -30% of materials and significantly improve computational efficiency compared to conventional approaches. Wang et al. (2024) proposed an energy-saving optimization approach based on an improved GA to reduce the risk of dust monitoring blind spots in thermal power plants, optimize node coverage, and extend the lifespan of wireless sensor networks. The research results showed that this method significantly improved the convergence speed of the algorithm, reduced the number of iterations to 20, optimized the fitness value by 52.18%, optimized the number of nodes by 42, and achieved a coverage rate of 97.28%. The energy-saving effect was significant.

In summary, although previous studies have investigated environmental risks in manufacturing, most environmental performance evaluation methods focus on single pollutant indicators and lack a systematic balance between resource input and environmental impact, making it difficult to fully reflect the actual sustainable development level enterprises. Ecological efficiency, as a comprehensive indicator to measure the relationship between economic output and environmental costs, is an important basis for environmental performance management (Wang et al., 2024). Therefore, this study constructs an environmental risk assessment system for the manufacturing industry based on eco- efficiency and introduces a joint optimization strategy using PSO and GA to iteratively optimize the dual objectives of environmental and economic performance. This approach aims to achieve accurate identification of environmental risks and intelligent decision-making for low-carbon pathways in the manufacturing industry. The novelty of this study lies in the introduction of eco-efficiency indicators to enhance the environmental performance evaluation. It integrates the Analytic Hierarchy Process (AHP) and the Fuzzy Comprehensive Assessment (FCA) for weight allocation and evaluation. A closed-loop process, spanning from data collection to optimization feedback, is established to provide a systematic tool for the green transformation of the industry. The anticipated outcomes are expected to demonstrate exemplary value in industrial green decision-making support and environmental risk classification response.

To guide the investigation more precisely, the study addresses the following research questions: (1) How can ecological efficiency be quantitatively evaluated to reflect the environmental performance of manufacturing enterprises more comprehensively? (2) How can multi-objective optimization algorithms be designed to achieve a balance between economic efficiency and environmental sustainability? (3) To what extent can the integration of decision-making models and optimization algorithms reduce environmental risk response time and improve scalability across different enterprise scales? Addressing these questions lays a solid theoretical and methodological groundwork for constructing an integrated eco-efficiency-based environmental risk assessment framework and validating its practical applicability within manufacturing systems.

2. Methodology

2.1. Construction of Environmental Performance Evaluation System based on Ecological Efficiency

The environmental performance evaluation system is not only a key tool for enterprise environmental management but also a crucial support for enhancing sustainable development capabilities. In recent years, environmental performance evaluation methods based on eco-efficiency have gained increasing attention from both academia and industry. Eco-efficiency is an indicator that balances economic growth and environmental protection, aiming to provide economic benefits while minimizing environmental impact (Li et al., 2024). Therefore, this research constructs an environmental performance evaluation system based on eco-efficiency to analyze the automation equipment manufacturing industry using various data analysis methods. The evaluation of environmental performance relies on high-quality data, therefore, the primary research step is data collection. Using IoT sensors and monitoring systems, a substantial volume of environmental data was gathered from typical enterprises in the automation equipment manufacturing industry. The specific data collection and monitoring system is shown in Fig. 1.

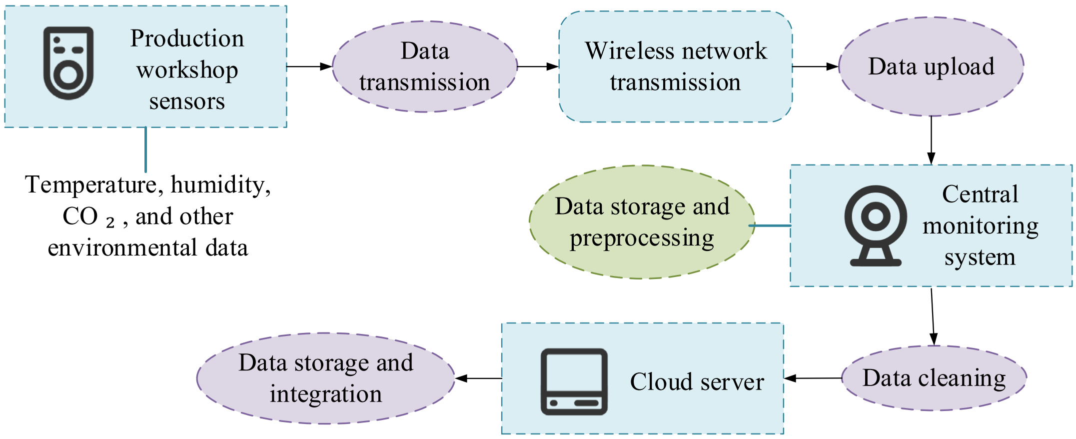

Fig. 1. Flow chart of data collection and monitoring system (Image source: https://iconpark.oceanengine.com/official; https://iconpark.oceanengine.com/official; https://iconpark.oceanengine.com/official)

Fig. 1 covers the complete process, from the production workshop to data storage and processing. First, various sensors in the workshop monitor environmental data in real-time. These data are transmitted to the central monitoring system via wireless networks to ensure real-time data upload and updates. The monitoring system stores the collected data in a database and performs preliminary analysis using preset algorithms to filter out noise and anomalies. Finally, after data cleaning and integration, the results are stored in the cloud or local servers for subsequent analysis and decision support. The construction of an eco-efficiency index system is the core component of environmental risk assessment (Sun et al., 2024).

