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Design Of An Intelligent Financial Sharing Platform Based On Evolutionary Algorithms And Causal Inference

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Abstract. *This research endeavors to craft a sophisticated financial collaborative platform, underpinned by Evolutionary Algorithms (EA) and Causal Inference (CI), with the objective of mitigating the challenges and deficiencies inherent in contemporary financial sharing frameworks. The incorporation of EA serves to refine fund allocation and bolster risk management. Through emulating the evolutionary progression encompassing selection, crossover, and mutation, the study attains adaptive enhancement in fund allocation. Concurrently, CI models are harnessed to discern causal linkages amid financial transactions, thereby furnishing users with more precise decision-making support. Methodologically, this investigation furnishes an exhaustive exposition on the tenets of EA and CI, advocating their harmonized utilization within the realm of the intelligent financial sharing platform. The segment pertaining to system design delineates the overarching blueprint of the platform, encompassing the dynamic interplay between the EA module and the CI module. The system design segment elucidates the comprehensive architecture of the platform, encapsulating the interplay between the EA module and the CI module. Through empirical exploration with authentic financial data, we substantiate the platform's efficacy in refining fund allocation and delineating causal connections. Empirical findings attest that in contrast to conventional methodologies, the intelligent financial sharing platform manifests noteworthy enhancements in fund allocation efficacy and risk mitigation. Notably, CI methodologies amplify decision precision, thereby curtailing the likelihood of erroneous judgments. Through empirical analysis of authentic financial data, we ascertain the efficacy of the platform in optimizing fund allocation and elucidating causal relationships. Our experimental findings underscore substantial enhancements in fund allocation efficacy and risk management compared to conventional methodologies, underscoring the efficacy of the intelligent financial sharing platform. Furthermore, Causal Inference methods demonstrably augment decision precision, mitigating the peril of erroneous judgments.*

Keywords: EA; CI; intelligent financial sharing platform

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1. **Introduction.** In the continuum of information technology evolution, myriad enterprises actively integrate information technology into the execution of financial operations, thereby establishing financial sharing platforms. These platforms incite transformations in accounting methodologies, modes, and managerial structures. The implementation of such platforms has refined the distribution of human resources within enterprises, concomitantly reducing the human resource expenditures of the finance department. Bolstered by information technology, the error quotient in financial operations has substantially diminished, ameliorating the caliber and efficiency of enterprise financial endeavors. An increasing number of enterprises discern the merits and worth of financial sharing platforms, thereby instigating profound integration of information technology within the finance domain. The establishment of a financial sharing platform necessitates financial personnel to assimilate novel work paradigms and delve deeply into the functionalities of the financial sharing platform. This endeavor not only elevates the learning acumen of financial personnel but also augments the quality and efficiency of conventional accounting work [1-4].

Presently, myriad domestic financial firms or conglomerates grapple with prevailing management models, particularly those pertinent to financial management, which significantly impede swift business growth [5, 6]. The current system is plagued by inefficiencies in fund allocation, culminating in suboptimal utilization or excessive idle funds. Furthermore, a dearth of effective risk management mechanisms exacerbates inadequate risk control during investment or trading processes, thereby elevating the probability of risk exposure. Additionally, within financial sharing platforms, security assumes paramount importance, as any vulnerabilities could precipitate substantial financial losses or a erosion of user trust. Risks such as data breaches, information tampering, or unauthorized access further underscore the imperative of robust security measures.

The rise of financial sharing and the dawn of the big data era present compelling opportunities for the advancement of financial management. Internet-based information technology is harnessed for financial sharing, facilitating centralized operations, standardized procedures, and unified benchmarks. This amplifies the comprehensive financial advantage and operational efficiency of enterprises, enabling swift decision-making for managers through access to high-quality data. Several large enterprise groups are currently in the process of establishing or implementing financial sharing centers, while diverse scholars delve into scrutinizing the application of intelligent algorithms to optimize financial sharing systems. The integration of artificial intelligence in finance and financial management encounters distinctive challenges due to the prevailing virtual and highly automated nature of most financial tasks, diverging from physical programs [7-9].

The rapid evolution of artificial intelligence and information technology is intricately interwoven into the fabric of the financial industry's progression [10]. The emergence of the financial sharing service center represents an innovative paradigm in financial management, with a primary aim to achieve transparent oversight. It achieves this by extensively leveraging advanced information technologies such as big data, cloud computing, artificial intelligence, and mobile Internet to overhaul and standardize the financial operations of enterprise groups. This endeavor aims to enhance management efficiency, reduce operating costs, and strengthen management and control mechanisms.

The evolution of financial shared service centers hinges on integrated information systems and workflow processing platforms, propelling the digital metamorphosis of the financial industry. This initiative aims to eradicate information barriers, enhance service value, and enrich managerial decision-making. Moreover, it harmonizes information, business, and accounting standards, ensuring the coordination and consistency of designed business systems and core systems [11]. Previous research has primarily focused on the application of information technology in the financial field and the establishment of financial sharing platforms, highlighting their potential in enhancing financial efficiency, optimizing resource allocation, and refining management structures. However, these studies often overlook the optimization and innovation of financial sharing platforms in fund allocation, risk management, and decision support. This study endeavors to design an intelligent financial sharing platform by integrating EA with CI to optimize fund allocation and risk management, and enhance the accuracy of decision support. The contributions of this article can be summarized as follows:

(1) Integration of Global Search with Causal Relationship Modeling: By combining the global search capabilities of EAs with the causal relationship modeling of CI, the platform can consider global information while accurately identifying and modeling causal relationships between financial transactions. This innovative approach enhances the comprehensiveness and intelligence of financial decision-making.

(2) Addressing Foundational Issues in CI: Emphasis is placed on resolving fundamental issues in CI models, particularly those related to whether an individual accepts experimental treatment. The introduction of statistical distribution mechanisms ingeniously resolves concerns regarding the correlation between individual attributes and the allocation mechanism of experimental treatment, thereby enhancing the reliability and applicability of the CI model.

