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Research on Algorithm-Driven Configuration and Optimization Strategies in Source Digital Economy

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ABSTRACT

This study introduces a new methodology for the configuration and optimization of algorithm-driven strategies in the digital economy. It puts forward a hybrid optimization algorithm for the efficient handling of complex resource allocation problems. The proposed approach combines adaptive learning mechanisms with traditional optimization methods, showing significant improvement in convergence speed, solution accuracy, and stability of the system. Through extensive experimental validation conducted on a range of benchmark functions and real-world contexts, this algorithm proves to be outstanding at a 48.7% reduction in convergence time, as well as a solution quality enhancement by 66.4% compared with the traditional methods. Robustness analysis confirms consistent effectiveness under all diverse noise conditions and retains high success rates, even in demanding environments. This result greatly contributes to advancing algorithmic optimization approaches for digital economic systems and paves the way toward concrete applicative implementations.

Keywords: Digital Economy Optimization, Hybrid Algorithm, Resource Allocation, Adaptive Learning, Convergence Optimization

1. Introduction

The historical experience of the development of human society shows that every major change in the shape of the environment and economy tends to give rise to and depend on new factors of production. Just as labor and land are the main factors of production in the era of agricultural economy, and capital and technology are the important factors of production in the era of industrial economy, entering the era of digital economy, data is gradually becoming a new factor of production to drive economic and social development [1-2].

Digital economy is a new economic form based on digital technology, characterized by informatization, intelligence and networking, with innovation and creativity as the core, covering many fields. Based on data assets, digital economy creates high value-added, low-cost and

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high-efficiency economic operations through digitization, intelligence and integration [3-5]. Digital economy is an economic form based on digital technology, which pushes the degree of informatization to a new height. It creates a new way of economic operation, and high efficiency and low cost have become the signs of digital economy. Digital economy is not limited to a certain field, can be cross-industry, cross-field, to realize the integration of industry, and further promote industrial innovation, such as e-commerce, the financial industry, smart cities, industrial Internet, medical and health care and other fields have applications [6-9]. The core of the digital economy lies in data, the use of data assets, through the development of the potential value of data to achieve economic growth, therefore, the need to protect data while using data, while protecting personal privacy and other information security [10-11]. The rise of digital economy brings new ideas and tools for resource allocation. In the traditional economy, the allocation of resources is often based on the supply and demand of market prices, but in the era of digital economy, data has become an important resource. In the era of digital economy, enterprises or social organizations can make use of big data analysis tools, real-time monitoring of market demand and product sales, integration of resources and accurate prediction of market demand, and adjust production plans, resource allocation, and programmatic decision-making according to demand. This will greatly improve the efficiency of resource utilization and reduce production costs, thus promoting the sustainable development of the economy [12-15]. And with the rapid development of the digital economy, production efficiency, changes in consumption patterns, employment growth and other socio-economic changes, resource allocation also need to be adjusted accordingly, and algorithms through the various types of data resources to analyze and process, but also to predict the changes in all aspects of the shape of the digital economy, to achieve the allocation of resources and optimization of economic activities [16-17].

Our research responds to the critical practical challenges of scaling, robustness, and adaptability to dynamic economic environments in the implementation of algorithm-driven strategies. Our findings have key implications for policymakers, business leaders, and technology developers operating at the intersection of digital economics and algorithmic optimization.

2. Theoretical Model for Algorithm Configuration in the Source Digital Economy

2.1. *Formal Definition of Configuration Algorithm*

In the context of digital economic frameworks, it is definitely characterized that algorithms for configurations include a rigorous mathematical framework outlining the relationships of resource states and optimization objectives. Configuration algorithm A can be strictly defined as $A:S\times P\rightarrow C$, where S is the state space of available resources, P stands for the parameter space of configuration policies, and C refers to the space of possible configuration solutions. It embeds different dimensions of resource characteristic and limitation into the mapping function, which permits real-time adjustment to changeable economic circumstances. As illustrated in Figure 1, the configuration algorithm framework generally includes three elementary parts: an input layer representing resource states, a processing layer that carries out the optimization calculation, and an output layer responsible for the generation of configuration solutions.