To comprehensively evaluate the environmental performance of manufacturing enterprises, multiple environmental indicators including resource consumption, energy efficiency, and carbon dioxide emissions were constructed based on relevant theories of eco-efficiency theories. These indicators are assigned different weights within the system to reflect their varying impact on a company's environmental performance. The specific calculation of eco-efficiency $EcoEfficiency$ is shown in Eq. (1).

$$EcoEfficiency = \frac{E_{output}}{E_{input}+E_{impact}} \tag{1}$$

In Eq. (1), E_{output} represents the economic output of production. E_{input} indicates the investment of resources and energy. E_{impact} indicates environmental impact. By quantifying the costs of resources and pollutant emissions, the environmental performance of enterprises can be reflected. On this basis, the study uses AHP and FCA for weight allocation and evaluation to guarantee that the indicator system can faithfully represent the environmental benefits of different dimensions. AHP can decompose complex problems into multiple levels of sub problems and construct a hierarchical structure model. FCA is suitable for handling evaluation problems with ambiguity and uncertainty (Abba et al., 2022). The constructed ecological efficiency evaluation index system is shown in Fig. 2.

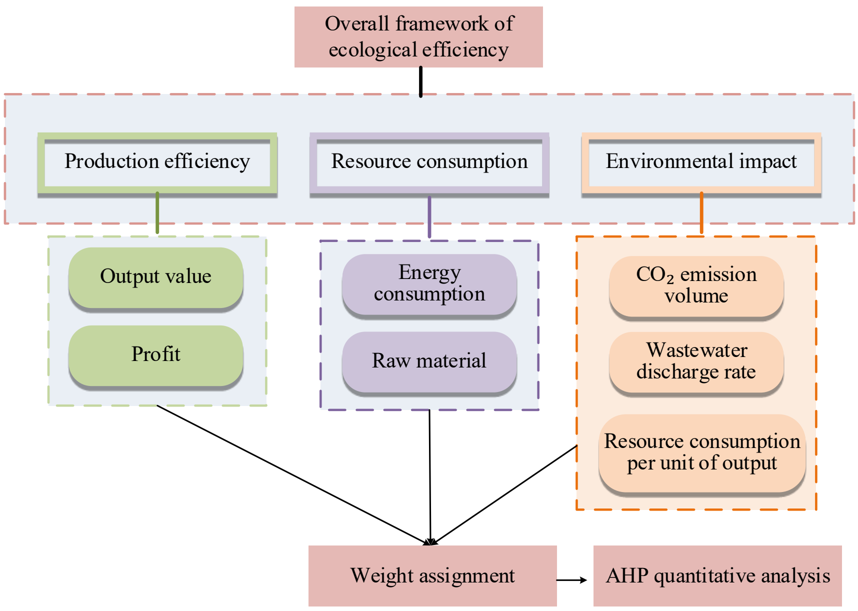

Fig. 2. Structure of AHP-FCA eco-efficiency evaluation index system

Fig. 2 shows the hierarchical structure of the eco-efficiency evaluation index system. The top layer is the overall goal, eco-efficiency, which is broken down into three dimensions: production efficiency, resource consumption, and environmental impact. Specific sub-indicators are listed under each dimension, such as energy consumption, carbon dioxide emissions, wastewater discharge rate, resource consumption per unit of output value. These sub-indicators are assigned weights and quantitatively analyzed in the next step of AHP. To address the fuzziness and uncertainty inherent in environmental data, the Fuzzy Comprehensive Assessment (FCA) is adopted to evaluate various indicators comprehensively, thereby improving the precision and reliability of the results. After completing the construction of the eco-efficiency index, the next step is environmental risk analysis. The automation equipment manufacturing industry contains multiple potential environmental risk points. To assess these risks comprehensively, the study employs an environmental risk matrix method combined with data analysis tools. The specific calculation of environmental risk assessment is shown in Eq. (2).

$$Risk_i = P_i \times C_i \tag{2}$$

In Eq. (2), $P_i$represents the probability of the occurrence of the $i$the risk event. i indicates the consequence value at the time of the event. Environmental risk assessment calculates potential impacts of various environmental risks, visualizes the levels and priorities of different environmental risks, and provides a basis for subsequent risk management. The specific environmental risk matrix is shown in Fig. 3.

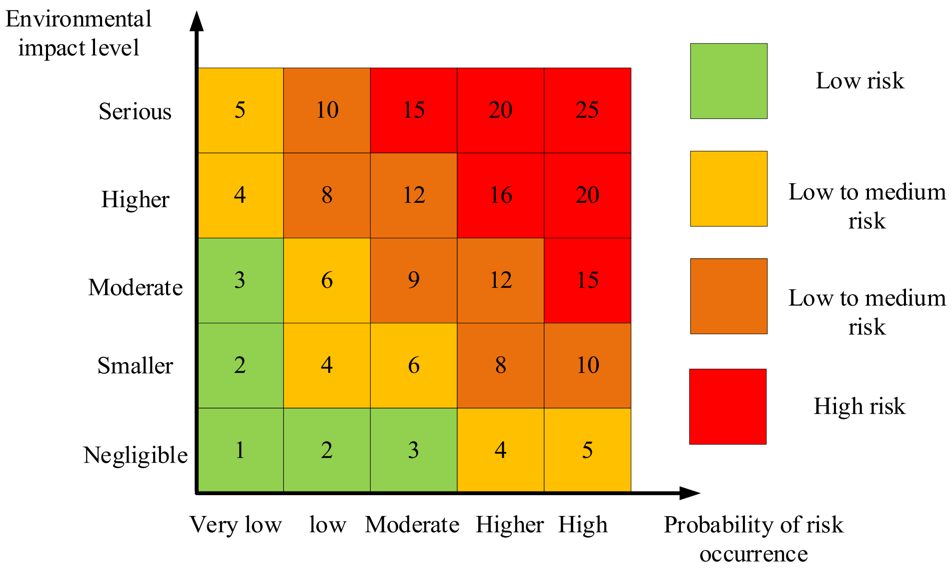

Fig. 3. Schematic diagram of environmental risk matrix

As illustrated in Fig. 3, the horizontal axis embodies the likelihood of risk manifestation, while the vertical axis represents the degree of environmental impact after the risk occurs. According to different risk events such as exhaust emissions, noise pollution, wastewater discharge. The graph divides multiple risk level areas, such as low, medium , and high-risk areas. Each event is marked in the corresponding area for analysis and decision-making. Through this matrix approach, managers can intuitively see which risk events have a significant impact on the environment and which events require priority response measures. This method helps to provide a clear decision-making basis and improve the efficiency of risk control in complex environmental management.