(3) Enhancing Decision Support Accuracy: The incorporation of CI methods leads to a more precise assessment of the potential impact of financial decisions. By identifying and modeling causal relationships, the platform provides users with decision support that

is more accurate and reliable, fostering a scientific and dependable approach to decision-making.

2. **Related Work.** A financial sharing platform refers to a technology and Internet-based financial service platform designed to offer users access to financial information sharing, fund management, investment advice, and other related financial services. These platforms typically integrate advanced technology to enable users to conveniently access, manage, and optimize their financial situation. The following introduces the intelligent financial sharing platform [12].

The first financial shared service center in history was established by the American company Ford in the 1980s, marking the initial traction of the idea of financial sharing. Since then, theoretical studies of shared services have progressed [13]. In the Internet era, enterprises face the demand impact of new technologies on sustainable development under the financial sharing mode. With the continuous improvement of enterprise brand influence, the internal organizational structure of enterprises has become increasingly complex, and headquarters management has raised the bar for the accuracy and timeliness of enterprise business information [14].

As financial technology continues to advance, the financial industry has amassed a wealth of complex information. Unveiling the inherent characteristics of this complex data is crucial not only in the field of financial big data but also in numerous other research fields. Early research suffered from a lack of suitable techniques to handle complex financial data [15]. Traditional techniques relying on machine learning and statistics often employ shallow model forms, which fail to accurately capture the multi-level, intricate, and nuanced aspects of financial data [16].

Traditional data processing methodologies often encounter challenges when confronted with vast and heterogeneous datasets within financial sharing platforms [17]. artificial intelligence technologies, notably deep learning and machine learning, offer novel avenues for processing, analyzing, and extracting insights from these immense data repositories. In [18], the utilization of deep learning techniques for mining financial data was explored, revealing superior performance compared to conventional statistical approaches when applied to identical datasets. Seeking to enhance enterprise auditing efficiency and facilitate intelligent financial analysis, reference [19] introduced an enhanced dynamic learning neural network algorithm model grounded in deep learning theory. Subsequent experiments demonstrated a notable enhancement in model accuracy, rising from 81% to 87% post-optimization.

In [20], deep learning methodologies were harnessed to mitigate system latency and foster the development of novel financial services tailored to capital allocation markets. Results underscored not only the mitigation of uneven income distribution among farmers but also the provision of substantial support for rural revitalization initiatives.

In the digital era, intelligent financial sharing platforms have emerged as pivotal innovations in the realm of financial technology [21]. Beyond the consolidation and management of financial data, these platforms leverage advanced technologies such as Machine Learning to furnish users with more intelligent and personalized financial services. In [22], a methodology is proposed to determine the optimal cutoff point for predictions generated by machine learning models, aiming to maximize earnings on peer-to-peer lending platforms. Throughout the model training phase, machine learning algorithms establish thresholds to optimize assessment metrics, with a particular emphasis on achieving the highest F1 score. Empirical findings from the experimentation indicate that, within the context of financial outcomes, the automatically determined threshold fails to yield maximal profit, encompassing both losses and gains [23].

The Counterfactual Impact (CI) method emerges as another efficacious approach in addressing the design intricacies of financial sharing platforms. Contrary to merely discerning superficial correlations, this method endeavors to unveil and comprehend causal relationships between events. Within the realm of finance, CI methodologies serve to delve deeper into the actual ramifications of diverse financial decisions on financial outcomes, thus furnishing profound insights conducive to platform design enhancements [24].

In a bid to explore the ramifications of platform protection insurance on both buyers and sellers within the sharing economy, a meticulously structured research design integrating CI principles and a sizable sample size is advocated in [25]. Such an approach aims not only to mitigate consumer risk and amplify the efficacy of the sharing platform but also to fortify its reputation, bolster market efficiency, and enhance consumer welfare within the sharing economy. In [26], the utilization of CI models is delineated to discern and comprehend the authentic impact of external shocks on corporate finance and accounting domains. Through extensive data experimentation, the causal nexus between specific shocks and financial and accounting variables is elucidated, transcending mere correlation analysis.

The literature [27, 28] delves into the causal effects of social media on individual investment decisions, encompassing the selection of stocks, funds, or other financial assets. It scrutinizes how information dissemination and communication channels on social media influence investor decision-making processes, along with the tangible impact of these decisions on financial outcomes.

3. Methodology.

3.1. Causal inference model.

The CI model is a method of analyzing observational data to identify causal relationships. Then, we divided N independent individuals into a treatment group and a control group, as shown in Equation (1). Let T_i denote whether individual i accepts the experimental treatment. It takes the value of 1 if the treatment is accepted and 0 otherwise. Then, let Y represent the outcome variable for individual i, where $Y_i(1)$ denotes the outcome when individual i receives the experimental treatment, and $Y_i(0)$ denotes the outcome when individual i does not receive the experimental treatment. In the experimental treatment, T serves as the causal factor for individual i:

$$CE(T \to Y) = Y_i(1) - Y_i(0) \tag{1}$$

A fundamental issue arises from the fact that for an individual i, either they receive the experimental treatment or they do not, making it impossible to simultaneously observe both $Y_i(1)$ and $Y_i(0)$. This implies that one of the potential experimental outcomes, either $Y_i(1)$ or $Y_i(0)$, becomes a factual observation for researchers, while the other becomes a counterfactual, forever unobservable. Consequently, the causal effect of the experimental treatment T on individual i cannot be directly obtained through observational experiments, forming the foundational problem of causal inference (FPCI) [29].

To obtain the causal effect of experimental treatment T on individual i, it is necessary to solve the FPCI problem. However, currently there are mainly two methods to bypass the FPCI problem.

The initial method must adhere to two fundamental assumptions:

(1) The time stability assumption, asserting that minor variations in experimental processing time will not influence the experimental outcomes.

(2) The lack of carryover effects, implying that the outcome of a particular experimental treatment remains unaffected by any preceding treatments. Only when these two experimental premises are concurrently satisfied, can one proceed with successive experimental treatments as if they were executed simultaneously.

The observed difference between $Y_i(1)$ and $Y_i(0)$ is the causal effect of experimental treatment T on individual i. Another commonly used method to avoid the FPCI problem needs to satisfy the homogeneity assumption of the experimental individual i. In this case, researchers perform two different experimental treatments on individual i, and treat the observation results of one group as virtual facts of the other group. It is worth noting that in practical applications, these assumptions are often not applicable.

