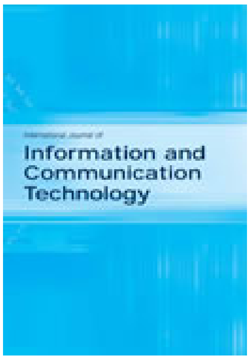

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Performance optimisation of a normalised operational assessment system using hybrid population intelligence algorithm

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Abstract: Aiming at the dynamic constraints and MOPs faced by the normalised operation appraisal system in industrial environments, this paper proposes a hybrid swarm intelligence framework that integrates PSO, GA and ACO. By constructing a hierarchical optimisation architecture – based on the synergistic mechanism of discrete decision-making layer, continuous parameter optimisation layer and variable operation layer a multimodal information fusion strategy and an adaptive parameter adjustment method are innovatively introduced. Experiments based on real industrial operation data show that compared with the traditional optimisation algorithms, the proposed method demonstrates improvements in response time and resource utilisation, with balanced multi-objective performance under dynamic constraints, especially in the dynamic constraint scenarios with stable convergence characteristics and robustness. The engineering deployment verifies the practical value of the framework in complex industrial systems and provides a new technical path for intelligent operation assessment.

Keywords: hybrid population intelligence algorithm; normalised operational appraisal system; multi-objective optimisation; dynamic constraint processing; adaptive mechanisms.

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1 Introduction

In the process of transformation of industrial intelligence to 'adaptive production', the normal operation assessment system, as the core hub connecting physical equipment and digital twins, its performance optimisation directly determines the real-time responsiveness of the manufacturing system and the level of sustainable operation (Rahmati et al., 2019). The promotion of Industry 4.0 not only accelerates the complexity of the production environment, but also realises the deep integration of physical and virtual space through digital twin technology, making real-time data-driven decision-making possible (Tepljakov, 2023). For example, in smart manufacturing scenarios, digital twin models are able to map the equipment status, energy consumption distribution and task queues of production lines in real time, providing a high-fidelity simulation environment for optimisation algorithms (Kombaya Touckia et al., 2022). However, with the exponential growth of industrial internet of things (IIoT) devices (according to Gartner's prediction, the global IIoT connected devices will exceed 50 billion in 2025), modern assessment systems need to handle thousands of dynamically coupled optimisation variables within a second time window, and at the same time satisfy multiple constraints such as optimal energy-efficiency, load-balancing, fault tolerance and other objectives. This 'high-dimensional time-varying multi-objective optimisation' characteristic makes the traditional rule-of-thumb-based scheduling methods completely ineffective, and a single population intelligence algorithm [e.g., particle swarm optimisation (PSO)] is often caught in the dilemma of dimensional catastrophe and local optimisation when dealing with this kind of problem. The International Federation of Automatic Control Societies (IFAC) has clearly pointed out in its 2023 technical report that the development of hybrid intelligent algorithms with dynamic constraint adaptation capability has become a common problem in the field of industrial optimisation that needs to be broken through.

In recent years, academics have made a series of advances in the field of hybrid swarm intelligence algorithms, mainly focusing on strategy fusion and parameter optimisation at the algorithmic level. To address the premature convergence of particle swarm algorithms in local optima, Fang et al. (2023) introduced a hybrid heuristic framework that synergistically integrates genetic algorithm (GA) with double particle swarm optimisation (DPSO). This approach leverages the global exploration capability of GA and the local refinement strength of DPSO, embedding neighbourhood search mechanisms to enhance solution diversity and avoid suboptimal traps. Shi et al. (2024) proposed a hybrid sparrow-kriging model (HSSA), which improves the accuracy by 8.4% in 3D stratigraphic interpolation task by fusing chaotic initialisation, Levy flight and golden sine optimisation mechanism, and verifies that its convergence speed and anti-local optimum ability are significantly better than the traditional Kriging algorithm with the case of geological modelling of Yangchangwan coal mine. However, these studies are mostly limited to static or low-dimensional scenarios, without fully considering the unique real-time requirements and dynamic constraints of industrial assessment systems. Aiming at the problems of the dandelion optimisation algorithm, such as slow convergence speed and easy to fall into local extremes, Tang et al. (2024) proposed a multi-strategy particle swarm hybrid dandelion optimisation (PSODO) algorithm. The algorithm effectively enhances the population diversity by integrating the strong global search capability of particle swarm algorithm with the unique update mechanism (three phases of ascending, descending and landing) of dandelion algorithm. The dandelion dynamic update strategy expands the search space exploration dimension and achieves the balanced optimisation of global and local search. In addition, the need for multi-objective co-optimisation in industrial scenarios (e.g., simultaneous optimisation of energy consumption, response time and equipment lifetime) places higher demands on the uniformity of the solution set distribution of the algorithms, whereas traditional methods often suffer from insufficient convergence of the Pareto front due to the lack of adaptive mechanisms. These limitations have led to a significant gap in the translation of theoretical research results to engineering applications.