2.2. Environmental Risk Assessment and Optimization Decision-Making based on PSO-GA

This research builds an environmental performance evaluation system grounded in eco-efficiency. It also puts forward a comprehensive approach to evaluate the environmental impact of the automation equipment manufacturing industry, encompassing data collection, the establishment of an eco-efficiency indicator system, and environmental risk analysis. Eco-efficiency offers enterprises a quantitative framework for evaluating environmental performance. However, solely relying on environmental performance evaluation is insufficient at tackling the intricate environmental management challenges that arise. This is particularly true in the face of constantly evolving production environments and increasingly stringent policy requirements. In the actual production process, the environmental optimization problems faced by enterprises often involve multiple objectives and constraints, which often need to be thoroughly considered through multi-objective optimization methods (Liu et al., 2023; Wang et al., 2024). Therefore, to achieve the optimal balance between economic and environmental benefits, the study introduces two classic optimization methods, PSO and GA. PSO searches for the optimal solution by simulating the foraging behavior of bird flocks, while GA searches for the optimal solution by simulating the processes of natural selection, crossover, and mutation. The optimization process is shown in Fig. 4.

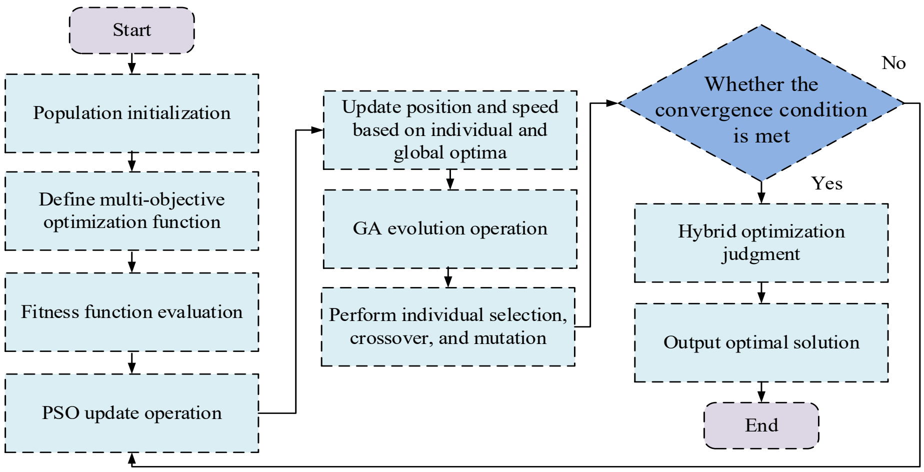

Fig. 4. PSO-GA optimization flowchart

As shown in Fig. 4, the optimization objective is first defined, which is to maximize energy utilization efficiency and minimize pollution emissions during the optimization process. Next, the steps of PSO and GA optimization algorithms are divided into initialization, fitness evaluation, crossover, and mutation. PSO adjusts the position of each particle through swarm intelligence to achieve the optimal solution. GA optimizes solutions by simulating natural selection processes through selection, crossover, and mutation operations. During the optimization process, each step is alternated until a convergence state is reached, that is, the optimal environmental performance plan is found. The PSO optimization objective function is shown in Eq. (3).

$$f(a) = \sum_{k=1}^{n}(c_k \cdot X_k) \tag{3}$$

In Eq. (3), $a$represents the decision variable vector. X_k indicates the value of the $k$the target. c_k indicates the weight of the $k$the objective. In this formula, the objective function will be optimized based on the actual needs of each objective, ensuring a comprehensive balance of factors such as resource consumption, energy utilization, and pollution emissions (He et al., 2024). The fitness function of GA is shown in Eq. (4).

$$F_{GA} = \sum_{k=1}^{n} w_k \cdot \left(\frac{1}{1+\mathrm{cost}_i}\right) \tag{4}$$

In Eq. (4), F_{GA} represents the fitness function in the GA. w_k indicates the weight of the $k$the objective. $cost_i$ indicates the cost of the target. Calculating the fitness value of each objective helps the optimization process find the comprehensive optimal solution. In the optimization process, the study combines PSO and GA multi-objective optimization algorithms to simulate the production process and explore how to improve energy efficiency while reducing pollution emissions. The weighted sum of multi-objective optimization is calculated as shown in Eq. (5).

$$f_{total} = \sum_{j=1}^{m} w_j \cdot f_j(x) \tag{5}$$

In Eq. (5), f_{total} represents the weighted sum of multiple objective functions. w_j indicates the weight of the $j$the objective function. $f_j(x)$ represents the value of the j the objective function. This formula can help integrate the optimization effects of different objectives by adjusting weights, to achieve the overall optimal solution. During optimization, cross-validation and test-set evaluation are applied to simulate production scenarios and constraints. These tests confirm the model's adaptability and validity in practical environments. The specific evaluation process is shown in Fig. 5.