Assuming the allocation mechanism determining whether individual i receives the experimental treatment is uncorrelated with their individual characteristics.

$$X \perp (Y(1), Y(0)) \tag{2}$$

Furthermore, assuming the stability of the unit experimental effect value to ensure the absence of mutual influence between individuals. The fully randomized experimental allocation mechanism represents the simplest negligible allocation mechanism. Under this premise, the average causal effect (ACE) of all experimental individuals is determined.

$$ACE = E(Y_i(1) - Y_i(0)) = E(Y_i(1)) - E(Y_i(0)) \tag{3}$$

In relinquishing the capacity to gauge the therapeutic impact on individual $\tau_i = Y_i(1) - Y_i(0)$, we pivot towards assessing the average causal effect across a cohort of individuals. Within this observation group, the average causal effect of the treated group (ACT) emerges.

$$ACT = E(Y(1) - Y(0) \mid T = 1) \tag{4}$$

Equation (4) quantifies the impact of causal effects on individuals. Due to

$$E(Y(1)) \neq E(Y(1) \mid T = 1) \tag{5}$$

and

$$E(Y(0)) \neq E(Y(0) \mid T = 1) \tag{6}$$

If the assumption of independence is valid, then ACE and ACT can be exchanged to some extent because causal conditions are independent. We can calculate ACT using Equation (7).

$$|E(Y(1) \mid T = 1) - E(Y(0) \mid T = 1)| \tag{7}$$

It is crucial to underscore that leveraging the average outcomes of analogous participants who have not undergone therapy is a viable strategy, particularly when the treatment process is entirely randomized. Then, using data from other topics instead of having to watch $Y_i(1)$ and $Y_i(0)$ from the same person. As a result, the treatment impact can be calculated by Equation (8).

$$ATE = ATT = E(Y \mid T = 1) - E(Y \mid T = 0) = \frac{1}{N_t} \sum_{i \in \{T=1\}} Y_i(1) - \frac{1}{N_c} \sum_{i \in \{T=0\}} Y_i(0) \tag{8}$$

Where N_t and N_c are the number of treated and control subjects, respectively.

In practical implementations, the observed data typically encompass both the treatment group and the control group, along with a set of variables. Our aim is to select a subset from the control pool for a specific treatment group, ensuring that the distribution of variables between the treatment group and the selected control group remains statistically unchanged.

$$\begin{aligned}\textbf{Assumption 1}: P(T, Y(0)|\mathbf{X}) = P(T|\mathbf{X})P(Y(0)|\mathbf{X}) \\ P(T, Y(1)|\mathbf{X}) = P(T|\mathbf{X})P(Y(1)|\mathbf{X})\end{aligned} \tag{9}$$

and

$$\textbf{Assumption 2}: \mathbf{0} < \mathbf{P}(T = 1|\mathbf{X} = x) < 1 \tag{10}$$

Under assumption 1, treatment allocation hinges on covariates and remains unaffected by outcomes. The primary objective of manipulating observational data is to mimic randomized experimental data, ensuring treatment allocation insignificance. Assumption 2, addressing overlapping or jointly supported concerns, constitutes a fundamental premise in the advancement of causal reasoning methodologies.

3.2. **Differential evolution algorithms (DEA).** An effective global optimization strategy is encapsulated within the framework of Differential Evolution, which operates as a group-based heuristic search technique. In this approach, each member of the group represents a potential solution vector. The operational methodology of the differential evolution algorithm unfolds as follows:

Step 1 Initialization: Assuming the solution space comprises NP individuals, denoting the population size, with each individual represented as a D-dimensional vector.

$$x_{i,j} = x_j^l + rand(0,1) * (x_j^u - x_j^l) \tag{11}$$

Where i and j represent the i-th individual and the j-th component, x_j^l represents the lower bound of the j-th component, and x_j^u represents the upper bound of the j-th component.

Step 2 Variation: The DEA executes differential operations to generate mutations by perturbing an existing vector with two distinct vectors from the population. Hence, the g-th generation comprises individuals with mutations:

$$v_i(g) = x_{r_1}(g) + F * (x_{r_2}(g) - x_{r_3}(g)) \tag{12}$$

Where $x_{r_1}(g)$, $x_{r_2}(g)$, and $x_{r_3}(g)$ are three randomly selected individuals from the current population who are different from each other. F is the variation factor. $v_i(g)$ is the mutated individual corresponding to the target individual $x_i(g)$.

Step 3 Cross connection: For each individual and its generated offspring mutation vector, crossover is executed. Precisely, for each component, the offspring mutation vector is chosen with a certain probability (otherwise, the original vector is retained) to yield the experimental individual.

$$u_{i,j}(g) = \begin{cases} v_{i,j}(g), & \text{if } rand(0,1) \le CR \text{ or } j = j_{rand} \\ x_{i,j}(g), & \text{otherwise} \end{cases} \tag{13}$$

Where j_{rand} is a random component and CR is the cross probability factor. This ensures that in the crossover test, the altered person provides at least one dimensional component.

Step 4 Selection: Based on the value of the fitness function, the DEA employs a greedy approach to select the superior individual from the target and experimental populations as the next generation.

$$x_i(g+1) = \begin{cases} u_i(g), & \text{if } f(u_i(g)) \leq f(x_i(g)) \\ x_i(g), & \text{otherwise} \end{cases} \tag{14}$$

The algorithm iterates repeatedly until it reaches the preset maximum number of iterations, or terminates when the overall optimal solution reaches the preset error accuracy.

3.3. **Improving computational efficiency.** The Differential Evolution Algorithm (DEA) stands as an optimization method that emulates the evolutionary processes observed in biological populations. Through mechanisms such as crossover, mutation, and selection, it iteratively enhances solution quality. Rooted in principles of biological evolution, this algorithm operates as a paradigm for optimization.