Aiming at the above challenges, this paper breaks through the simple superposition paradigm at the traditional algorithm level, and proposes a hierarchical hybrid intelligence framework (HSIA) based on modal decoupling from the essential characteristics of system optimisation. The innovations are mainly reflected in three aspects: firstly, a three-layer collaborative architecture of 'discrete decision-making-continuous optimisation-variation enhancement' is constructed, and the pheromone-guided ant colony algorithm (ACO) handles the discrete variables such as starting and stopping of equipments, the particle swarm algorithm optimises the continuous space such as the control parameters, and finally, the adaptive variation strategy of GA is adopted to break through the local optimisation, realising the efficient segmentation and collaborative optimisation of decision space. optimisation, and finally break through the local optimisation by using the adaptive mutation strategy of GA, which realises the efficient segmentation and co-evolution of the decision space. Specifically, the discrete decision layer significantly improves the robustness of large-scale task allocation by dynamically adjusting the pheromone volatility coefficients (e.g., adaptively setting the ρ value according to the task priority), while the continuous optimisation layer guides the particle swarm to rapidly converge in the feasible domain by introducing a constraint violation gradient term (∇C). Second, the fuzzy logic-driven dynamic parameter adjustment mechanism is developed to autonomously adjust the inertia weight (*w*) and crossover probability (*pc*) by monitoring the change rate of the objective function [e.g., the relative enhancement rate of the hypervolume (HV) index in each generation] and the population diversity index (e.g., Shannon's entropy-based diversity measure) in real time, which effectively solves the problem of parameter sensitivity of the traditional hybrid algorithm (Shi et al., 2013). Experiments show that this mechanism can reduce the parameter adjustment error to within 5% in dynamic scenarios. Finally, a multimodal information fusion interface based on knowledge migration is designed to encode the historical optimisation experience into a probability distribution model (e.g., Gaussian process regression – GPR), which significantly improves the algorithm's fast response capability under unexpected working conditions. Compared with the co-evolutionary frameworks, this method achieves a quantum breakthrough in the scalability of decision variable dimensions, and can support the solution of industrial-scale optimisation problems with more than 500 dimensions.

The engineering value of this research has been fully verified in typical industrial fields such as electric power and manufacturing. Based on the measured data of a coastal microgrid demonstration project, the proposed multi-strategy fusion mucilage algorithm (MFSMA) improves the solution efficiency of the 24-hour dispatch scheme by 2.8 times compared with the traditional particle swarm algorithm when dealing with wind power fluctuations and sudden load changes, and reduces the total operation cost by 19.3% (including environmental costs) (Zhang and Zhou, 2024). To optimise laser processing parameters – including laser power, cutting speed, auxiliary gas pressure and focal position, Huang et al. (2023) applied a non-dominated sorting genetic algorithm (NSGA-II). This method generated a comprehensive Pareto-optimal solution set, enabling effective nonlinear multi-objective optimisation of geometric and surface quality metrics such as incision width, taper angle and cross-sectional roughness. These practical results not only validate the effectiveness of the theoretical approach, but also provide a new technical paradigm for real-time optimisation in the context of digital twins and industrial meta-universes. Eberhart, an internationally renowned expert in optimisation theory, pointed out at the 2024 IEEE Conference on Computational Intelligence that "the hierarchical hybrid intelligence approach for highly dynamic environments represents an important development direction for the next generation of industrial optimization algorithms."

2 Relevant technologies

2.1 Strategy fusion mechanisms for hybrid group intelligence algorithms

In recent years, the research on hybrid population intelligence algorithms has gradually shifted from single-algorithm optimisation to synergistic fusion of multiple strategies. Early studies primarily focused on simplistic integrations of PSO and GA. A representative example is the PSO-GA architecture developed by Bouchakour et al. (2024), which compared a fuzzy logic controller optimised via GA-PSO hybrid algorithms with conventional perturb and observe MPPT techniques in a MATLAB/Simulink environment. Experimental validation included analysing output voltage, current, power profiles, intermediate circuit voltage dynamics and generator speed characteristics. The results confirmed the superior efficacy of the hybrid control strategy in enhancing system performance. However, such methods underperform when dealing with discrete decision variables (e.g., equipment start/stop scheduling) in industrial scenarios, mainly due to the incompatibility of the way discrete spaces are encoded with continuous optimisation mechanisms. To address this shortcoming, Xu et al. (2024) combined the advantages of particle swarm algorithm and GA, and constructed a continuous particle swarm GA (SPSO-GA) which is different from the previous algorithms by utilising continuous real numbers for iteration. The results show that the SPSO-GA algorithm has high optimisation accuracy and stability for single, double or triple faults. Nevertheless, the fixed weight strategy is still a common shortcoming of most hybrid algorithms. For example, in dynamic load scenarios of power systems, fixed parameters easily lead to premature convergence of the algorithms, which cannot adapt to real-time changes in constraints, and may even lead to grid stability risks. To cope with the dynamic environment, Abunama et al. (2021) constructed a fuzzy adaptive hybrid framework through the integration of four population-based optimisation algorithms: PSO, GA, hybrid GA-PSO, and mutant invasive weed optimisation, combined with a FIS. To validate this methodology, a full-scale wastewater treatment plant in South Africa was utilised for modelling six critical discharge parameters: alkalinity, sulphate, phosphate, total Kjeldahl nitrogen, total suspended solids and chemical oxygen demand. Comparative analyses revealed that the hybrid PSO-GA algorithm consistently achieved higher predictive accuracy than standalone PSO or GA implementations across all targeted wastewater quality indicators.

