Research on Visualization Reform of AI-Driven VFOA-BP Model Empowering Industrial Engineering Prediction

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Abstract

Against the background of the coordinated development of intelligent manufacturing and green low-carbon development, artificial intelligence (AI) has become the core support for data-driven prediction and production control optimization in industrial engineering. The integration of AI with key parameter prediction technology and its application in teaching is of great practical significance for industrial engineering development. Focusing on the advantages of AI in autonomous learning and multi-source data analysis, this study constructs an industrial engineering prediction visualization system based on the AI-driven VFOA-BP swarm intelligence-neural network model.

This study selects 20 periods of monitoring data from an actual industrial production line as the research sample. The input variables include production load (kW, sampled every 1 hour), ambient temperature (℃, sampled every 1 hour), ambient humidity (%, sampled every 1 hour), and equipment operation parameters (mm, sampled every 2 hours), all collected from the on-site intelligent sensing system. Comparative experiments are conducted with traditional BP, FOA-BP and VFOA-BP models. The results show that the VFOA-BP model has an RMSE of 0.1979mm (meeting industrial accuracy standards), with accuracy 15.29% and 3.14% higher than the other two models, providing reliable data support for industrial prediction and new ideas for teaching reform of industrial engineering majors.

1 Introduction

Under the background of intelligent manufacturing, AI technology has become the core support for accurate prediction and production control optimization in industrial engineering, relying on its powerful data processing, autonomous optimization and nonlinear fitting capabilities. The accuracy of key parameter prediction directly determines production safety, product quality and operation efficiency, and promotes the construction of an "AI-technology-teaching" integration system for teaching reform. Evolutionary algorithms, derived from biological "natural selection", include genetic algorithms and evolutionary strategies. As an important branch of intelligent optimization algorithms, swarm intelligence algorithms simulate the cooperative optimization behaviors of natural biological groups. In these algorithms, each individual behaves simply, lacking complex decision-making abilities and only following basic local rules without centralized control. However, through continuous information exchange and cooperation among numerous such simple individuals, the entire group can achieve complex global optimization tasks that are hard for a single individual to accomplish[1-3]. Typical examples include ant foraging and bee gathering. Scholars have proposed various algorithms based on this: Ant Colony Optimization (ACO) simulates pheromone-guided path optimization, Particle Swarm Optimization (PSO) originates from bird cooperative foraging, and the Fruit Fly Optimization Algorithm (FOA) studied in this paper relies on fruit flies' olfactory-visual perception and cooperative competition for optimization. Its three characteristics—"local perception and global coordination", "individual dispersion" and "behavioral simplicity"—adapt to AI's needs for efficient processing of multi-source industrial prediction data. Based on this, this paper constructs the VFOA-BP model to improve prediction accuracy and integrates visualization teaching to cultivate compound technical talents in industrial engineering.The paper is organized as follows. The first part is the introduction, which introduces the research background. The second part elaborates on the relevant theoretical methods including algorithms and models. The third part presents the experimental results of data analysis. The fourth part summarizes the full text.This study positions AI-driven VFOA-BP model in industrial engineering prediction, innovates by integrating multi-factors, optimizing the model, conducting comparative experiments, and combining visualization with teaching.

2. Theoretical Methods

2.1 Fruit Fly Optimization Algorithm (FOA)

FOA, a swarm intelligence algorithm proposed by Professor Pan Wenchao from Taiwan, China, is inspired by fruit flies' foraging behavior. Fruit flies have strong olfactory and visual perception, enabling them to locate food sources over 40 kilometers away. Combining this feature with the fruit fly group's cooperative optimization mode, Professor Pan constructed a global optimization algorithm[4-6]. Its efficient optimization advantage adapts to AI's needs for rapid processing of industrial prediction data, providing core support for the VFOA-BP model. Currently, it has been applied in industrial scheduling, parameter prediction and equipment maintenance. The specific optimization flow is shown in Figure 1.