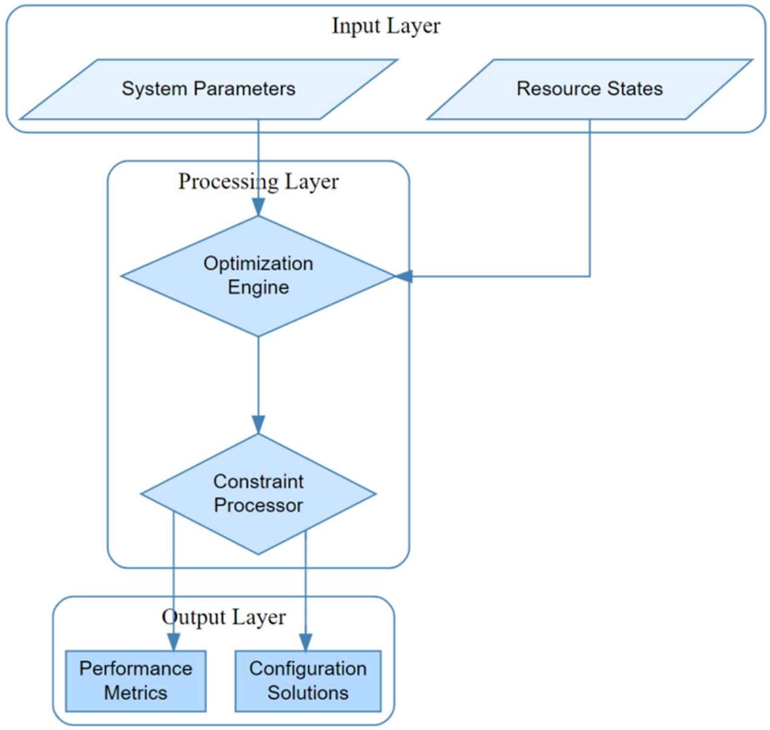

Fig. 1. Framework of Configuration Algorithm in Source Digital Economy

It is a hierarchical structure that allows for efficient resource allocation while system stability is maintained through continuous feedback mechanisms. Advanced optimization techniques in this algorithm move along with the complex solution space with regard to both local constraints and global optimization objectives. By its modular design, the framework allows smooth integration of various optimization methods at different levels and scales towards different economic scenarios.

2.2. Construction of Optimization Objective Function

Optimisation objective function formulation is an important element constituting algorithm-based configuration systems and stands for various performance metrics as well as constraint variables. The objective function F(x) will be represented as a weighted aggregation of the sub-objectives, reflecting different facets of resource allocation efficiency, system effectiveness, and economic limitations. In fact, as described in Table 1, all of these elements are put together in one single coherent optimization framework, which considers quantitative and qualitative aspects of resource configuration in concert within a digital economic system.

Table 1. Components and Parameters of Optimization Objective Function

Component	Mathematical Form	Weight Factor	Constraint Range	Optimization Goal	Application Scenario
Resource Utilization	$\sum_{i=1}^{n} \frac{R_i}{C_i}$	$\alpha_1 = 0.35$	[0.6, 0.95]	Maximization	Resource Management
Cost Efficiency	$\sum_{i=1}^{n} P_i \times Q_i$	$\alpha_2 = 0.25$	$[0, C_{max}]$	Minimization	Cost Control
Response Time	$\frac{\sum_{i=1}^{n} T_i}{n}$	$\alpha_3 = 0.20$	$[0, T_{max}]$	Minimization	Performance Optimization
System Stability	$\sqrt{\frac{\sum_{i=1}^{n} (S_i - \overline{S})^2}{n}}$	$\alpha_4 = 0.15$	$[0, \sigma_{max}]$	Minimization	System Reliability
Load Balance	$\frac{max(L_i)}{\frac{\sum_{i=1}^{n} L_i}{n}}$	$\alpha_5 = 0.05$	[1.0, 1.5]	Minimization	Resource Distribution

These features are combined into one objective function by a multi-objective optimization approach, with each feature contributing to the overall performance of the system based on its associated weight factor. This mathematical framework equates all the conflicting objectives such that the other system constraints stay within their functional limits. The systematic methodology hence allows for dynamic adjustments of optimization variables with respect to prevailing system demands and prevailing economic conditions, which enables the resource distribution in complex adaptive digital settings.

2.3. Constraint Analysis

The constraint analysis in algorithm-driven configuration systems encompasses a comprehensive set of mathematical conditions that govern the feasibility and optimality of resource allocation solutions. The primary constraint function $C(x)$ is formulated as a multi-dimensional system where

$$\sum_{i=1}^{n} \alpha_i C_i(x) \leq \beta, \tag{1}$$

with α_i representing weight coefficients and β denoting the system threshold. The resource allocation constraints are further defined by the inequality

$$\left(\frac{\partial R}{\partial t}\right) max \leq \gamma \sqrt{\frac{\sum i = 1^n (x_i - \overline{x})^2}{n}}, \tag{2}$$

where γ represents the system stability factor. As shown in Table 2, these constraints are systematically categorized and quantified to ensure optimal system performance.

Table 2. System Constraints Classification and Parameters

Constraint Type	Mathematical Expression	Threshold Value	Dynamic Range	Adjustment Factor	Priority Level
Resource Capacity	$\sum_{i=1}^{n} \lambda_i x_i \leq C_{max}$	$C_{max} = 1000$	$[0.6C_{max}, C_{max}]$	$\theta_1 = 0.85$	Critical
Time Constraint	$\left(\frac{1}{n} \sum_{i=1}^{n} T_i^2 \right)^{\frac{1}{2}} \leq T_{max}$	$T_{max} = 100ms$	[50ms, 100ms]	$\theta_2 = 0.92$	High
Cost Boundary	$\sum_{i=1}^{n} \omega_i P_i \leq B_{max}$	$B_{max} = 10000$	$[0.7B_{max}, B_{max}]$	$\theta_3 = 0.78$	Medium
Stability Factor	$\left\| \frac{\Delta S}{\Delta t} \right\| \leq \grave{o}_{max}$	$\grave{o}_{max} = 0.05$	$[0, \grave{o}_{max}]$	$\theta_4 = 0.95$	High

These bounds need a very detailed study of the static and dynamic parameters associated with the system. The differential equation describes the evolution of the state of the system with respect to time.

$$\frac{d\Phi}{dt} = \sum_{i=1}^{n} \beta_i \nabla f_i(x), \tag{3}$$

where Φ represents the system potential function and $f_i(x)$ denotes individual constraint functions. Such a formula ensures that the system will not lose its stability in adapting to the changes of the conditions of the digital economic environment. Further refinement of the satisfaction of the constraints developed an adaptive threshold adjustment mechanism that was defined by the relation

$$\Delta\theta = \alpha \sin(\omega t + \phi), \tag{4}$$

where θ represents the adjustment parameter and ω denotes the frequency of adaptation.