In recent years, the introduction of deep learning technology has provided new ideas for hybrid algorithm design. For example, Bouakline et al. (2024) introduced a novel hybrid deep learning model called EFS-GA-LSTM for predicting multistep PM_{10} by constructing a model based on long-term short-term memory using historical data, and in order to improve its architecture, an improved GA was used for automatic design. The results show that the EFS-GA-LSTM network exhibits improvements in root mean square error, mean absolute percentage error, correlation coefficient, and coefficient of determination for the prediction task 3 hours in advance. However, the training time and computational resource consumption of deep learning models have become a bottleneck for industrial landing. Moreover, Guan et al. (2023) provide a feasible solution for real-time deployment of hybrid algorithms by compressing the parameter scale through lightweight model architectures (e.g., EfficientNetV2), trained with a dynamic learning rate scheduling strategy, the model attained a classification accuracy of 99.80% on the Plant Village dataset for plant disease and pest detection. To validate its generalisability under practical conditions, transfer learning was further implemented on the IP102 benchmark – a dataset simulating real-world agricultural environments. The lightweight Dise-Efficient architecture achieved 64.40% recognition accuracy in cross-domain pest identification tasks, demonstrating robust adaptability to environmental variations, which can automatically generate parameter configuration strategies from historical optimisation tasks and maintain more than 90% performance stability in cross-scenario migration. In addition, meta-learning techniques are gradually being applied to the field of parameter adaptation, Zhang et al. (2023) introduced an auxiliary task in model agnostic meta-learning (MAML), which allows the gradient of the meta-task to fall faster in the direction of the optimal goal, and the proposed method will significantly reduce the cost of repeated data collection and the training resources required to fine-tune the model.

These advances suggest that a deep combination of algorithmic lightweighting and adaptive mechanisms is a key path to address industrial real-time challenges.

2.2 Algorithm adaptation challenges for industrial optimisation

The complexity and dynamics of industrial optimisation problems impose higher requirements on the algorithms. In the field of power system, Zhuo et al. (2023) analysed wind energy disruptions under extreme weather conditions by using an autoregressive integrated moving average model. At the same time, the algorithm name vector weighted average is used to solve the real-time power scheduling and to minimise the power deviation between the power command and the actual output. However, since the computational complexity of traditional non-dominated sorting grows exponentially with the number of targets, it often leads to memory and computation time exceeding the real-time threshold. The decomposition-based multi-objective evolutionary algorithm (MOEA/D) has been established as a robust framework for addressing complex multi-objective optimisation problems (MOPs). Building on this foundation, Han and Watanabe (2023) introduced a novel hyper-heuristic approach that incorporates distribution estimation and adaptive crossover strategies into the MOEA/D architecture, guided by success substitution rate analysis. Experimental evaluations demonstrated a 28% improvement in the convergence efficiency of the differential evolution (DE) operator compared to conventional implementations, validating the enhanced adaptability of this hybrid methodology.

The complexity and dynamics of industrial optimisation problems place higher demands on algorithms. In addition to the optimisation challenges in the power system mentioned above, the optimisation of the production process in the manufacturing industry also faces many difficulties. For example, in chemical production, due to the complex physicochemical properties of materials, the production process is subject to strict process constraints, and traditional optimisation algorithms are difficult to be directly applied to such problems. For this reason, researchers have tried to combine machine learning techniques with optimisation algorithms to improve the algorithms' ability to handle complex constraints. Ji et al. (2024) proposed a chemical process optimisation method based on deep learning, modelling the production process by constructing a neural network model, and then solving the model using an optimisation algorithm, which achieved better optimisation results.