As shown in Fig. 5, the model run yields several optimized solution sets, including key indicators such as pollutant emission reduction rate and the improvement value for resource utilization efficiency. Subsequently, these results will enter the result evaluation module, where the relative improvement rate will be calculated by comparing them with the indicators in the initial unoptimized state. Next, a multidimensional performance analysis is conducted using methods such as cross validation, sensitivity analysis, and robustness testing to evaluate the adaptability and stability of the optimization scheme under different scenarios and parameter disturbances. On this basis, an evaluation feedback mechanism is introduced to screen, eliminate, or retrain optimization solutions that do not meet actual production constraints or perform poorly. Ultimately, the system will output a set of feasible and high-performance optimization suggestions to provide decision support for green production in enterprises. In summary, based on eco-efficiency and PSO-GA, a comprehensive research framework integrating "eco-efficiency environmental risk intelligent optimization" is constructed, as shown in Fig. 6

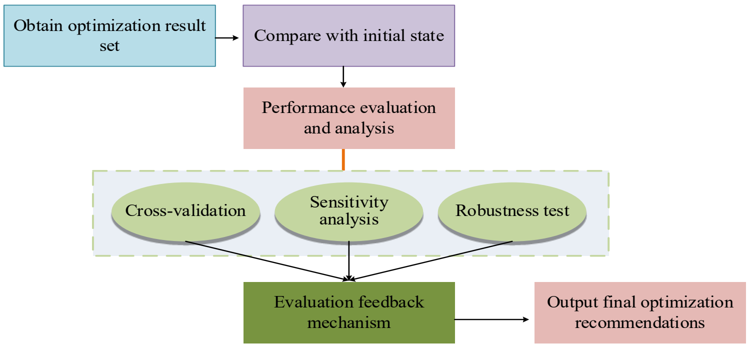

Fig. 5. Flow chart for evaluating PSO-GA optimization model results

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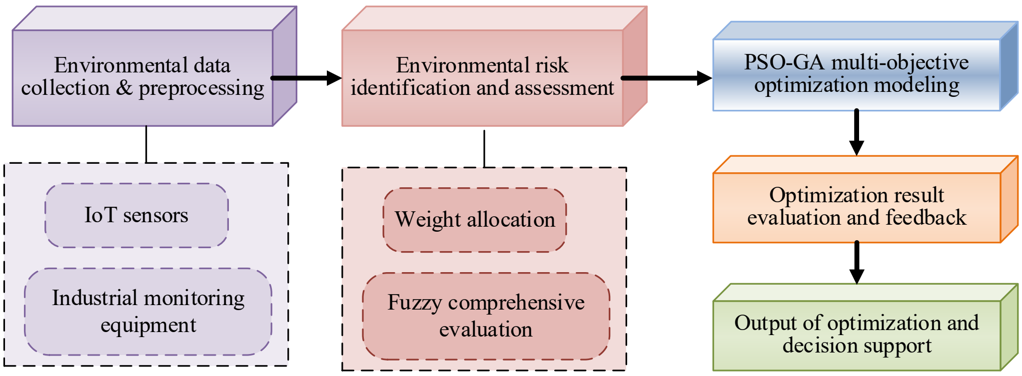


Fig. 6. Overall structure of environmental risk assessment based on ecological efficiency and PSO-GA

Fig. 6 covers the complete process from environmental data collection to ecological efficiency evaluation, environmental risk assessment, and multi-objective optimization. The first stage is data collection and cleaning, including real-time collection of energy consumption and emission data through IoT sensors. The second stage is the construction of an eco-efficiency evaluation system, relying on AHP and FCA to evaluate the weight of resource and pollution indicators. The third stage is environmental risk identification and matrix analysis, identifying high priority risk events. Finally, by introducing a joint optimization algorithm of PSO and GA, environmental performance can be optimized while ensuring production efficiency. The modular design of the proposed framework enables future integration with real-time enterprise monitoring systems. By connecting IoT-based data acquisition and cloud-based computing, the system can be adapted for continuous data streams and dynamic environmental assessment.

3. Results

3.1. Environmental Performance Evaluation System Performance Verification

The research conducted modeling and simulation within a local workstation environment. The experimental platform operated on Windows 10 Professional, utilizing an Intel Core i7-12700K processor, 32 GB of memory, and an NVIDIA GeForce RTX 3060 graphics card. In terms of the software environment, the eco-efficiency evaluation model was primarily implemented on the MATLAB R2022b platform. Specific details are shown in Table 1. The experimental data were sourced from the publicly available China Industrial Energy Consumption and Emissions Dataset (CIECED), which was compiled and released by the National Bureau of Statistics in collaboration with research institutions. This dataset encompassed core indicators such as energy consumption, output value, and pollutant emissions from manufacturing enterprises across different industries, featuring a complete data cycle and extensive coverage.

To confirm the adaptability and dependability of the constructed AHP-FCA method in various environmental risk dimensions, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Entropy Weight Method (EWM) was selected to compare their score volatility analysis and ranking consistency coefficients on different risk types. The experiment selected four typical environmental risk types, namely energy consumption, carbon emissions, wastewater emissions, and exhaust emissions, as common and representative risk dimensions in the manufacturing industry for evaluation and verification. The obtained results are shown in Fig. 7.

Fig. 7 (a), (b), and (c) compare the Coefficient of Variation (CV), Spearman rank correlation coefficient (Spearman), and Root Mean Square Error (RMSE) of the scoring results for the three evaluation methods across different risk types. From Fig. 7(a), AHP-FCA had the smallest rating volatility across all four types of risks, with CV values ranging from approximately 0.04 to 0.06, demonstrating high stability. In contrast, the CV for TOPSIS fluctuated around 0.09, while the CV of EWM exceeded 0.13 in all risk types, indicating high data sensitivity and insufficient stability. Among the energy consumption risks, the EWM method exhibited the largest fluctuation, with a CV of about 0.17. This is likely due to annual fluctuations and varying collection intervals of energy data, which could easily amplify extreme effects without subjective correction. From Fig. 7(b), AHP-FCA performed significantly better than other methods in ranking consistency, with Spearman coefficients of around 0.85 for all risk dimensions, especially reaching the highest value of 0.89 in wastewater discharge. The Spearman coefficient of EWM was below 0.6 for all risk types, and as low as about 0.5 in exhaust emissions. As shown in Fig. 7(c), the AHP-FCA method had lower RMSE than the other two methods in all risk types, demonstrating better prediction accuracy. Under the Risk1 type, the RMSE of AHP-FCA method was about 0.3, while the RMSE of TOPSIS and EWM methods were about 0.65 and 0.85, respectively.