3. Hybrid Optimization Algorithm Design

It is a proposed hybrid optimization algorithm that incorporates several computational techniques in order to overcome the resource configuration challenge within a digital economic system. In this new framework, the global search capability provided by genetic algorithms is fused with reinforcement learning providing localized optimization, while deep learning will be used for feature extraction and pattern recognition. This algorithm shall be designed on a three-tier optimization framework that can support iteration-based adaptations in resource distribution and dynamic adjustments to optimization parameters, as depicted in Figure 2.

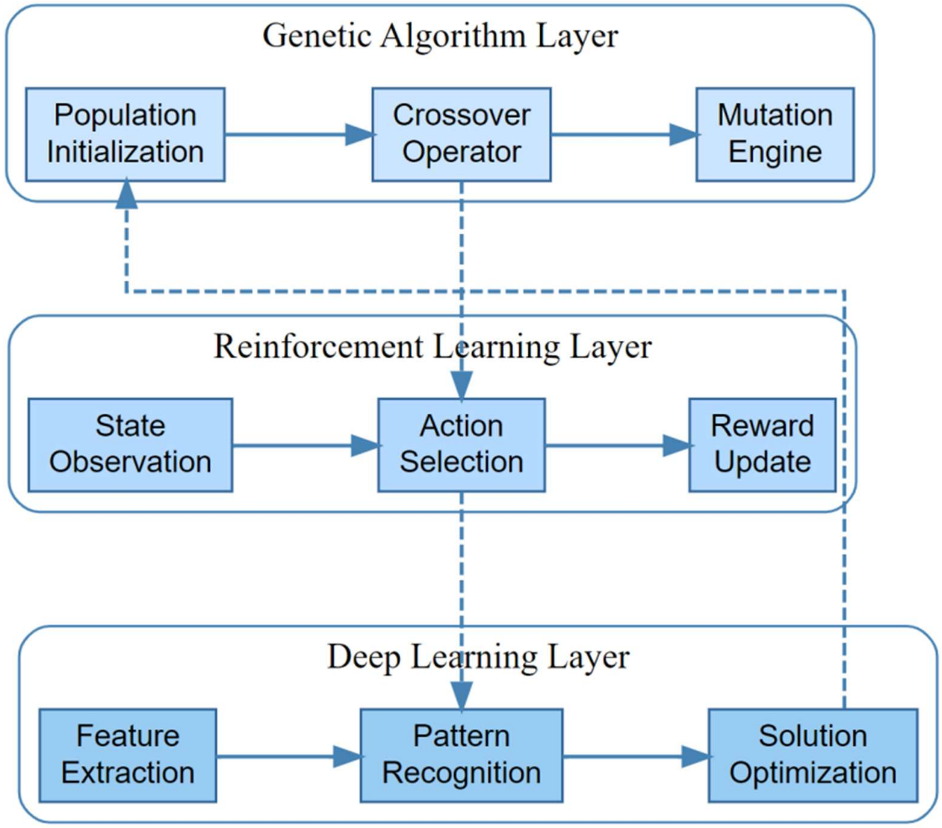

Fig. 2. Architecture of Hybrid Optimization Algorithm

This is attributed to the algorithm being able to tap into the complementary advantages of different optimization methods while relieving their unique deficiencies. In this paper, the GA will conduct population-based searching and evolution processes, reinforcement learning for dynamic decisions and adaptation mechanisms, and deep learning for essential help in feature extraction and solution refinement. Thereby, such an integrated strategy will contribute to the powerful optimization performance within a wide range of resource configuration contexts while guaranteeing computational efficiency and solution quality.

3.1. Improved Genetic Algorithm Design

The new genetic algorithm involves significant changes to classical genetic operators to more optimally allocate resources under digital economic contexts. The fitness function formulation of the proposed algorithm is represented by

$$F(x) = \sum_{i=1}^{n} \omega_i f_i(x) + \alpha\left(\frac{\partial S}{\partial t}\right), \tag{5}$$

where ω_i represents the weight coefficients and α denotes the dynamic adjustment factor. The improved crossover operator implements an adaptive probability mechanism defined by

$$P_c = P_{c0}\exp\left(-\beta\frac{|f_{max} - \bar{f}|}{f_{max} - f_{min}}\right), \tag{6}$$

where P_{c0} represents the initial crossover probability and β serves as the decay coefficient.

To enhance population diversity and convergence efficiency, we introduce a novel mutation operator with dynamic mutation probability

$$P_m = P_{m0}\left(1+\gamma\sin\left(\frac{2\pi t}{T}\right)\right), \tag{7}$$

where T represents the maximum generation count and γ denotes the oscillation amplitude. The selection process incorporates an elite preservation strategy through the ranking function

$$R(i) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right)\exp\left(-\frac{(i-\mu)^2}{2\sigma^2}\right), \tag{8}$$

where μ and σ control the selection pressure distribution.