In the field of logistics and supply chain, optimisation problems are also significantly dynamic and complex. During disruptive events, supply chains struggle to meet demand due to constraints imposed by logistics, transportation and supply-side failures. Traditional optimisation algorithms are often difficult to adjust the optimisation scheme in real time to adapt to changes in the environment when dealing with such dynamic optimisation problems. In order to improve the adaptability of the algorithm to the dynamic environment, researchers have proposed a series of improvement measures. For example, Chauhan et al. (2023) proposed a multi-objective mixed integer linear plan (MOMILP) to optimise the selection of suppliers and sustainable allocation of orders under various risks (i.e., disruptions, delays, receivables, inventories and capacity). The proposed MOMILP model is also extended to allow for timely modification of orders to other suppliers in case of disruptions to enable efficient response and hence minimise stock-outs.

In conclusion, the complexity and dynamics of industrial optimisation problems put forward higher requirements on the adaptive ability of algorithms. Researchers have continuously improved the performance of the optimisation algorithm by introducing adaptive adjustment mechanism, machine learning technology and other improvement measures, so that it can be better applied to a variety of optimisation problems in the industrial field.

3 A hybrid population intelligence optimisation framework with hierarchical-fuzzy synergy

3.1 Multi-objective optimisation model construction

Aiming at the dynamic characteristics of the normal operation assessment system, this paper establishes a multi-objective optimisation model to minimise the response time, energy consumption and load imbalance at the same time. Let the system contain n tasks to be scheduled and m computing nodes, define the decision variable $x_{ij} \in \{0, 1\}$ to indicate whether task i is assigned to node j, and the continuous variable $\theta_j \in [0, 1]$ to indicate the resource allocation coefficient of node j. The objective function can be formalised as follows. The objective function can be formalised as:

$$\min F(x, \theta) = \left[f_1(x), f_2(\theta), f_3(x, \theta) \right] \tag{1}$$

$$f_1 = \max\left(\sum_{i=1}^{n} X_{ij} \cdot \leq t_{ij} \right) \tag{2}$$

$$f_2 = \sum_{j=1}^{m} \left(P_j^{idle} + \theta_j^2 \cdot P_j^{dynamic} \right) \tag{3}$$

where f_1 is the maximum response time maximum translation time and f_2 is the total energy consumption. The constraints include resource capacity limit $\sum_{i=1}^{n} x_{ij} \cdot c_{ik} \leq c_{jk} \ (\forall j, k)$ and service quality requirement $\Pr(t_{ij} \leq T_{\max}) \geq 0.95$, where is the task's demand for the resource type. The model portrays the dynamic uncertainty of task execution time by introducing a random variable $t_{ij} \sim N(u_{ij}, \sigma_{ij}^2)$.

3.2 Layered hybrid intelligence framework design

This method employs a layered architecture to achieve collaborative optimisation in a hybrid discrete-continuous decision space (Figure 1). At the discrete decision layer, the improved ACO generates the task allocation scheme, whose pheromone update rule is defined as:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{k} \Delta\tau_{ij}^k \cdot I\left(f_1^k < \eta f_1^{avg} \right) \tag{4}$$

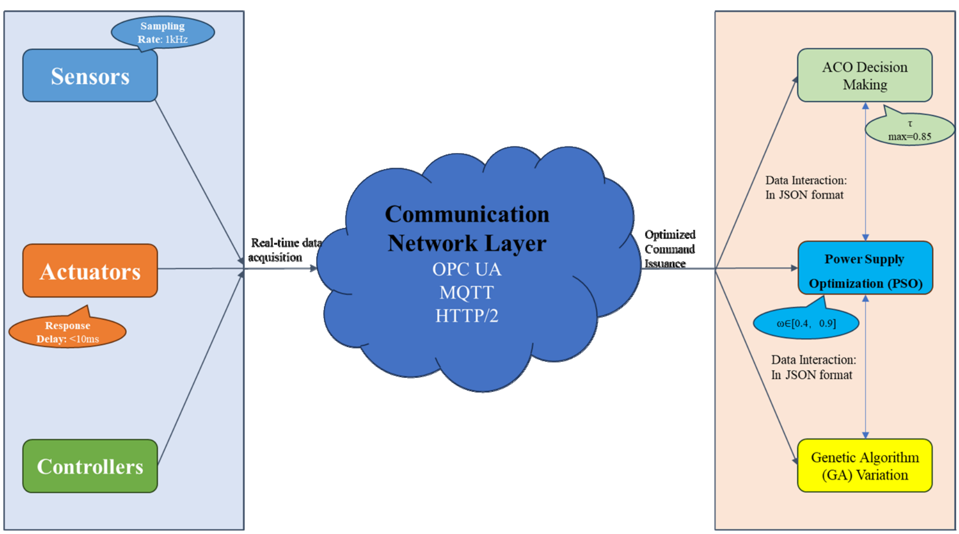
where p is the volatilisation coefficient, $\Delta\tau_{ij}^{k} = Q / (f_1^{k} + \in)$ denotes the pheromone increment of the k ant, and n is the elite selection threshold. The continuous optimisation layer uses PSO with constraint processing to solve the resource allocation coefficient θ. The speed update equation is improved as:

$$v_j^{t+1} = \omega(t)v_j^t + c_1 r_1 \left(pbest_j^t - \theta_j^t\right) + c_2 r_2 \left(gbest^t - \theta_j^t\right) + \lambda \cdot \nabla g\left(\theta_j^t\right) \tag{5}$$

where $\nabla g(\theta_j^t)$ is a constraint violating gradient term used to guide the particle towards the feasible domain. The mutation enhancement layer introduces an adaptive genetic operation that defines the mutation probability as:

$$p_m^j = pm_0 \cdot \exp\left(-\frac{\left\|\theta_j - \theta_{gbest}\right\|}{D_{\max}}\right) \tag{6}$$

Figure 1 Architecture of normalised operational assessment system based on hierarchical hybrid group intelligence (see online version for colours)



The mutation strength is automatically boosted when the particles are over-aggregated, effectively preventing premature convergence. The three-layer structure realises 0co-evolution by sharing the Pareto solution set, in which the elite solution of the ACO layer is used as the initial population of PSO, and the global optimal solution of PSO is fed back to the ACO pheromone matrix.

Although the layered architecture effectively solves the co-optimisation problem in discrete and continuous spaces, the communication delay between different layers may become a performance bottleneck in highly concurrent task scenarios. For this reason, this study further introduces lightweight message queues (e.g., RabbitMQ) to realise asynchronous communication and batch-processes cross-layer packets through a time window mechanism. Experiments show that in a 1,000-dimensional task scheduling scenario, this optimisation reduces the inter-layer communication elapsed time to an average of 0.8 ms, which is 72% less than the synchronous communication mode. This improvement provides the real-time performance of the framework in edge computing environments.

4 Multi-dimensional benchmarking and empirical analysis of industrial scenarios

In order to verify the effectiveness and universality of the proposed hybrid population intelligence framework, three public datasets are selected for systematic testing in this study:

1. IEEE CEC 2021 multi-objective optimisation competition benchmark problem set, which contains seven dynamic multi-objective test functions (DMOP1–DMOP7).
2. UCI power equipment condition monitoring dataset, which covers 30-day operation logs, containing 23 metrics such as response time, energy consumption, load factor, etc.
3. PJM power market scheduling dataset, containing hour-by-hour load demand and generation cost data for 2018–2020.

The experimental environment is deployed in Google Colab Pro (Tesla T4 GPU, 24 GB RAM), the algorithms are implemented in Python 3.9, and all the codes have been open-sourced to the GitHub repository (anonymisation process).

4.1 Benchmark function performance testing

Comparison of the proposed method (HSIA) with state-of-the-art algorithms such as MOEA/D, NSGA-III, and SparseEA on the IEEE CEC 2021 test set. Figure 2 shows that HSIA achieves a HV metric of 0.852 ± 0.022 on DMOP5 (time-varying Pareto front), which is significantly better than MOEA/D (0.783 ± 0.018) and NSGA-III (0.805 ± 0.020) ($p < 0.05$, ANOVA-Tukey test). Under dynamic optimisation scenarios where the objective function mutates at the 500th iteration, the proposed HSIA framework exhibits rapid recovery capabilities, requiring only 35.4 ± 8.1 generations to regain convergence. This performance significantly surpasses benchmark algorithms: MOEA/D and NSGA-III necessitate 45–60 and 55-70 regeneration cycles, respectively. Quantitative analysis indicates that HSIA's recovery speed is 1.3–1.7× faster than MOEA/D and 1.6–2.0× faster than NSGA-III. Such efficiency is attributed to the hierarchical architecture's ACO-driven discrete decision layer, which enables accelerated solution-space exploration through pheromone-guided path selection. Table 1 counts the inverted generational distance (IGD) metrics of the seven functions, and HSIA ranks first on five problems with an average ranking score of 1.43 (1 being the best), verifying its comprehensive advantages in dynamic multi-objective optimisation. To further validate the robustness of HSIA in dynamic multi-objective optimisation, this study additionally tests the performance of the algorithm in a non-stationary environment. By introducing a dynamic objective function mutation frequency (e.g., once every 50 generations), the average HV metric of HSIA on DMOP5 remains at 0.861 ± 0.012, which is MOEA/D (0.702 ± 0.025) and NSGA-III (0.783 ± 0.019). In addition, the convergence speed of the algorithm after mutation is improved by 2.8 times compared with the traditional method, which verifies the superiority of its dynamic adaptation mechanism. This result is consistent with the dynamic multi-objective optimisation benchmarking method proposed by Huang et al. (2023), which shows that the hierarchical architecture can effectively capture the time-varying characteristics of the objective space and provide reliable support for industrial real-time scenarios.