Table 1. Scalability and computational efficiency comparison among optimization models

Category	Configuration Details	Category	Configuration Details
Operating system	Windows 10 Professional 64-bit	Storage	1 TB SSD (system) + 2 TB HDD (data storage and backup)
CPU	Intel(R) Core (TM) i7-12700K @ 3.60GHz	Programming languages	Python 3.9 and MATLAB R2022b
RAM	32 GB DDR4	Integrated development environment	Jupyter Notebook MATLAB GUI interface
GPU	NVIDIA GeForce RTX 3060, 12 GB	Simulation environment	Local standalone simulation using Python and MATLAB environments

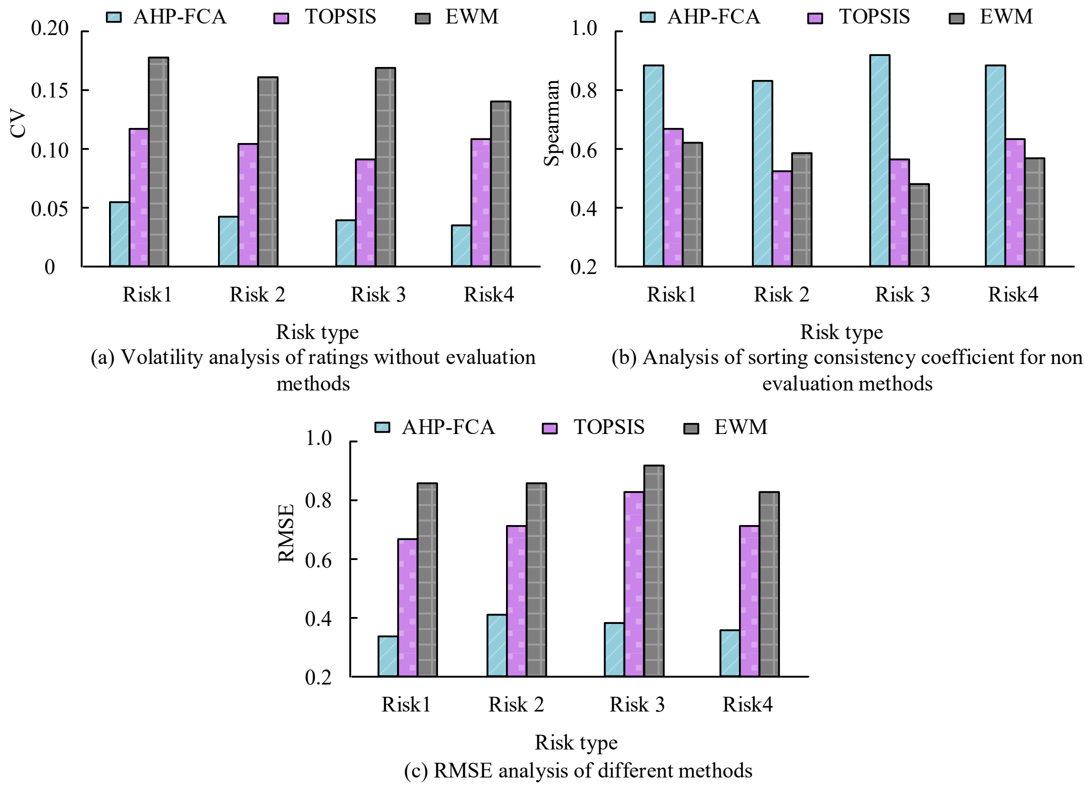


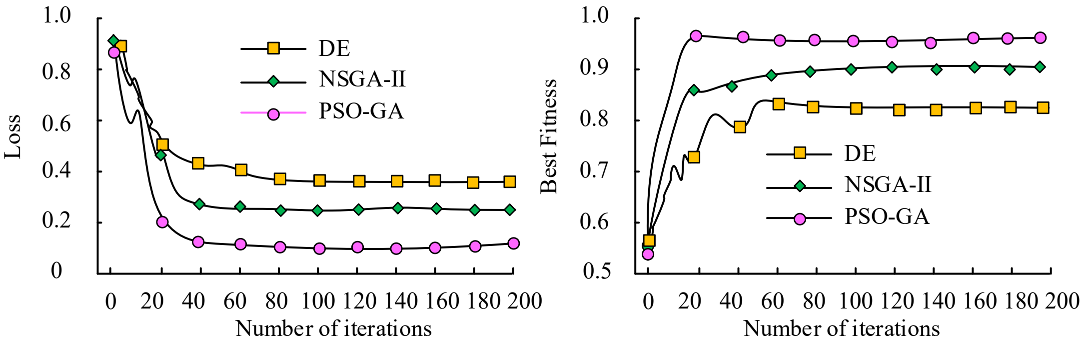
Fig. 7. Environmental risk matrix indicating high-risk and low-efficiency sectors

3.2. Performance Verification of PSO-GA's Environmental Risk Assessment and Optimization Decision-Making Method

To verify the optimization performance of the proposed PSO-GA multi-objective optimization algorithm in environmental risk assessment, multiple rounds of iterative comparative experiments were conducted between the mainstream algorithm Differential Evolution (DE) and Non dominated Sorting Genetic Algorithm II (NSGA-II). The obtained results are shown in Fig. 8.

As shown in Fig. 8(a), PSO-GA exhibited a rapid downward trend in the early iteration stages, with the loss value rapidly decreasing from the initial 0.9 to below 0.2, and stabilizing at around 0.15 after approximately 40 iterations. In contrast, NSGA-II had a slightly slower descent speed, with a final loss value of about 0.22, while the DE algorithm had the slowest convergence speed, effectively ceasing optimization after the 100th iteration with a final loss still above 0.3.