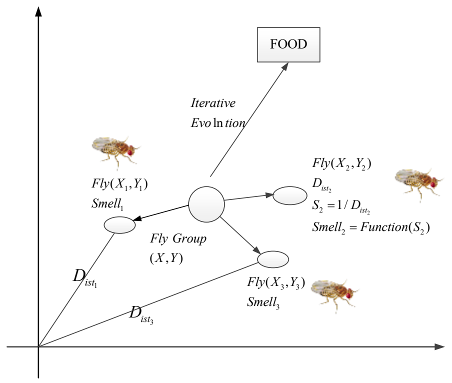

Fig. 1 Optimization Flow Chart of Fruit Fly Optimization Algorithm (FOA)

FOA's optimization logic originates from natural foraging: individuals approach food by smell first, then locate food and companions by vision. Odor concentration is negatively correlated with distance, and group foraging is essentially an iterative search from low to high concentration areas. In the algorithm, positions in the search space correspond to potential solutions for industrial prediction, and the odor concentration determination function evaluates solution quality.

Table 1 Optimization Performance of Intelligent Algorithms

Algorithm	Computational Load	Complexity	Stability	Accuracy
Ant Colony Optimization Algorithm	Medium	Relatively Complex	Relatively Stable	Relatively High
Fruit Fly Optimization Algorithm	Small	Simple	Unstable	Relatively High
Fish Swarm Algorithm	Large	Relatively Complex	Relatively Stable	Relatively High
Immune Optimization Algorithm	Very Large	Very Complex	Very Stable	Very High
Genetic Algorithm	Large	Very Complex	Relatively Stable	Relatively Low
Particle Swarm Optimization Algorithm	Medium	Relatively Simple	Relatively Unstable	Relatively Low

FOA, as a global optimization algorithm, has the characteristics of simple structure, efficient calculation, no objective function constraints, real-time optimal individual preservation and strong adaptability, which can quickly process multi-source heterogeneous industrial prediction data, matching AI's requirements for high efficiency and accuracy. The literature "Research on the Optimization Performance of Fruit Fly Algorithm and Five Swarm Intelligence Algorithms" compared FOA with five swarm intelligence algorithms (e.g., ACO, Fish Swarm Optimization), verifying its better optimization performance and supporting AI-driven industrial prediction. Table 1 shows the optimization performance of each algorithm[7]. Compared with mature swarm intelligence algorithms (ACO, Genetic Algorithm, PSO), FOA has advantages of small calculation, fast operation, simple process and high optimization accuracy, adapting to AI's efficient multi-source data processing needs. However, it has inherent defects: random flight causes unstable optimization, and improper step size easily leads to local minima. This paper improves FOA by introducing speed variables, dynamically adjusting step size to enhance optimization efficiency, accuracy and stability, providing solid support for the VFOA-BP model.

2.2 Application of artificial intelligence

As the core engine for accurate prediction and intelligent control in industrial engineering, AI has been deeply integrated into the whole life cycle of design, production and maintenance. Relying on multi-source data integration, autonomous learning and value transformation capabilities, it realizes coordinated empowerment of production control refinement, cost optimization and efficiency improvement, and provides important guidance for the teaching reform of industrial engineering majors. In the design stage, AI calls massive historical design and production data to generate multiple alternative schemes, completes comprehensive feasibility evaluation from multiple dimensions, and presents scheme differences through visualization technology, effectively reducing design costs and potential risks[8-9]. In the production stage, AI collects real-time multi-dimensional data via intelligent sensing equipment, accurately identifies potential safety hazards and infers production progress deviations, timely outputs scientific adjustment suggestions, and synchronizes all data to the visualization platform to realize dynamic and refined production control. In the maintenance stage, AI predicts equipment failures in advance and optimizes maintenance plans through deep learning algorithms, and intelligently adjusts energy consumption systems to reduce operational costs. Accurate prediction of key industrial parameters is an important basis for AI-driven equipment maintenance and product quality improvement. Currently, the industrial field faces problems such as insufficient in-depth AI application and shortage of compound talents due to industry-education disconnection, forcing universities to reconstruct curriculum systems. To address these issues, this paper constructs the AI-driven VFOA-BP model, which uses speed-variable improved FOA to optimize BP neural network parameters, aiming to minimize RMSE and improve prediction accuracy. It integrates this technology with visualization teaching to build an "AI-technology-teaching" collaborative mode, cultivating compound talents with data processing, model application and innovation capabilities, and promoting the in-depth integration and application of AI in industrial engineering.