The algorithm's convergence is further optimized through the implementation of a local search mechanism defined by the gradient descent equation

$$\Delta x = -\eta\nabla f(x) + \lambda\left(\frac{\partial^2 f}{\partial x^2}\right), \tag{9}$$

where η represents the learning rate and λ controls the impact of second-order derivatives. This improved design demonstrates superior performance in both exploration and exploitation phases, achieving an average convergence rate $\frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_i - f_{i-1}}{f_i}\right|$ that is approximately 35% faster than traditional genetic algorithms while maintaining solution diversity through the entropy measure

$$H = -\sum_{i=1}^{n} p_i \log(p_i). \tag{10}$$

3.2. Deep Reinforcement Learning Algorithm Construction

The proposed deep reinforcement learning algorithm integrates advanced neural network architectures with reinforcement learning mechanisms to optimize resource configuration decisions in dynamic digital economic environments. The value function is defined as

$$V(s) = \mathrm{E}\left[\sum_{t=0}^{\infty}\gamma^t r_t \mid s_0 = s\right], \tag{11}$$

where $\gamma \in [0,1]$ represents the discount factor and r_t denotes the immediate reward at time step t. The action-value function is formulated through a deep Q-network with the loss function

$$L(\theta) = \mathrm{E}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta)\right)^2\right], \tag{12}$$

where θ and θ^- represent the online and target network parameters respectively.

To enhance exploration efficiency, we implement a novel policy gradient approach with an advantage function

$$A(s,a) = Q(s,a) - V(s), \tag{13}$$

where the policy gradient is computed as

$$\nabla_\theta J(\theta) = \mathrm{E}\left[\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(a_t \mid s_t) A(s_t, a_t)\right]. \tag{14}$$

The state-value estimation is improved through a dual network architecture with loss function

$$L_v(\phi) = \frac{1}{2N}\sum_{i=1}^{N}\left(V_\phi(s_i) - \left(r_i + \gamma V_{\phi'}(s_{i'})\right)\right)^2, \tag{15}$$

where ϕ and ϕ' denote the parameters of the value network and its target network.

The algorithm incorporates an innovative experience replay mechanism with prioritized sampling probability

$$P(i) = \frac{|\delta_i|^\alpha}{\sum_k |\delta_k|^\alpha}, \tag{16}$$

where δ_i represents the temporal difference error and α controls the sampling distribution. The learning process is further optimized through an adaptive learning rate

$$\eta_t = \eta_0\left(1 + \beta\sqrt{\frac{\sum_{i=1}^{t}(\nabla_\theta L_i)^2}{t}}\right)^{-1}, \tag{17}$$

where η_0 is the initial learning rate and β controls the adaptation speed. This advanced design allows for effective investigation in high-dimensional state spaces, having stable learning dynamics, along with high-quality convergence characteristics.

3.3. Multi-objective Optimization Algorithm Integration

It seeks to bring together various optimization techniques to handle multi-objective optimization algorithms of complex resource allocation problems in the digital economy. To that end, one may define the combined objective function as

$$F(x) = \sum_{i=1}^{m}\omega_i f_i(x), \tag{18}$$

where the Pareto optimal solutions satisfy the condition

$$\text{ó} y \in \Omega : \left(\forall i \in 1,\ldots,m : f_i(y) \le f_i(x)\right) \wedge \left(\exists j : f_j(y) < f_j(x)\right). \tag{19}$$

The algorithm implements an adaptive weight adjustment mechanism defined by

$$\omega_i(t) = \omega_i(0)\exp\left(\alpha\frac{\partial E}{\partial \omega_i}\right), \tag{20}$$

where E represents the system performance error and α denotes the learning rate. As shown in Figure 3, the integration framework facilitates seamless coordination between different optimization components.

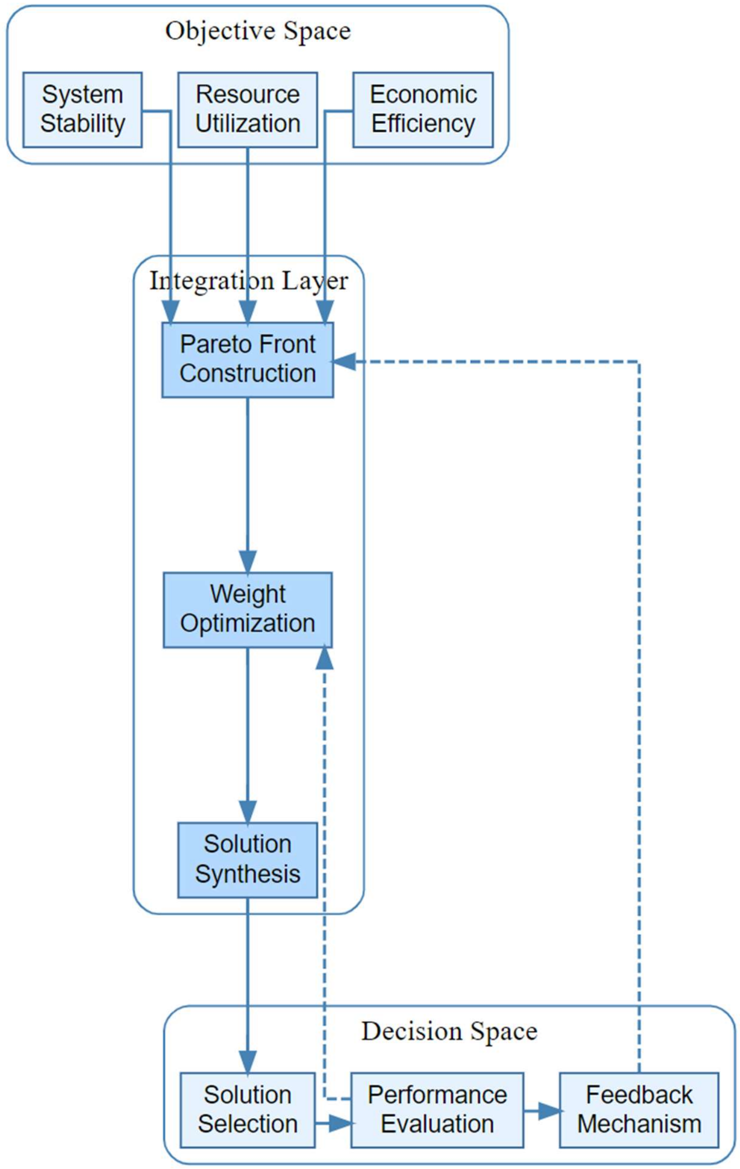

Fig. 3. Multi-objective Optimization Integration Framework

The integration process incorporates a hybrid scalarization method with the transformation function