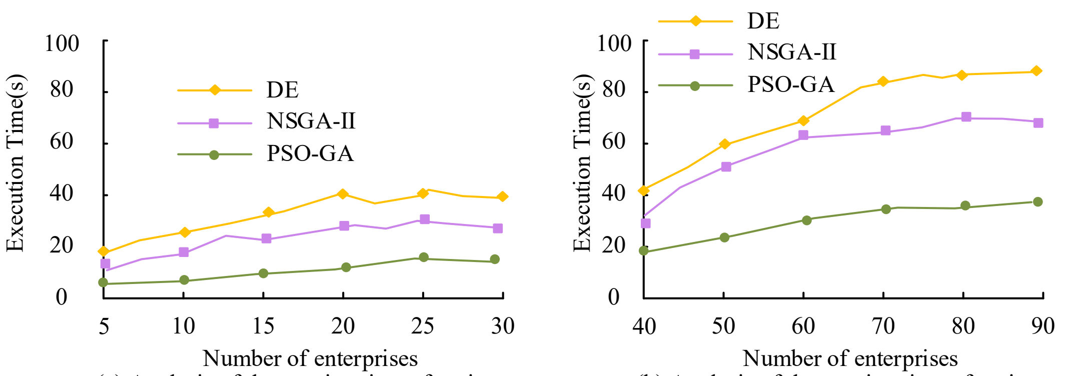
As shown in Fig. 8(b), PSO-GA quickly found the optimal individual within the first 20 iterations, achieving a fitness value close to 0.95, and then maintained high stability thereafter. The optimal individual fitness for NSGA-II ultimately remained at about 0.87, slightly lower than that of PSO-GA. The optimal individual fitness for DE remained between 0.80-0.83, exhibiting significant fluctuations and poor convergence quality. To evaluate the computational efficiency of multi-objective optimization algorithms at different enterprise scales, we compared the runtime performance of three algorithms using both small and large-scale enterprise samples. The obtained results are presented in Fig. 9.



(a) Analysis of loss values for different algorithms

(b) Analysis of optimal individual fitness values for different algorithms

Fig. 8. Comparison and analysis of loss values and individual fitness during the iteration process of various optimization algorithms



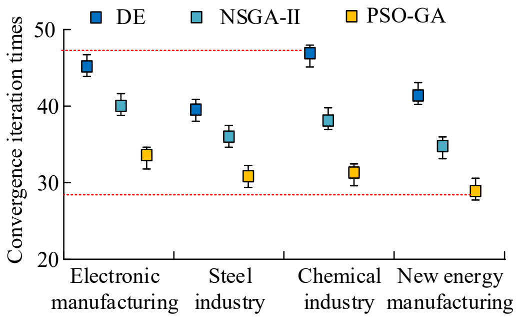
(a) Analysis of the running time of various algorithms under the condition of the number of small-scale enterprises

(b) Analysis of the running time of various algorithms under the condition of a large number of enterprises

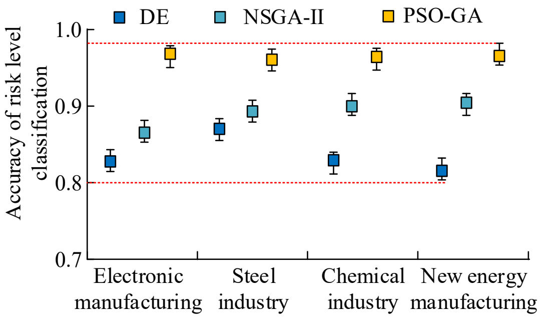
Fig. 9. Scalability performance reflected by runtime comparison

As presented in Fig. 9(a), under the condition of small-scale enterprises, the runtime of all three algorithms increased with the number of enterprises, but there were significant differences in the magnitude of the increase. PSO-GA always maintained the lowest runtime, initially only about 9 seconds, and was still below 20 seconds in 30 enterprises, with steady growth. The initial time of NSGA-II was about 15 seconds, and it eventually reached about 30 seconds, slightly higher than PSO-GA. The DE algorithm had the heaviest computational burden, with time increasing from about 18 to over 40 seconds. The reason for this was that DE had slow iterative convergence and high computational redundancy when the search space increased, leading to a decrease in efficiency. As shown in Fig. 9(b), under the condition of a large number of enterprises, the computational pressure of the three algorithms significantly increased. The runtime of PSO-GA in 90 enterprises was only about 42 seconds, which was still significantly better than other methods. NSGA-II remained stable at around 70 seconds at this scale, while DE showed the most significant growth, rising from around 50 seconds to nearly 95 seconds. To further evaluate the generalization and risk identification abilities of optimization algorithms in different industry scenarios, comparative experiments were conducted on the convergence efficiency and classification accuracy of three algorithms in multiple manufacturing industries. The obtained results are shown in Fig. 10.

Fig. 10(a) and (b) respectively show the comparison results of the iteration count required for convergence and the accuracy of environmental risk level classification for three optimization algorithms in four typical industries: electronic manufacturing, steel, chemical, and new energy manufacturing. From Fig. 10(a), PSO-GA exhibited the least number of convergence iterations in all industries. In the electronic manufacturing and new energy industries, optimization could be completed in only about 30 iterations, while the minimum number of iterations required for new energy manufacturing was about 28. In contrast, NSGA-II required approximately 35-40 iterations. DE generally exceeded 40 times, and some industries even reached 48 times, with the slowest convergence speed. Especially in the chemical industry, the number of DE iterations was close to 50. PSO-GA, due to its integration of global particle search and genetic evolution strategy, had faster global convergence ability and was suitable for industry environment evaluation problems under multidimensional constraints. According to Fig. 10(b), PSO-GA achieved the highest risk level classification accuracy in all industries, exceeding 0.95. Among them, it was close to 0.98 in the electronic manufacturing and new energy industries, significantly better than NSGA-II's about 0.90 and DE's about 0.88. To evaluate the contribution of each key module to the overall performance of the model, ablation experiments were designed to compare the performance differences between the PSO-GA complete model with ecological efficiency constraints and the model without different modules. The outcomes obtained are presented in Table 2.