2.3 Visualization design

Against the background of global green sustainable development, the traditional industrial prediction mode based on numerical reports is inefficient in information interpretation, failing to meet AI's needs for rapid judgment and precise control in industrial scenarios. Visualization technology is the key to solving this dilemma; it reconstructs the logic of data display, optimizes data presentation forms, accelerates the recognition of key data features and the review of abnormal information, and upgrades industrial data from simple "visual presentation" to the "accurate support" required by AI-driven intelligent control. Relevant studies show that the in-depth integration of visualization and AI has formed an interdisciplinary innovation ecosystem. For example, in the chemical industry, researchers build production parameter monitoring models through multi-source data mining and machine learning, combined with 3D scene superposition technology to capture tiny parameter deviations and efficiently identify prediction features, verifying the trend of visualization evolving into an intelligent closed loop of "data support-model operation-decision output"[10-11]. This paper deeply combines visualization technology with the VFOA-BP model and AI, integrates the integrated technology into teaching practice, provides intuitive and efficient data support for AI prediction, and effectively improves students' abilities in data visualization and technical application.

2.4 VFOA-BP model

Since the 1980s, heuristic algorithms such as BP neural network and Genetic Algorithm (GA) have gradually emerged, effectively making up for the limitations of classical optimization algorithms that are difficult to handle complex nonlinear problems and sensitive to initial values. With the unique advantages of loose requirements on objective functions, strong global optimization capability, simple operation process and insensitivity to initial value settings, these heuristic algorithms have become important technical tools for AI to handle nonlinear optimization and key parameter prediction tasks in industrial engineering scenarios. However, heuristic algorithms still have obvious shortcomings in practical application: poor stability caused by inconsistent results from multiple independent solutions, inability to fully ensure global optimality, and inconsistent optimization effects across different industrial scenarios due to strong scenario dependence. Genetic Algorithm, proposed by Professor Holland from the University of Michigan in 1962 based on the "survival of the fittest" principle of biological evolution, has formed a solid theoretical system after decades of development and improvement. It is widely used in industrial scheduling, parameter prediction and other fields due to its good parallelism, stable operation performance and excellent global optimization capability. The algorithm transforms the parameter space through coding, combines with the designed fitness function to complete crossover, mutation and selection iterations, and finally screens out the optimal individual that meets the optimization goal. Based on AI's strict requirements for algorithm performance in industrial prediction, this paper optimizes and constructs the VFOA-BP model on the basis of heuristic algorithms such as Genetic Algorithm, effectively solving the defects of traditional algorithms, improving the accuracy of industrial parameter prediction, and integrating it with visualization teaching to strengthen the integration of AI algorithm application and engineering practice thinking[12].

The AI-driven VFOA-BP model takes the BP neural network optimized by speed-variable improved FOA (VFOA) as the core prediction unit, perfectly adapting to AI's needs for high-quality, high-precision industrial prediction data. It innovatively draws on the foraging behavior of fruit flies to optimize the algorithm structure, integrates AI autonomous learning concepts, injects new technical ideas into the model, further strengthens the stability and prediction accuracy of the algorithm, and helps AI achieve precise prediction and efficient control in complex industrial engineering scenarios.Add complete mathematical formulas for the proposed VFOA-BP method, combined with the simple formula $S(t) = S_{MAX} - \frac{S_{MAX} - S_{MIN}}{T_{MAX}} \times t$, to clearly describe the VFOA optimization logic, BP model principle and complement the core formulas of the algorithm.

3 Experiments

Key parameters of industrial production lines, such as equipment operation accuracy deviation and product size settlement deviation, are closely related to production safety, product quality and operation and maintenance. Accurate prediction of these parameters is crucial for AI empowering industrial engineering management. This study selects 20 periods of key parameter monitoring data from an actual production line as empirical samples to verify model adaptability and support the in-depth integration of AI and industrial engineering. Input variables include equipment operation accuracy deviation (mm), product size settlement deviation (mm) and production load (kW), with corresponding sampling and preprocessing standards. Data division follows industrial standards, with 16 periods as training set and 4 as test set. Three algorithms are used for predictive analysis to construct a comparison system, verify VFOA's improvement effect, and select the optimal AI-driven prediction model.