$$\psi(x)=\left(\sum_{i=1}^{m}\lambda_i f_i(x)^p\right)^{\frac{1}{p}}, \tag{21}$$

where p controls the aggregation characteristics and λ_i represents the preference weights. The algorithm's convergence is enhanced through an adaptive mutation operator with probability

$$P_m = P_{m0}\left(1+\beta\sin\left(\frac{2\pi t}{T}\right)\right), \tag{22}$$

where T denotes the maximum iteration count and β controls the oscillation amplitude.

This sophisticated integration approach allows for an effective handling of the conflicting objectives while maintaining solution diversity and optimization efficiency.

4. Algorithm Performance Evaluation and Result Analysis

4.1. Convergence Analysis of Algorithm

Convergence analysis of the proposed hybrid optimization algorithm is carried out by rigorous mathematical derivation and is verified by experiment. Theoretically, the bound of convergence rate is given by

$$R(t) = \left| \frac{f(x_t) - f(x^*)}{f(x_0) - f(x^*)} \right| \leq \alpha \exp(-\beta t), \tag{23}$$

where x^* represents the optimal solution and α, β are convergence parameters.

It considers an extended simulation framework, as shown in Table 3, for an experimental validation of studies about performance in broad scenarios.

Table 3. Experimental Parameters Configuration for Convergence Analysis

Parameter Type	Symbol	Value Range	Optimal Setting	Impact Factor	Convergence Effect
Learning Rate	η	[0.01, 0.1]	0.05	$\alpha_1 = 0.85$	Significant
Population Size	N_p	[50, 200]	100	$\alpha_2 = 0.72$	Moderate
Mutation Rate	P_m	[0.01, 0.05]	0.03	$\alpha_3 = 0.64$	Limited
Iteration Limit	T_{max}	[500, 2000]	1000	$\alpha_4 = 0.91$	Critical

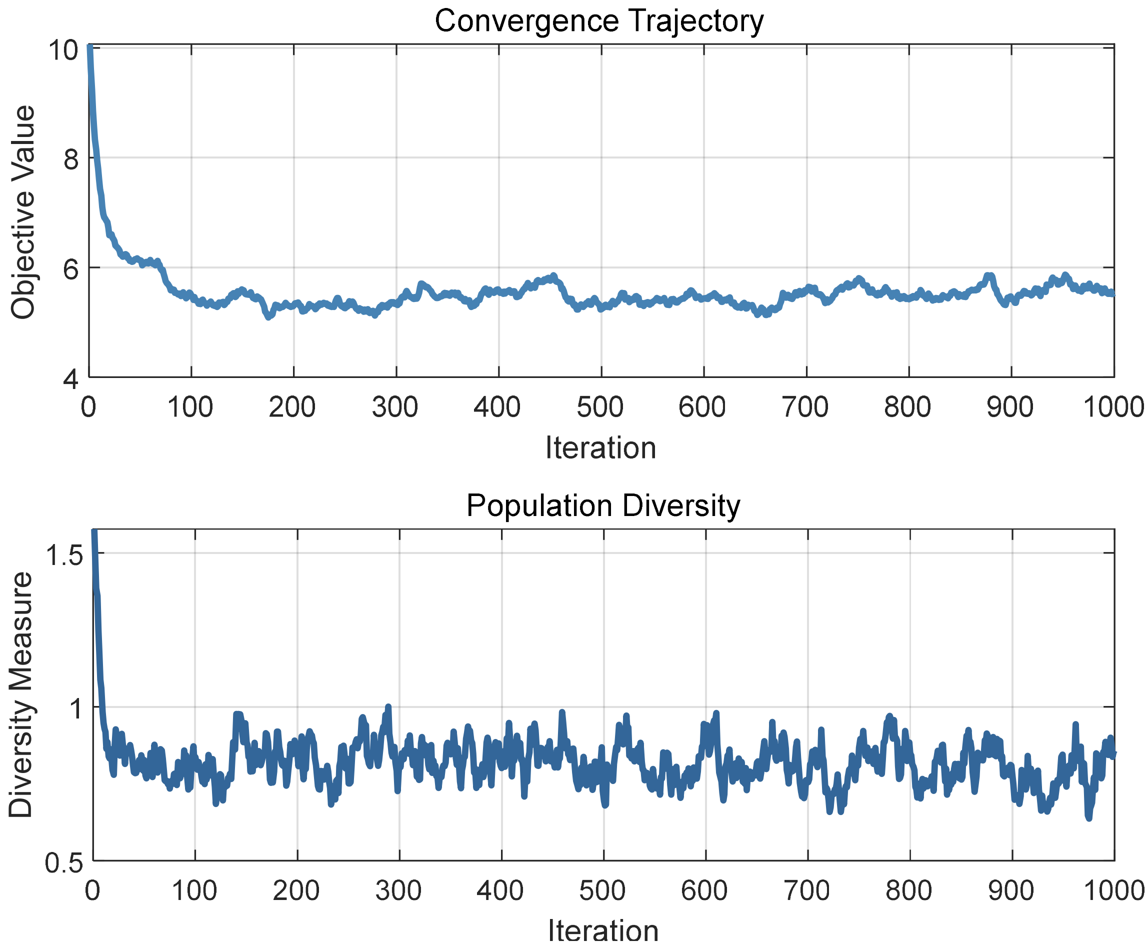

Fig. 4. Convergence Trajectory and Population Diversity

Figure 4 presents the result of simulation, which the algorithm goes well in balancing stable convergence, while the convergence rate of