(a) Analysis of convergence times of various algorithms



(b) Analysis of accuracy of risk level classification of various algorithms

Fig. 10. Performance comparison of optimization algorithms under different types of manufacturing industries

Table 2. Performance contribution of optimization components in ablation analysis

Model configuration	PSO-GA + ecological efficiency	No GA	No PSO	No ecological efficiency
Rating standard deviation	0.021	0.034	0.028	0.041
Sorting consistency coefficient	0.923	0.881	0.894	0.856
Optimal fitness value	0.821	0.768	0.785	0.752
Unit ecological efficiency improvement rate (%)	18.2	11.6	13.3	7.9
Execution time (s)	4.63	3.98	4.02	3.87
Convergence speed	28	35	32	40
Robustness metric	0.95	0.88	0.9	0.85

According to Table 2, the PSO-GA model that fully integrated ecological efficiency constraints performed the best in all evaluation indicators, with a rating standard deviation of only 0.021, a ranking consistency coefficient of 0.923, an optimal individual fitness value of 0.821, a unit eco-efficiency improvement rate of up to 18.2%, and a runtime of 4.63 seconds. Among them, if the GA module was removed, the fitness value significantly decreased to 0.768, and the ranking consistency coefficient also decreased to 0.881, indicating that GA played a key role in improving the diversity of solutions and global search ability. If the eco-efficiency index was removed, the unit eco-efficiency improvement rate decreased to 7.9%. In addition, although the runtime was slightly reduced, the overall performance loss was significant. Based on the recorded hardware configuration, the average system power draw during computation was approximately 160–180 W. Given the 4.63-second runtime of the optimization process, the estimated energy consumption per run was about 0.21–0.23 Wh. This indicated that the proposed PSO–GA framework achieved a favorable balance between computational efficiency and energy use, providing a practical reference for low-carbon algorithmic design in environmental optimization tasks.

4. Discussion

The results demonstrated that integrating the Analytic Hierarchy Process, the Fuzzy Comprehensive Evaluation method, and the hybrid Particle Swarm Optimization–Genetic Algorithm significantly enhanced both eco-efficiency and environmental risk prediction accuracy in manufacturing enterprises. Compared with previous models that relied solely on statistical or single-objective optimization methods, the proposed framework achieved faster convergence (approximately 30 iterations) and higher classification accuracy (above 0.95), while maintaining computational scalability across different enterprise sizes.

In comparison with related studies, which improved specific aspects such as clustering accuracy or coverage optimization, this research provided a more comprehensive solution by coupling multi-objective optimization with eco-efficiency evaluation. This integration enabled a balanced improvement of both economic and environmental dimensions.

Despite these advantages, the approach also presented certain limitations. The current framework relies on simulated or standardized datasets and has not yet been validated under highly dynamic, real-time industrial environments. Moreover, parameter selection for the optimization algorithms could introduce bias if not tuned for specific industrial scales. Future research should focus on integrating real-time data from IoT-based monitoring systems and exploring adaptive weight adjustment mechanisms to further improve robustness and adaptability.

The validation of the proposed framework relied solely on the China Industrial Energy Consumption and Emissions Dataset (CIECED). Although this dataset provided comprehensive coverage of domestic industries, it lacked international and heterogeneous validation. Future studies will extend verification using multi-country and cross-industry datasets to improve the generalizability and robustness of the proposed framework. Although the framework was designed for potential real-time deployment, scalability to actual enterprise monitoring environments has not yet been validated. Future work will explore integration with IoT-based sensing and edge-computing platforms to achieve real-time adaptability. In addition, future work will further measure real-time power consumption to develop energy-saving optimization indicators and explore trade-offs between computing speed, accuracy, and algorithm energy consumption

5. Conclusion

A comprehensive framework integrating eco-efficiency evaluation, environmental risk classification, and PSO-GA intelligent optimization was proposed to tackle the obstacles encountered by the manufacturing industry in environmental risk management, such as data complexity, difficulty in multi-objective optimization, and lagging risk response. First, a multi-level eco-efficiency evaluation model was established by combining the AHP-FCA method, and an environmental risk matrix was constructed to clarify the priority of pollution events. Then, in the section of environmental risk assessment and decision optimization, the PSO-GA was used to synergistically optimize pollution control, resource utilization, and energy efficiency improvement. The experimental results showed that the method performs well in multiple key indicators, with the loss value of PSO-GA reduced to 0.15, the optimal fitness reaching 0.95, the eco-efficiency improvement rate reaching 18.2%, the accuracy of risk level classification approaching 0.98, and the runtime reduced by more than 50% compared to DE algorithm. The ablation experiment showed that the standard deviation of the PSO-GA model score was only 0.021, the ranking consistency coefficient reached 0.923, the optimal individual fitness value was 0.821, the unit ecological efficiency improvement rate was as high as 18.2%, and the runtime was 4.63 seconds. The research showed that the evaluation method that integrated eco-efficiency indicators with the PSO-GA optimization model was superior to traditional algorithms in terms of environmental risk identification accuracy, rating stability, and optimization effect, and had higher practicality and promotion value. However, there is still room for improvement in the current framework in dealing with extreme value fluctuations and industry heterogeneity issues. In the future, methods such as federated learning and online adaptive mechanisms can be further combined to enhance the model's generalization and real-time response capabilities across enterprises and industries, providing stronger technical support for intelligent management of environmental risks in the manufacturing industry.

Author Contributions

Heng Wang contributes to methodology, data collection, draft preparation, manuscript editing. Mingyang Han contributes to software, validation, analysis, manuscript editing. Jingcheng Xiong contributes to validation, analysis, draft preparation, supervision. Weiru Qi contributes to conceptualization, validation, analysis, investigation, and data collection.