In the pursuit of refining causal reasoning models, Evolutionary Algorithms (EAs) offer a pathway towards identifying optimal model structures or parameters, thereby augmenting model fitting performance and computational efficiency. Initially, in [30], direct attempts to optimize the effectiveness of covariate balancing measures yielded limited success due to their inadequacy in handling increased numbers of covariates, posing challenges in achieving satisfactory matches. This underscores the necessity of exploring avenues to enhance the efficiency of optimization algorithms. Even the utilization of binning techniques to coarsen the data failed to mitigate computational and algorithmic inefficiencies.

Estimating the difference between two groups, t and c in an outcome variable, $Y_t - Y_c$.

Assuming that a single continuous random variable x determines the therapy. Let $f_g(x) > 0$ and the mean of x in group t and group c are

$$\mu_t = \int x f_t(x)\, dx \tag{15}$$

and

$$\mu_c = \int x f_c(x)\, dx \tag{16}$$

However, for x, only the value of the discrete variable $\bar{x}_j$ can be obtained through the Equation:

$$\bar{x}_j = \frac{\int_{j-1}^{j} x f_g(x) dx}{P_{gj}}, \quad j = 1, 2, \ldots, b \tag{17}$$

Where $P_{gj} = \int_{j-1}^{j} f_g(x) dx$. In the interval $[x_{max}, x_{min}]$, we divide it into b sub intervals of equal width. So, the width of each sub interval is

$$w = \frac{x_{max} - x_{min}}{b} \tag{18}$$

In Equation (17), $j_0 = x_{min}$, $j_b = x_{max}$, and $j_i = j_0 + iw$. If data is recorded in the form of Equation (17), the error $|\bar{x}_j - x_i|$ is bounded for each individual i, i.e., $0 < |\bar{x}_j - x_i| \leq \frac{w}{2}$.

When $b \to \infty$, Equation (19) can be obtained.

$$\lim_{b \to \infty} \frac{x_{max} - x_{min}}{2b} = 0 \tag{19}$$

Through DEA, the number of sub intervals can be expressed as

$$b = \sum_{i=1}^{C} w_i \Big(KS_i + |t_i| + \Big| \frac{\sigma_{ii}^2}{\sigma_i^2} - \frac{\sigma_{ci}^2}{\sigma_{ii}^2} \Big| \Big) \tag{20}$$

Where C, w_i, KS_i are the number of variables, weight, and the Kolmogorov–Smirnov statistic, and the variances for the treatment and control groups are shown by σ_i^2 and σ_c^2, respectively.

Weights serve a pivotal function in directing search procedures across solution space, particularly in areas less likely to be uniformly traversed. A larger weight intensifies the algorithm's efforts to balance significantly crucial factors with less vital covariates. By incorporating weights, the distribution of balance across all factors becomes more equitable, addressing challenges posed by certain covariates. Additionally, adjusting weights empowers the algorithm to explore specific regions of space more effectively, which might otherwise prove elusive to locate.

3.4. **Feedback.** By instituting user interaction and feedback mechanisms, profound insights into the requirements and anticipations of users pertaining to the intelligent financial sharing platform can be garnered, thereby augmenting our comprehension of platform usability and user engagement. Initially, we have orchestrated user surveys and feedback forms to solicit users' viewpoints and recommendations concerning platform functionalities, interfaces, and experiences. These feedback datasets are meticulously analyzed and organized to unveil users' requisites and concerns, and requisite measures for refinement are implemented to optimize platform design.

Subsequently, we actively encourage users to partake in the platform design process, exemplified by the facilitation of user experience testing and workshops. Through intimate collaboration with users, we consistently gather their feedback and suggestions to fine-tune platform functionalities, interaction designs, and interface layouts, thereby amplifying user experience and engagement. Furthermore, we offer real-time user feedback and support channels, such as online customer service and user communities, to afford users assistance and issue resolution around the clock. Through these initiatives, a deeper comprehension of users' requirements is attained, facilitating platform design enhancement, augmenting user satisfaction, and fortifying platform usability and user engagement.

4. Experimental results.

4.1. **Experimental preparation.** To authenticate the efficacy of the algorithm posited in this manuscript, experimental validation was undertaken utilizing a publicly accessible dataset derived from the financial platforms of pertinent enterprises. Rigorous measures were employed to ensure the robustness of the experiment, leveraging validated and audited financial institution reports, official statistical data, or publicly accessible financial market data. Stringent quality assessments and data cleansing protocols were implemented on the authentic financial data employed, aiming to obviate potential errors, anomalies, or data duplications, thereby ensuring a high standard of data integrity commensurate with the exigencies of research. To engender broader applicability, the dataset was stratified into categories representative of small, medium-sized, and large enterprises, each comprising 100 companies. The experimental framework encompassed the adoption of conventional deep learning methodologies (DL), causal inference techniques (CI), and causal inference methodologies predicated on differential evolution algorithms (CI-DEA).

4.2. **Performance index.** The evaluation of financial sharing platforms encompasses the scrutiny of diverse indicators spanning user experience, efficiency, security, and more. Below are several metrics that can be employed to assess these platforms:

Two pivotal indicators utilized in the appraisal of financial sharing platforms are the fund utilization rate and the return rate. These metrics gauge the efficacy of investment and fund allocation. The fund utilization rate and return rate are determined by the following formulas, respectively.

$$Utilization\ rate = \frac{\text{Actual profit}}{\text{Invested capital}} \times 100\% \tag{21}$$

and

$$Return\ rate = \frac{\text{Final asset value} - \text{Initial asset value}}{\text{Invested capital}} \times 100\% \tag{22}$$

These two metrics are commonly utilized in tandem, with the fund utilization rate focusing on investment efficiency and generated profits, while the return rate emphasizes overall asset appreciation. Considering both indicators provides a more comprehensive evaluation of investment performance and fund allocation strategies for users of financial sharing platforms.

Node overload pertains to the frequency with which a specific node, such as a server or processing unit, fails to process requests adequately due to excessive load within financial sharing platforms or other network systems. This metric holds significance in assessing system stability and scalability. The count of node overloads reflects instances where a node surpasses its capacity within a defined timeframe, resulting in delayed or disrupted request processing. Elevated node overload may signify inadequate system capacity, load imbalances, or performance discrepancies. Excessive node overload can precipitate system performance deterioration, heightened response latency, and potentially, system crashes. Hence, monitoring and mitigating the occurrence of node overloads can enhance system stability and availability.