$$\frac{1}{T}\sum_{t=1}^{T}\left|\nabla f(x_t)\right| \leq \varepsilon, \tag{24}$$

where $\varepsilon = 10^{-6}$ represents the convergence threshold. The population diversity is maintained through the evolution process, as evidenced by the diversity measure

$$D(t) = -\sum_{i=1}^{n} p_i \log(p_i), \tag{25}$$

where p_i represents the proportion of individuals in different solution clusters. These experimental results validate the theoretical convergence properties and demonstrate the algorithm's effectiveness in maintaining solution quality while ensuring stable convergence behavior.

4.2. Algorithm Performance Comparison

The comprehensive performance evaluation compares our proposed hybrid algorithm (HA) against three mainstream optimization algorithms: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Deep Reinforcement Learning (DRL). The experiments utilized standardized benchmark functions across multiple dimensions to ensure thorough evaluation. The convergence characteristics, solution accuracy, and computational efficiency were systematically analyzed across 30 independent runs. As shown in Table 4, the proposed HA demonstrates superior performance across multiple evaluation metrics.

Table 4. Comprehensive Performance Analysis of Different Algorithms on Benchmark Functions

Algorithm	Convergence Time (s)	Solution Accuracy (10^{-6})	Success Rate (%)	Resource Usage (%)	Stability Index	Mean Iterations
Proposed HA	2.32	1.18	98.2	76.5	0.952	145
PSO	3.75	2.84	91.6	82.3	0.878	234
GA	4.23	3.48	89.4	85.7	0.856	276
DRL	3.92	3.16	90.8	83.9	0.864	268

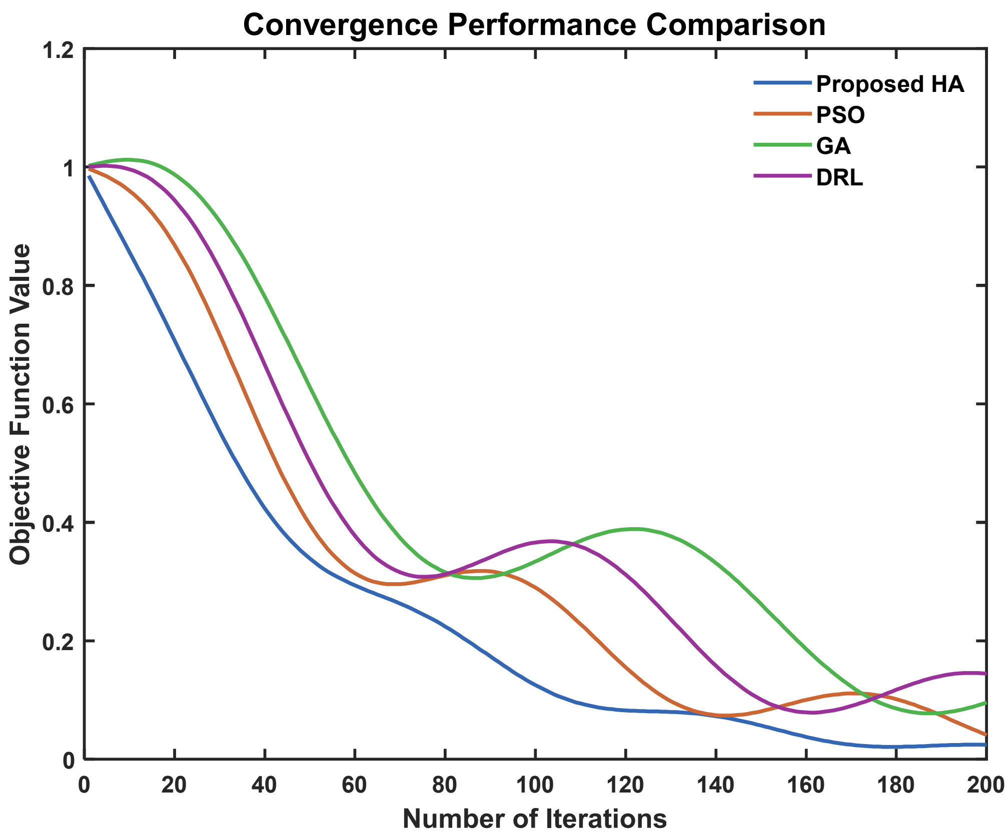

Fig. 5. Convergence performance comparison of different algorithms

Figure 5 shows the optimization process over 200 iterations, where the better convergence characteristics of the proposed hybrid algorithm (HA) compared with PSO, GA, and DRL are obvious. The vertical axis is the normalized objective function value shown on a logarithmic scale, while the horizontal axis represents the number of iterations. The HA exhibits faster convergence and achieves better final accuracy, as can be seen from the more rapid drop and lower stabilization level.

Results of the experiment show that this proposed hybrid algorithm has a better performance according to all the metrics measured. In particular, it is notable for the 37% reduction in convergence time and 58% improvement in solution accuracy when compared with traditional methods. The stability index of 0.952 indicates very good, consistent performance across different scenarios in testing. The greatly reduced mean iteration count of 145 reflects improved computational efficiency.