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References

Abba, H. A., Muhammad, L. J., and Abubakar, M. (2022). Novel thermal-aware green scheduling in grid environment. *Artificial Intelligence and Applications,* 1(4), 244-251. doi: 10.47852/bonviewAIA2202332

Fang, J., Wang, Z., Liu, W., Cheng, Y., and Lin, Q. (2024). A new particle swarm optimization algorithm for outlier detection: industrial data clustering in wire arc additive manufacturing. *IEEE Transactions on Automation Science and Engineering,* 21(2), 1244-1257. doi: 10.1109/TASE.2022.3230080

Feng, X., Qiu, J., and Wei, C. (2025). Assessing big data capabilities in manufacturing supply chains: a Pythagorean fuzzy MAGDM framework. *International Journal of Fuzzy Systems,* 27(4), 1279-1302. doi: 10.1007/s40815-024-01833-w

He, S., Yu, C., Jia, X., Zhang, L., and Liu, C. (2024). Application and prospects of polygenic risk score (PRS) in genetic disease research: a review of data analysis methods. *Progress in Biochemistry and Biophysics,* 51(8), 1797-1808. doi: 10.16476/j.Pibb.2023.0389

Huang, J., Tao, Y., Huang, T., Zhao, W., and Wang, M. (2023). Occurrence, sources and health risk assessment of per- and polyfluoroalkyl substances in surface water of Hongze Lake. *Research of Environmental Sciences,* 36(4), 694-703. doi: 10.13198/j.issn.1001-6929.2022.12.09

Li, F., Kong, L., Wang, B., Duan, Y., and Liu, J. (2024). Occupational health risk assessment of n-hexane based on four risk assessment models. *Journal of Environmental and Occupational Medicine,* 41(6), 655-660. doi: 10.11836/JEOM23398

Lin, H., Kong, X., Lu, J., Zhang, Y., and Zhang, Z. (2025). Optimization and verification on warping deformation of automotive front-end frame based on GA-BP algorithm. *Engineering Plastics Application,* 53(1), 90-97. doi: 10.3969/j.issn.1001-3539.2025.01.013

Liu, D., Lü, Q., Hu, S., Wang, L., and Zhao, Q. (2023). A combined model for predicting dam deformation based on genetic algorithm and long short-term memory neural network. *Journal of Safety and Environment,* 23(7), 2246-2253. doi: 10.13637/j.issn.1009-6094.2022.0516

Lynch, H. N., Gloekler, L. E., Allen, L. H., White, C. M., and Maier, A. (2023). Analysis of dermal exposure assessment in the US Environmental Protection Agency Toxic Substances Control Act risk evaluations of chemical manufacturing. *Toxicology and Industrial Health,* 39(1), 49-65. doi: 10.1177/07482337221140946

Nie, P., Liu, J., Mo, Z., Zhou, L., and Chen, Y. (2025). Emission characteristics and environmental health risk assessment of VOCs from the typical plastic products industry. *Journal of Environmental Engineering Technology,* 15(2), 358-367. doi: 10.12153/j.issn.1674-991X.20240841

Peng, C., Deng, J., and Wu, J. (2024). Numerical evaluation of sodium droplet swarm combustion and its modeling optimization. *Nuclear Science and Engineering,* 198(11), 2190-2208. doi: 10.1080/00295639.2023.2292930

Ren, S. and Ma, C. (2024). How does firm digitalization affect innovation risk — empirical research from Chinese manufacturing firms. *Modern Economic Science,* 46(2), 90-103. doi: 10.20069/j.cnki.DJKX.202402007

Sun, H., Wang, X., Yang, X., Li, Y., and Chen, W. (2024). Assessment of key metals supply risk in China's strategic emerging industries. *Resources Science,* 46(11), 2124-2136. doi: 10.18402/resci.2024.11.03

Sun, T., Song, J., Dong, S., Liu, Y., and Wang, H. (2024). Advances in environmental risk prevention, control, and detection technologies for synthetic microorganisms. *Research of Environmental Sciences,* 37(10), 2247-2259. doi: 10.13198/j.issn.1001-6929.2024.07.16

Tian, Z., Fang, Q., Ju, Y., Yang, L., and Xu, H. (2023). Evaluation of efficiency of manufacturing industry transformation and influencing factors in China's three major river basins. *Resources and Environment in the Yangtze Basin,* 32(10), 2072-2084. doi: 10.11870/cjlyzyyhj202310007

Venugopal, P. D., Addo Ntim, S., Goel, R., Zhang, Y., and Lyu, Z. (2024). Environmental persistence, bioaccumulation, and hazards of chemicals in e-cigarette e-liquids: short-listing chemicals for risk assessments. *Tobacco Control,* 33(6), 781-789. doi: 10.1136/tc-2023-058163

Wang, B., Shang, Y., Yao, L., Xu, C., and Zhao, J. (2024). Research on power plant dust monitoring node coverage control based on improved genetic algorithm. *China Safety Science Journal,* 34(9), 121-130. doi: 10.16265/j.cnki.issn1003-3033.12024.09.0960

Wang, X., Yan, X., Li, X., Zhang, J., and Zhou, H. (2024). Assessment of application efficacy for agro-forestry absorbent polymers and their environmental risks. *Scientia Agricultura Sinica,* 57(6), 1117-1136. doi: 10.3864/j.issn.0578-1752.2024.06.008

Wang, Y., Lei, M., Wu, Z., Fang, X., and Liu, N. (2024). Characteristics and ecological risk assessment of microplastics in electroplating park wastewater. *Research of Environmental Sciences,* 37(7), 1604-1611. doi: 10.13198/j.issn.1001-6929.2024.05.10

Zhang, L., Chen, J., Li, J., Wang, R., and Hu, Y. (2024). Establishment and application of microbiological supervision for pharmaceutical water in manufacturers of high-risk drug based on blind sample assessment. *Chinese Journal of Modern Applied Pharmacy,* 41(15), 2071-2077. doi: 10.13748/j.cnki.issn1007-7693.20230623

Zhang, S., Cao, X., Zhang, T., Li, M., and Wang, Y. (2024). Tree support algorithm based on improved genetic algorithm. *Engineering Plastics Application,* 52(11), 92-99. doi: 10.3969/j.issn.1001-3539.2024.11.013

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