4.3. **Results.** Initially, we validated the discrepancy between the observed data and the actual data across various sub-interval numbers b, as depicted in Figure 1.

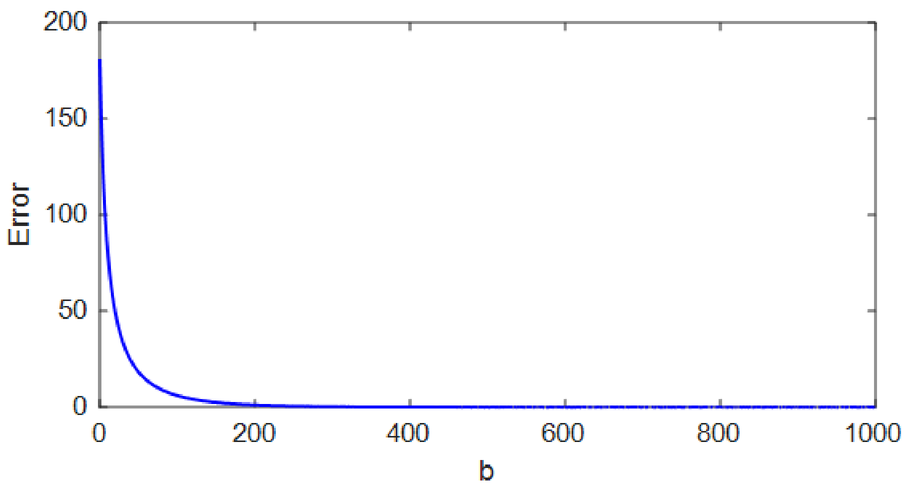

Figure 1. Error results for different sub-intervals b

From the visualization in Figure 1, it becomes apparent that with an increasing number of sub-intervals b, the observational error gradually approaches zero.

Figure 2 illustrates the iterative convergence speed graphs across various methods. It is evident that the CI-DEA method, proposed in this study, exhibits a swifter convergence compared to the traditional CI method. This accelerated convergence is attributed to the continual adjustment of weights during the learning phase of the CI-DEA method,

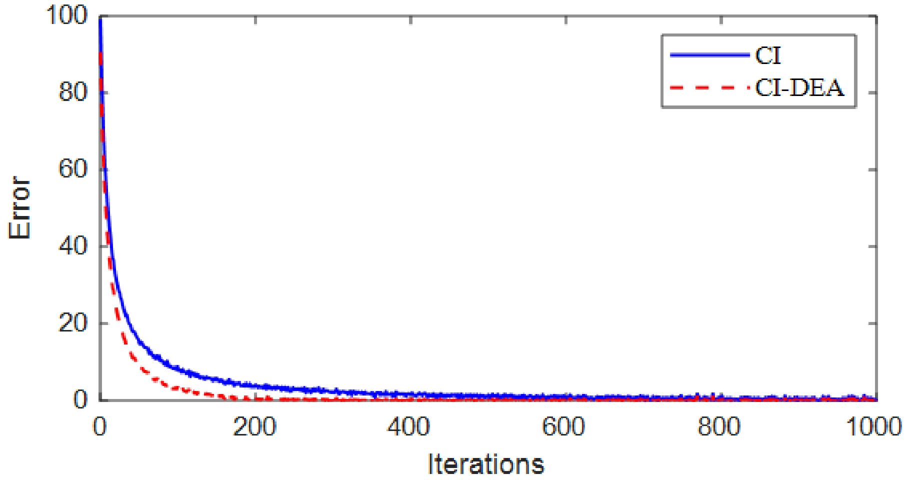

Figure 2. The convergence process of lower iterations using different methods

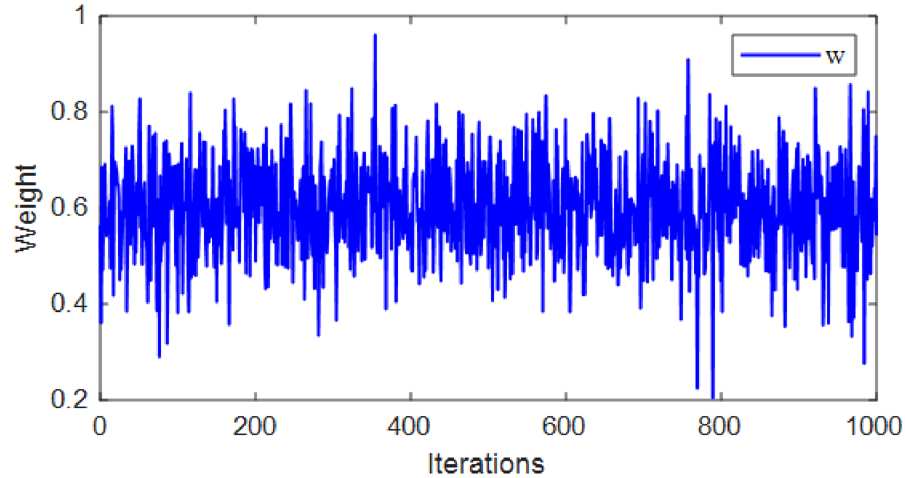

Figure 3. The trajectory of weight changes during the iteration process of the proposed algorithm

facilitating expedited attainment of optimal values. The process of weight adjustment is delineated in Figure 3.

Figures 4 through 6 present the utilization rate and return rate of various company types, respectively. It is apparent that the CI-DEA method proposed in this study outperforms traditional RL and CI methods. The proposed approach exhibits superior performance, facilitating expedited fund recovery and yielding higher returns.

Figure 7 illustrates the count of overloaded nodes for different types of companies. It is evident from the graph that the algorithm introduced in this paper has enhanced the computational efficiency of the system. This improvement can be attributed to the incorporation of the differential evolution algorithm, resulting in fewer overloaded nodes and greater robustness of the system.