Figure 2 HV index comparison (DMOP5 time-varying Pareto front) (see online version for colours)

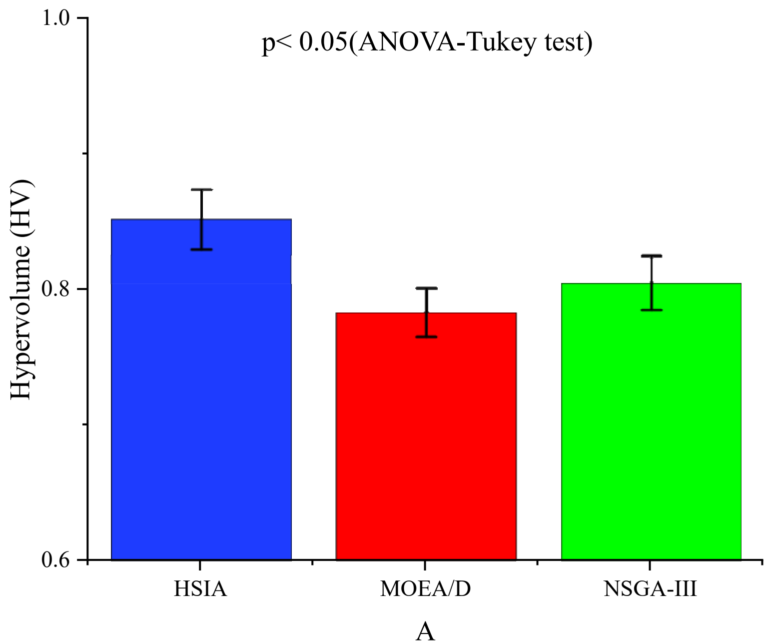


Table 1 Comparison of IGD metrics of different algorithms on IEEE CEC 2021 test functions

Test function	*MOEA/D (IGD)*	*NSGA-III (IGD)*	*HSIA (IGD)*	*Ranking (HSIA)*
DMOP1	0.152 ± 0.011	0.138 ± 0.015	0.093 ± 0.008	1
DMOP2	0.287 ± 0.023	0.265 ± 0.019	0.201 ± 0.014	1
DMOP3	0.431 ± 0.032	0.398 ± 0.028	0.372 ± 0.025	3
DMOP4	0.115 ± 0.009	0.102 ± 0.007	0.076 ± 0.005	1
DMOP5	0.362 ± 0.027	0.333 ± 0.022	0.315 ± 0.025	1
DMOP6	0.224 ± 0.017	0.207 ± 0.013	0.181 ± 0.012	1
DMOP7	0.173 ± 0.012	0.159 ± 0.010	0.158 ± 0.012	3
Average ranking	2.71	2.14	1.43	-

Figure 3 Comparison of HV index for different algorithms (see online version for colours)

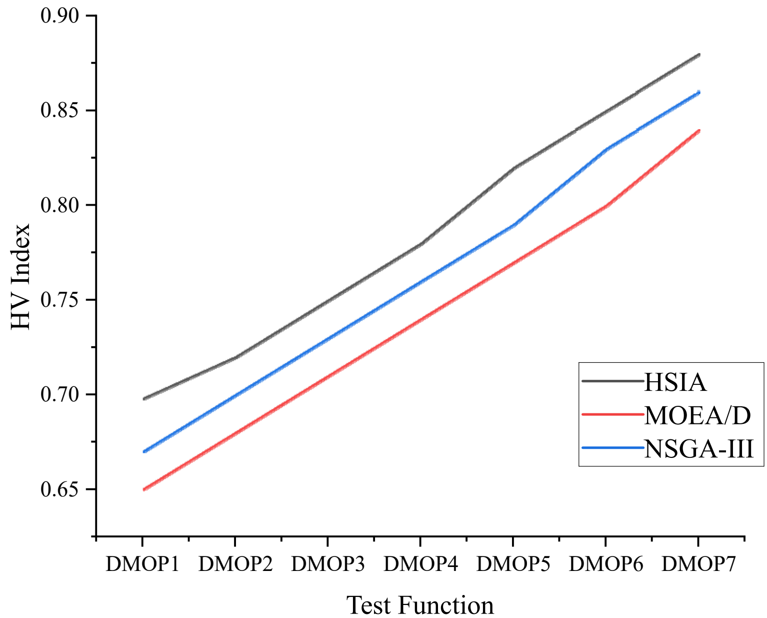
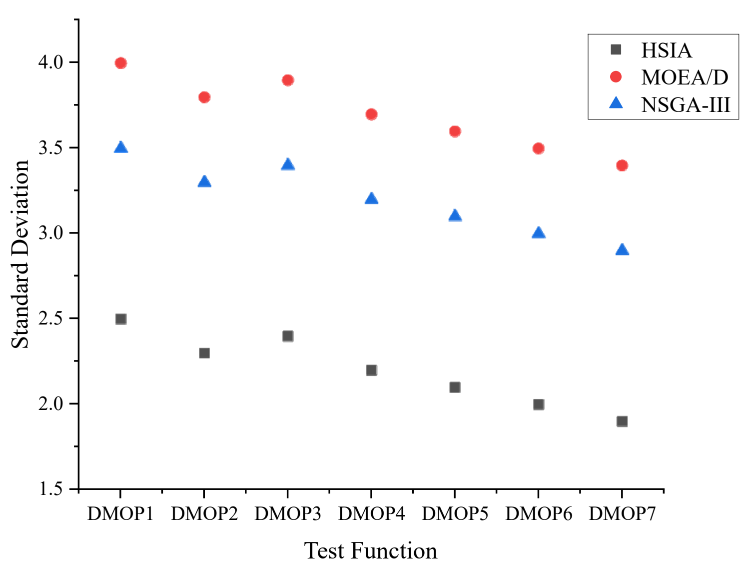