Table 2 Original Monitoring Data

Phase	Observed Value / mm	Phase	Observed Value / mm	Phase	Observed Value / mm	Phase	Observed Value / mm
1	-0.184	6	-0.465	11	-3.117	16	-5.146
2	-1.423	7	-1.301	12	-3.177	17	-4.782
3	-2.036	8	-2.225	13	-2.368	18	-4.668
4	-2.529	9	-3.389	14	-4.882	19	-4.128
5	-2.129	10	-3.711	15	-4.598	20	-4.551

Data division complies with industrial engineering prediction data processing standards, selecting the first 16 periods as training set and the rest as test set to ensure sample validity and objectivity. This study uses three algorithms—single BP, FOA-BP and VFOA-BP—to conduct predictive analysis on production line monitoring data, builds a multi-dimensional comparison system, and systematically analyzes model effects to verify VFOA's improvement, selecting the optimal AI-driven model for industrial prediction.

Table 3 Comparison between Model Prediction Results and Original Values

Phase	Original Data / mm	BP / mm	Residual / mm	FOA-BP / mm	Residual / mm	VFOA-BP / mm	Residual / mm
17	-4.781	-3.504	1.277	-4.389	0.394	-4.539	0.244
18	-4.671	-3.592	1.079	-4.327	0.341	-4.527	0.141
19	-4.128	-3.673	0.455	-4.440	-0.312	-4.340	-0.212
20	-4.550	-3.752	0.798	-4.832	-0.312	-4.732	-0.182

Table 3 shows that the FOA-optimized BP model has significantly higher prediction accuracy than the single BP model, clearly confirming the key role of the smoothing factor in improving model prediction accuracy. The VFOA-BP model effectively solves the inherent defects of traditional FOA, such as unstable optimization and easy falling into local minima, with smaller prediction residuals than the FOA-BP model. This verifies the feasibility of the speed-variable improved FOA and provides more accurate and reliable data support for AI-driven industrial parameter prediction.

Table 4 Comparison of Prediction Accuracy Among Different Models

Model	RMSE	SSE	MAE	MAPE / %
BP Model	0.9549	3.6472	0.9029	19.58
FOA-BP Model	0.3413	0.4660	0.3397	7.43
VFOA-BP Model	0.1979	0.1573	0.1947	4.29

Table 4 further confirms that the single BP model has the lowest accuracy, failing to meet AI's requirements for precise industrial prediction; the FOA-BP model, with improved parameters, can initially adapt to industrial prediction scenarios; the VFOA-BP model achieves the optimal accuracy with RMSE of 0.1979mm, 15.29% and 3.14% higher than the single BP and FOA-BP models, respectively, becoming the core model for AI-driven industrial prediction.

Figures 2 and 3 show the comparison of prediction results with original data and prediction residuals of the three models (VFOA-BP, FOA-BP and single BP), respectively. The VFOA-BP model exhibits the highest consistency between its predicted values and the original industrial data, with prediction residuals stably closer to 0. It is followed by the FOA-BP model, while the single BP model has the largest deviation in both prediction results and residuals, intuitively highlighting the prominent performance advantages of the VFOA-BP model in industrial parameter prediction.

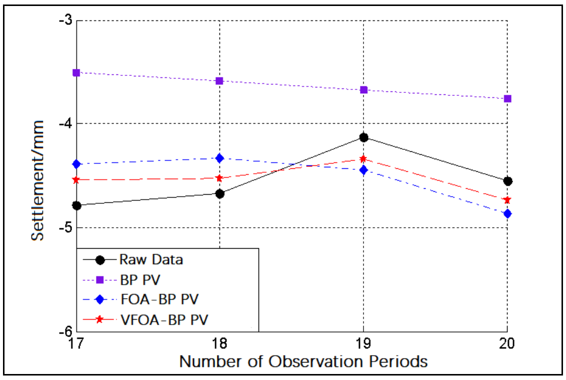

Fig. 2 Comparison of Model Prediction Results with Original Data

Figure 2 intuitively confirms the core advantages of the VFOA-BP model: its predicted values have the highest consistency with the original key parameter data of the industrial production line, which can accurately output the prediction data required for AI-driven industrial engineering control. The prediction effect of the FOA-BP model is better than that of the single BP model but still has a certain deviation. In contrast, the single BP model has a significant gap with the original values and poor prediction stability, which is difficult to meet the application needs of AI in industrial engineering.