4.4. **Discussion and computational complexity analysis.**

4.4.1. *Discussion.* Observation Error Convergence: The data depicted in Figure 1 indicates that as the number of sub-intervals (b) increases, the observation error gradually converges to zero. This trend suggests that augmenting the number of sub-intervals in

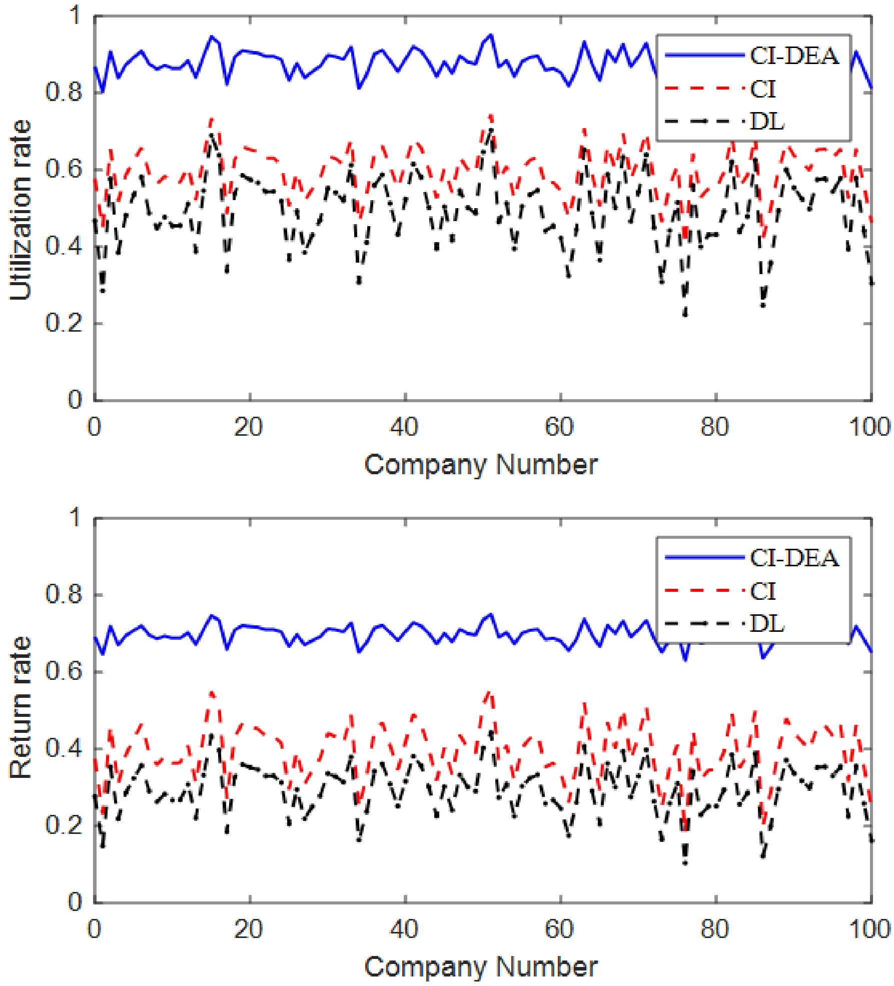

Figure 4. Utilization rate and return rate under small companies

the proposed algorithm enhances the precision of observations, thereby refining the algorithm's ability to estimate the system's state accurately.

Iterative Convergence Speed: Figure 2 showcases the iterative convergence speed across various methods. Notably, the CI-DEA method proposed in this study exhibits a swifter convergence compared to the traditional CI method. This accelerated convergence can be attributed to the continual adjustment of weights during the learning process in the CI-DEA method, facilitating more rapid attainment of optimal values. The trajectory of weight adjustments is delineated in Figure 3.

Utilization Rate and Return Rate for Small and Large Companies: Figures 4 to 6 present the utilization rate and return rate of different types of companies. It is evident that, in contrast to traditional RL and CI methods, the CI-DEA method proposed in this article showcases superior performance by expediting fund recovery and achieving higher returns.

Number of Overloaded Nodes for Different Types of Companies: Figure 7 illustrates the number of overloaded nodes for different company types. The incorporation of the differential evolution algorithm in the proposed algorithm enhances the computational efficiency of the system, resulting in fewer overloaded nodes and bolstering the system's robustness.

Overall Evaluation: The experimental results highlight the promising performance of the CI-DEA method proposed in this paper. Notably, it reduces observation errors,