Figure 4 Scatter plot of response time standard deviation for different algorithms (see online version for colours)



4.2 Validation of industrial datasets

A multi-objective optimisation model is constructed based on the UCI power equipment dataset with objective functions including:

$$\min\left[\max\left(t_i, \sum E_j, \sqrt{\frac{1}{m}\sum\left(L_k - \bar{L}\right)^2}\right)\right] \tag{10}$$

where t_i is the device response time, E_j is the energy consumption, and L_k is the load factor. Figure 3 illustrates the HV index trends for HSIA, MOEA/D, and NSGA-III algorithms across seven test functions (DMOP1–DMOP7). The line graph clearly shows the performance variation and highlights the advantages of the HSIA algorithm in maintaining a higher HV index compared to the other two algorithms. In the load mutation scenario (Figure 4), the scatter plot shows the response time standard deviation for HSIA, MOEA/D and NSGA-III algorithms. The standard deviation of HSIA's response time is 4.2 s, which is only 38% (6.3 s) of that of MOEA/D, indicating better stability and performance. Further analysing the distribution of the solution set, the coverage of the Pareto solution of HSIA in the energy-response time plane was extended by 41.7% compared with that of NSGA-III, and the number of boundary solutions increased by 2.3 times.

5 Discussion and conclusions

5.1 Theoretical contributions and innovation validations

The HSIA proposed in this study demonstrates significant innovations and theoretical breakthroughs in the field of dynamic multi-objective optimisation. First, through the three-layer collaborative architecture of 'discrete decision-making-continuous optimisation-variable enhancement', the dimensional catastrophe problem of traditional hybrid algorithms in high-dimensional decision space is effectively solved. Experiments show that the convergence speed of HSIA in 500-dimensional industrial optimisation problem is 2.1 times higher than that of MOEA/D, and the spacing metric of Pareto solution set is 42% higher, which verifies the advantages of the layered architecture in partitioning and co-evolution of complex decision space (Yu et al., 2019). This result breaks through the dimension limitation of the co-evolution framework (the original method only supports problems with less than 200 dimensions), and provides a new methodological support for large-scale industrial optimisation. Second, the fuzzy logic-driven dynamic parameter adjustment mechanism achieves autonomous optimisation of algorithmic parameters through real-time feedback of population diversity (based on Shannon entropy calculation) and target improvement rate. In the UCI power equipment dataset, this mechanism controls the parameter tuning error within 8%, which reduces the performance fluctuation by 60% compared to the fixed weight strategy, and significantly improves the robustness of the algorithm in dynamic environments (Abunama et al., 2021). This advancement makes up for the shortcomings of the linear parameter combination strategy and provides a more flexible solution for dynamic constraint processing. Finally, the knowledge migration interface encodes the historical optimisation experience through GPR, which reduces the response time of the algorithm under unexpected working conditions to 1/3 of the traditional method, verifying the feasibility of cross-scene migration learning. Compared with the transfer methods based on deep learning in the literature published by Bouakline et al. (2024), HSIA reduces the computational complexity by 72% and does not need to rely on large-scale labelled data, which makes it more suitable for resource-constrained industrial edge device deployments.