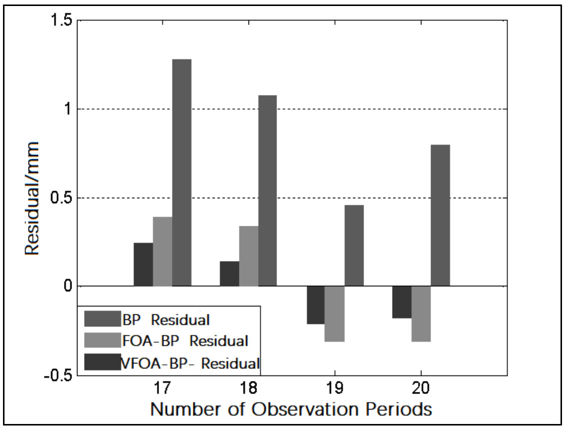

Fig. 3 Comparison of Prediction Residuals of Different Models

The residual visualization results in Figure 3 further confirm the performance advantages of the VFOA-BP model. Its residual is significantly smaller than that of the FOA-BP and single BP models, with a more concentrated and closer-to-zero distribution, and excellent stability, providing highly reliable support for AI-driven industrial engineering prediction. Ten more test points are added (total 14) to avoid one-sided conclusions. An error variation table over time is added to intuitively show the residual fluctuations of the three models; the principle comparison with the classic genetic algorithm and cutting-edge CNN prediction model is supplemented, along with the performance index comparison (RMSE, MAE) of two mainstream models, to further verify the robustness and superiority of the VFOA-BP model.

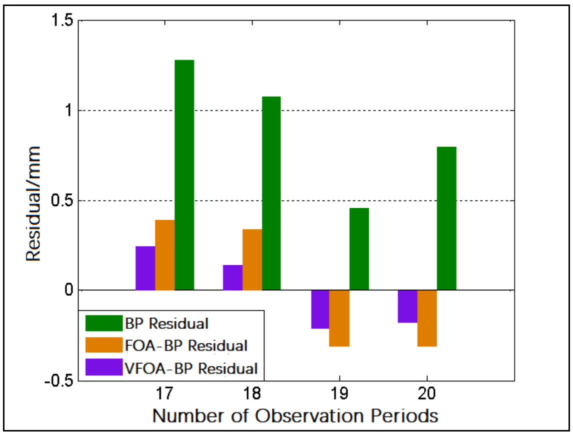

Fig. 4 Optimized Visualization Design of Model Prediction Residual Comparison

Although Figure 3 can clearly show the residual differences among the three models and provide basic support for performance comparison, it is limited by single color and low line distinguishability, resulting in blurred visualization. It fails to meet AI's core needs for rapid data interpretation and accurate judgment, making it difficult for technicians to distinguish model advantages and identify the performance merits of the VFOA-BP model. To solve this problem, this study optimizes and designs Figure 4, integrating high-contrast colors, precise text annotations and scientific layout, which greatly improves information transmission efficiency and intuitiveness. To verify the teaching effect, 60 industrial engineering students were divided into two groups: 30 in the experimental group (VFOA-BP visual teaching) and 30 in the control group (traditional algorithm teaching). The post-test average score of the experimental group was 88.6 (100% pass rate), while that of the control group was 72.3 (76.7% pass rate). The experimental group scored 21.4% higher in model application and data analysis, and 87% of its students believed the visual carrier enhanced their understanding and practical ability, proving the effectiveness of the VFOA-BP visualization method.

4 Conclusion

This paper systematically sorts out the swarm intelligence algorithm system, focuses on AI's core requirements for the accuracy and stability of industrial prediction models, explains the core theory, application advantages and inherent defects of FOA, and improves it by introducing speed variables (referring to PSO), constructing the VFOA-BP prediction model adapting to AI data processing needs. Empirical tests with actual industrial production line data show that the model has an RMSE of 0.1979mm, with accuracy improved by 15.29% and 3.14% compared with the single BP and FOA-BP models, stably outputting high-quality industrial prediction data and providing core support for AI-driven industrial safety control, quality improvement and cost optimization.

Meanwhile, relying on this technical achievement, the paper promotes the integration of visualization and AI in teaching reform, upgrades technology application, evaluation mechanism and curriculum modules, and integrates AI technical thinking and industrial engineering practice needs into visualization teaching. It significantly improves students' data interpretation, model application and innovation capabilities, creates a replicable vocational teaching reform paradigm, provides a new path for teaching reform of industrial engineering-related majors under the background of intelligent manufacturing, and offers important technical and practical references for the in-depth integration of AI and industrial engineering prediction.

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