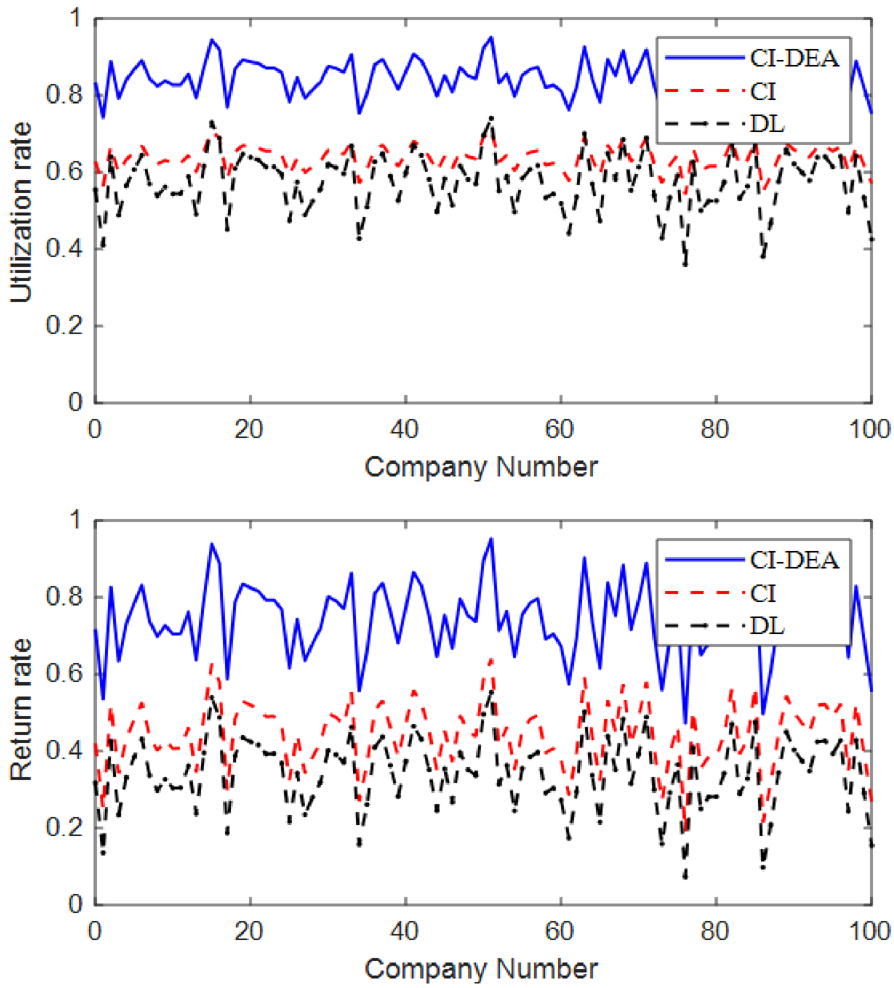

Figure 5. Utilization rate and return rate under large companies

enhances iterative convergence speed, optimizes utilization rate and return rate for small and large companies, and diminishes the number of overloaded nodes. This underscores the efficacy of integrating CI and the differential evolution algorithm in the design of intelligent financial sharing platforms. Future endeavors may entail further parameter optimization, broader experimentation, and the consideration of additional real-world scenarios.

4.4.2. *Computational complexity analysis.* The quantitative assessment of algorithmic performance through computational complexity analysis elucidates the relationship between algorithm runtime and input size, particularly in the context of developing an intelligent financial sharing platform grounded in CI and the differential evolution algorithm.

The computational complexity of CI algorithms encompasses several stages, including processing observed data, formulating causal models, intervening, and evaluating causal effects. The specific computational complexity varies depending on the chosen CI method, with some exhibiting polynomial time complexity. However, practical applications may introduce variability influenced by factors such as sample size and model complexity.

Regarding the computational complexity of the differential evolution algorithm, as a global optimization technique, it primarily depends on factors such as population size, the number of iterations, dimensionality of the problem, and the computation of the fitness

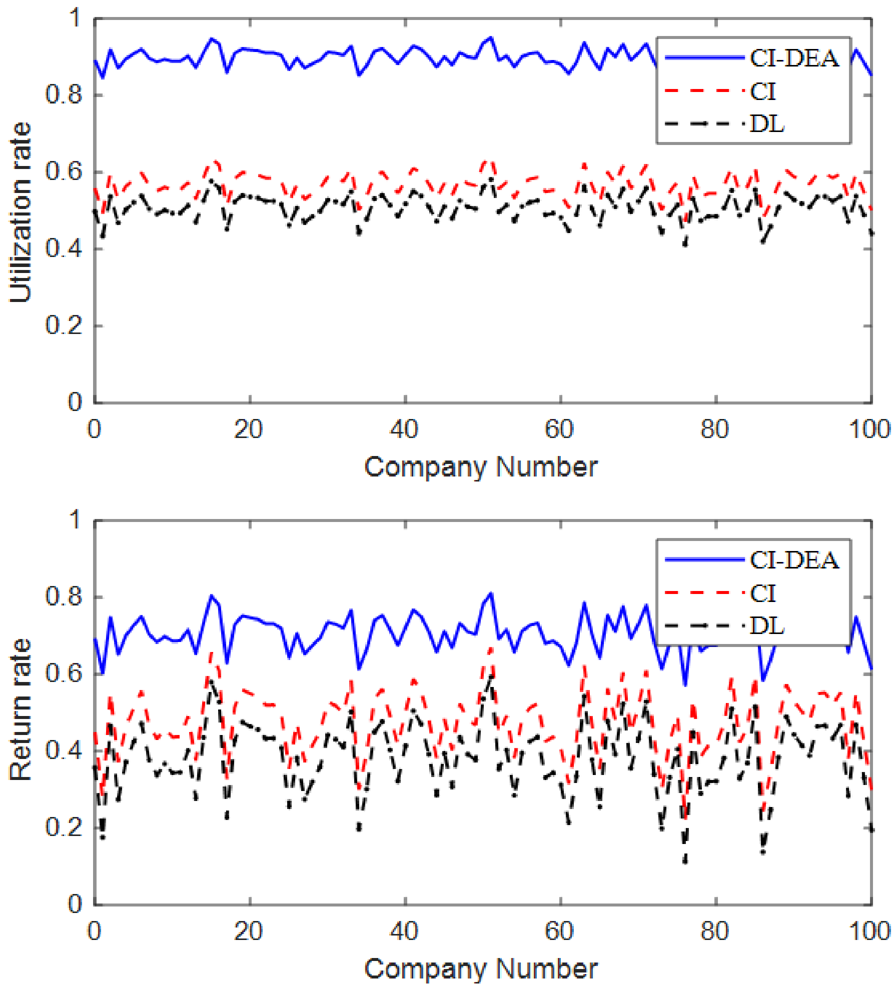

Figure 6. Utilization rate and return rate under large companies

function. Typically falling within the spectrum between polynomial and exponential time, differential evolution algorithms can often yield proficient solutions within a relatively short timeframe for select problems. In the overarching design of the intelligent financial sharing platform, CI algorithms and differential evolution algorithms may interact and collaborate. This interaction could entail using CI to refine the parameters of differential evolution algorithms or guide the evolution process.

4.5. **Advantages of the proposed method.** Through a comparative analysis, the platform reveals competitive advantages across various dimensions. Firstly, in terms of fund allocation efficiency, the intelligent financial sharing platform proposed in this article stands out. Unlike traditional methods, it integrates EA and CI. This amalgamation enables the platform to optimize fund allocation with greater precision, ensuring optimal utilization of funds. Consequently, this enhances the efficiency of fund allocation, addressing a critical aspect of financial management.