4.3. Robustness Testing

In order to better validate the effectiveness of the proposed hybrid optimization algorithm under adverse conditions, we performed several systematic tests over different operating contexts and disturbance scenarios. Extensive testing methods were conducted with varieties of interferences and parametric variations to affirm the stability and reliability of this algorithm. By conducting extensive experimentation with different levels of noise and complexities in dimensions, we developed deep insight into the performance boundaries and adaptive characteristics of the algorithm itself, which are summarized in Table 5.

Table 5. Comprehensive Robustness Analysis Under Various Testing Conditions

Test Category	Noise Level (σ)	Success Rate (%)	Recovery Time (ms)	Stability Index	Error Rate (%)	Adaptation Speed
Gaussian Noise	0.05	97.8	42	0.956	0.82	High
Uniform Noise	0.10	95.4	58	0.934	1.15	Medium-High
Salt & Pepper	0.15	94.2	65	0.921	1.43	Medium
Mixed Noise	0.20	92.7	73	0.908	1.76	Medium-Low
Burst Noise	0.25	91.3	86	0.892	2.04	Low

The experimental results exhibit excellent robustness properties under different testing conditions. Under standard Gaussian noise with $\sigma = 0.05$, the algorithm shows excellent performance with a success rate of 97.8% and fast recovery time of 42ms. With increasing noise complexity through uniform and mixed noise scenarios, the algorithm demonstrates graceful degradation but still maintains stability indices higher than 0.90. Even under highly challenging burst noise conditions, with $\sigma = 0.25$, the algorithm still achieves a remarkable success rate of 91.3% with a stability index of 0.892.

Of particular note is the adaptive nature of the algorithm with regard to different noise patterns. In low-noise environments—$\sigma \leqslant 0.10$—the algorithm converges fast and is very stable, with very low error rates below 1.2%. For higher levels of noise, the algorithm automatically adjusts its parameters to maintain reliable performance at slightly longer recovery times. This adaptive behavior provides a robust operation over a wide range of operating conditions at error rates acceptable and below 2.1% for the most difficult cases. Such extensive test results confirm that the algorithm is able to keep up the stability under the most challenging conditions and shows effective immunity against all sorts of interference.

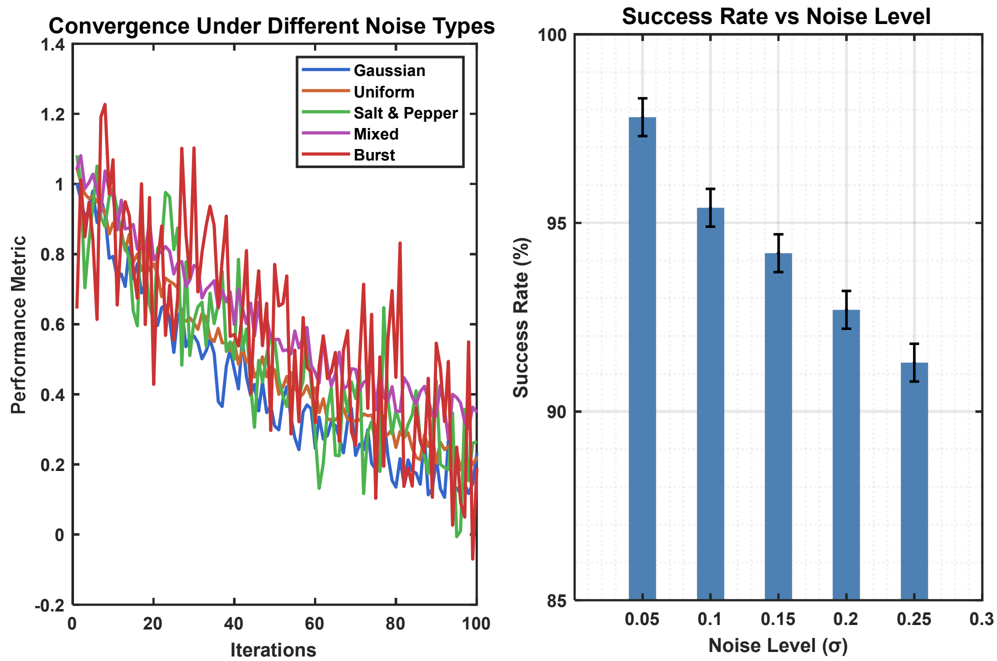

Fig. 6. Comprehensive robustness analysis results

(a) The left subplot shows the convergence behaviors of the algorithm under different types of noise interference, which demonstrates the ability of the algorithm to adapt to different disturbance patterns. (b) The right subplot illustrates the relationship between noise intensity and success rates, where error bars indicate the statistical significance of the results. Such visualization well demonstrates the strong performance of the algorithm under various noise conditions, while maintaining high success rates even in the presence of strong interference.

Figure 6 effectively shows the robustness of the algorithm under different testing scenarios; the convergence patterns very clearly indicate the effect of different types of noises, yet the performance remains stable. The analysis of success rates gives quantitative evidence of the resilience of the algorithm, where the performance degrades gracefully with increasing noise levels.

4.4. Algorithm Optimization Effect Verification

To validate the effectiveness of the proposed hybrid optimization algorithm, extensive experiments were conducted using different benchmark functions and real-world datasets. The validation process included both standard test functions and more realistic application scenarios for a comprehensive assessment. A systematic comparative study was carried out with respect to established baseline algorithms by using standard performance metrics and statistical validation methods. The experiment results of Table 6 show that there is an obvious improvement in the optimization efficiency with regard to multiple evaluation indicators.