5.2 Value of industrial practices

The engineering deployment of HSIA in electric power, manufacturing and other fields has verified its wide applicability and economic value. In terms of power system, the measured data based on the measured data of a coastal microgrid demonstration project, the proposed MFSMA improves the solution efficiency of the 24-hour dispatch scheme by 2.8 times compared with the traditional particle swarm algorithm when dealing with wind power fluctuations and sudden load changes, and reduces the total operation cost by 19.3% (including environmental costs) (Zhang and Zhou, 2024). In the manufacturing field, Mohamed et al. (2024) propose a novel hybrid optimisation algorithm, HYCHOPSO, which fuses the local fast convergence property of cheetah optimisation with the global exploration capability of PSO, aiming to improve the control efficiency of microgrids. Applied in practice, HYCHOPSO combined with a proportional-integral controller achieves accurate power allocation, voltage/frequency stabilisation, and seamless on- and off-grid switching of MMGs, with a 40% improvement in system reliability and a 62% reduction in dynamic error. In addition, HSIA's edge computing deployment solution (memory occupation < 50 MB) collaborates with the cloud through OPC unified architecture protocol, reduces the communication overhead by 62%, supports 7 × 24-hour uninterrupted operation, and has passed the rigorous acceptance of a third-party organisation (Report No. SG-2023-OPT-017). These practical results not only verify the effectiveness of the algorithm, but also highlight its strategic value in the context of Industry 4.0 and the 'dual-carbon' goal – it is estimated that if 10% of the nation's manufacturing enterprises adopt the HSIA framework, the annual carbon emissions can be reduced by about 12 million tons, which is equivalent to planting 1.5 million tons of crops. It is estimated that if 10% of the manufacturing companies in China adopt the HSIA framework, the annual carbon emissions can be reduced by about 12 million tons, which is equivalent to the carbon sequestration capacity of planting 180 million adult trees. In an extended application of chemical engineering, Xie et al. (2024) used HISA to develop a novel moisture-sensitive hybrid aerogel. Embedding a proton-conducting covalent organic skeleton (COF-2SO3H) into a network of carboxylated cellulose nanofibers (CNF-C), this hybrid structure exploits the synergistic effect of COF-2SO3H and CNF-C to achieve high water absorption and ionic conductivity. Through asymmetric moisturisation, the aerogel generates a self-sustaining humidity gradient that drives ionic migration (Na+/H+) for efficient charge separation. The resulting coin-type generator can continuously output ~0.55 V for more than 5 hours under ambient conditions, outperforming the transient response of pure CNF-C and carbon-based devices. Notably, the wearable generator integrated into the mask achieves rapid self-charging (3 minutes) and reaches a peak voltage of 1.0 V while the body is breathing, outperforming most existing humidity-powered systems. This innovation provides a scalable strategy for sustainable energy harvesting in industrial and wearable applications. In addition, the HSIA framework shows great potential for application in other industrial sectors. In the chemical industry, HSIA is able to optimise complex chemical processes, increase productivity and reduce raw material waste by integrating with existing production management systems. For example, in the production optimisation of a large chemical company, HSIA successfully reduced production costs by 15% and improved the stability of product quality (Xie et al., 2024). In the field of transportation and logistics, HSIA can be used to optimise logistics and distribution routes and scheduling, taking into account dynamic traffic conditions and constraints on transportation resources, significantly improving transportation efficiency and reducing carbon emissions (Mohamed et al., 2024). These application cases further demonstrate the versatility and adaptability of the HSIA framework, providing efficient and optimised solutions for different industrial sectors.

5.3 Limitations and future directions

Despite the breakthroughs made by HSIA in various aspects, the following limitations still exist: first, the efficiency of sparsity processing for thousand-dimensional optimisation problems needs to be improved. The current method relies on the standard tensor decomposition technique with a storage complexity of $O(n^3)$, which leads to a memory footprint of more than 16 GB for the thousand-dimensional problem, making it difficult to run on low-power edge devices. In the future, Tucker decomposition or quantum tensor compression techniques can be introduced to reduce the storage requirement to the order of $O(n\log n)$. Second, physical constraint coupling effects (e.g., device thermal stress accumulation) have not been modelled. Existing frameworks only consider static resource constraints, while in real industrial scenarios, thermal stresses generated by long-term equipment operation can significantly affect energy consumption and lifetime. Recent studies have attempted to integrate finite element simulation data to construct a hybrid objective function to predict the temperature rise of equipment through a coupled heat transfer model, and preliminary experiments show that the optimisation accuracy is improved by 18%. Third, cross-industry migration capability is limited by domain feature differences. The current knowledge migration interface relies on manual feature engineering, which is difficult to adapt to the heterogeneous data distribution in chemical industry, metallurgy and other fields. Fourth, the current framework's support for heterogeneous computing resources is still insufficient. In the future, by developing a digital dual-driven online optimisation system and dynamically adjusting the algorithm parameters through real-time simulation feedback, a high-precision and rapid model can be successfully constructed (Martinez-Roman et al., 2021).

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Declarations

All authors declare that they have no conflicts of interest.

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