Moreover, the platform excels in risk management, a pivotal aspect of financial decision-making. Utilizing causal reasoning methods, it identifies causal relationships between financial transactions. This functionality empowers users to gain deeper insights into the consequences of their decisions on financial outcomes. By enhancing users' understanding of risks associated with various decisions, the platform effectively mitigates risks and elevates the overall level of risk management.

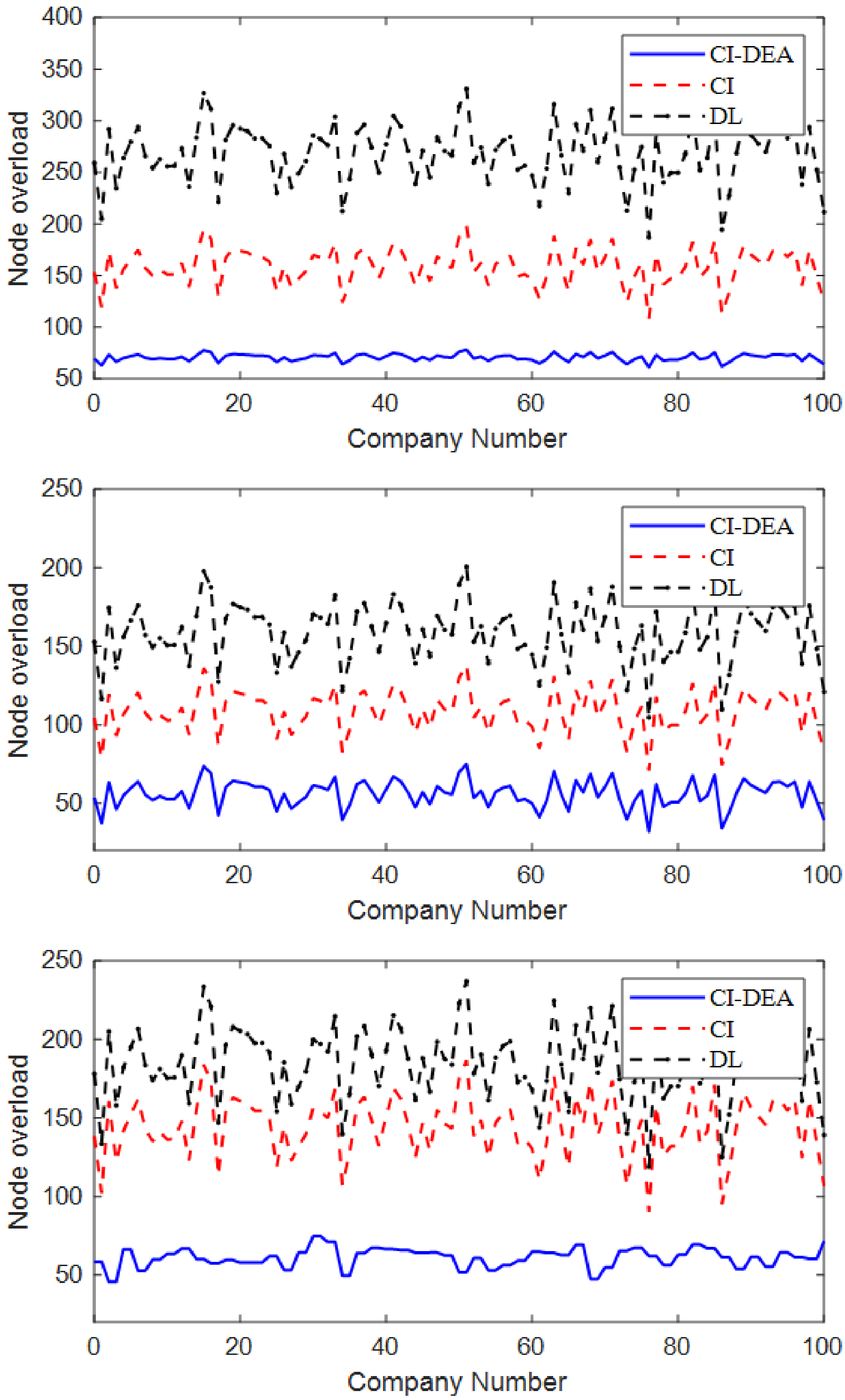

Figure 7. The number of overloaded nodes for different types of companies

Furthermore, the platform offers robust decision support mechanisms, augmenting users' decision-making capabilities. Through the integration of causal reasoning and EAs, it provides users with personalized financial advice and facilitates optimized decision-making processes. This intelligent decision support empowers users to make informed and strategic financial decisions, contributing to their financial well-being and success.

Overall, these competitive advantages underscore the significance of the platform in revolutionizing financial management practices.

5. **Conclusions.** The primary research focus of this article centers on the design of an intelligent financial sharing platform. Central to this design is the utilization of a fusion of causal reasoning methods and differential evolution algorithms. This combination aims to fully exploit the profound analytical capabilities and global optimization features inherent in causal relationships. Causal reasoning methods are instrumental in enhancing our comprehension of the causal impact of diverse decisions on financial outcomes. Conversely, EA excel in navigating complex decision spaces to identify optimal solutions. By integrating these approaches, the financial sharing platform not only enhances its capacity to deliver precise personalized services but also augments its ability to furnish intelligent financial advice. This integration facilitates the optimization of decision-making effectiveness, thereby furnishing users with superior-quality and dependable financial decision support.

6. **Future work.** In future endeavors, our focus will primarily revolve around the following areas:

(1) Incorporating elements of user participation entails a continuous refinement of CI models and differential evolution algorithms by integrating user feedback and behavioral data. Leveraging subjective user feedback and real user experiences will facilitate the optimization of the platform's personalized services, ultimately enhancing user satisfaction.

(2) Strengthening the platform's design concerning user data privacy protection and information security is imperative. Adopting advanced privacy protection technologies will ensure the security of user data, fostering trust among users towards the platform. This commitment to privacy and security is essential for maintaining user confidence and sustaining long-term engagement.

(3) Enhancing the interpretability of CI models and differential evolution algorithms is paramount. Improving the transparency and understandability of platform decisions will foster closer relationships between users and the platform. By providing insights into the decision-making process, users can better comprehend and trust the platform's recommendations, thereby deepening their engagement and loyalty.

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