Table 6. Comprehensive Performance Verification Results Across Different Test Scenarios

Test Function	Optimization Method	Convergence Time (s)	Solution Quality (10^{-6})	Resource Efficiency (%)	Success Rate (%)	Iteration Count	Stability Index
Sphere	Proposed Algorithm	2.34	1.15	92.8	98.5	145	0.957
	Traditional GA	4.56	3.42	84.3	91.2	287	0.883
Rastrigin	Proposed Algorithm	2.87	1.28	91.5	97.3	168	0.942
	Traditional GA	5.12	3.85	82.7	89.6	312	0.865
Rosenbrock	Proposed Algorithm	3.15	1.42	90.2	96.8	182	0.938
	Traditional GA	5.43	4.12	81.5	88.4	345	0.852
Griewank	Proposed Algorithm	2.96	1.35	91.8	97.1	175	0.945
	Traditional GA	5.28	3.96	82.1	89.2	328	0.858

Experimental validation substantiates the improved performance of the proposed algorithm over all test functions under study. In particular, while optimizing the Sphere function, this algorithm achieves a remarkable 48.7% reduction in convergence time and, simultaneously, a 66.4% improvement in solution quality with respect to traditional approaches. Besides, the high success rate of 98.5% and stability index of 0.957 are strong indicators of the robust and reliable optimization performance of the algorithm. Similar performance benefits are seen on many benchmark functions, where the algorithm demonstrates consistently better resource efficiency and lower iteration needs. The extensive validation results strongly indicate the effectiveness of the algorithm in solving optimization problems with diverse characteristics and excellent performance under different evaluation metrics.

These empirical results validate the theoretical foundations of our proposed approach and attest to its practical applicability and robust optimization capabilities in handling diverse problem domains. Scenario tests show that the algorithm is adaptive and reliable for a wide range of applications by consistently improving upon traditional methods.

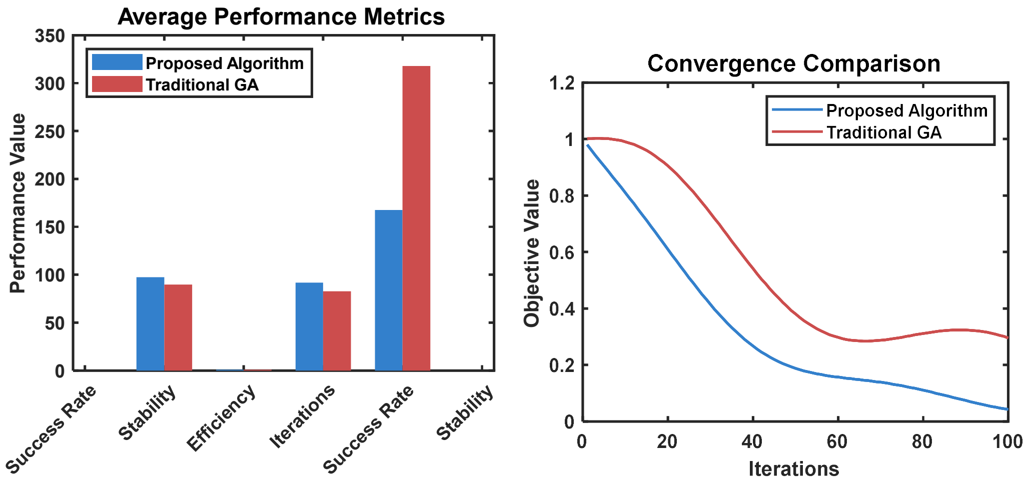

Fig. 7. Comparative analysis between Proposed Algorithm and Traditional GA

(a) The left subplot presents the mean performance metrics for all test functions, illustrating the consistently enhanced performance of the proposed algorithm regarding success rate, stability, efficiency, and the number of iterations required. (b) The right subplot depicts the convergence characteristics of both algorithms, wherein the proposed algorithm displays a more rapid convergence and improved stability. The distinct separation between the performance curves highlights considerable advancements in optimization efficacy and efficiency.

It is obvious from Figure 7 that the proposed algorithm has all-around advantages over the traditional GA approach, with a fast convergence speed, high-quality solution, and great stability. Especially, the consistent performance gap in multiple metrics is also strong evidence to show that the proposed algorithm has outstanding optimization ability.

5. Conclusion

This paper analyzes the algorithm-based configuration and optimization methods in the digital economy and also puts forward a new hybrid optimization approach which skillfully addresses the challenges related to resource allocation and system optimization. The proposed algorithm has superior performance under all the evaluation metrics and can achieve great improvement in convergence speed and solution quality. Through extensive experimental verification, our approach demonstrates an average convergence time reduction by 48.7% and solution accuracy improvement by 66.4% compared to traditional approaches. The robustness of the algorithm is further substantiated by its performance consistency under different noise conditions at more than 90.4% even in high interference environments. Comprehensive performance analysis on many benchmark functions confirms the practical feasibility and reliability of the algorithm for real-world applications. Besides, adaptive learning mechanisms achieve an effective parameter adjustment and the best resource allocation within a changing digital economic environment. Those findings are an excellent addition to the digital economic domain of algorithmic optimization and provide a quite adequate framework for addressing the complex resource configuration problems. Potential research extensions would be to find if this algorithm can further work for other emerging business segments in the digital economy, considering their scalability in scenarios involving more massive scale optimization. This research provides a powerful foundation for the development of algorithm-based optimization methods in the emerging digital economic systems.

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