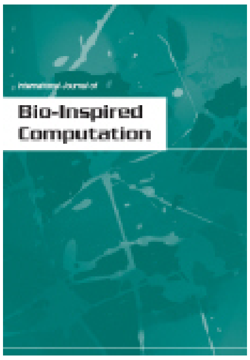

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A knapsack modelling approach to financial resource allocation problem using a dual search pattern firefly algorithm

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Abstract: The knapsack problem, a paradigm for constrained optimisation, underpins decision-making under scarcity in finance, logistics, and cognitive science. While classical methods (e.g., dynamic programming) handle small instances, real-world complexity demands metaheuristics like the firefly algorithm (FA), which balances exploration-exploitation trade-offs in dynamic, multi-objective scenarios (e.g., ethical resource allocation). Hybrid FA approaches integrating machine learning improve adaptability in noisy environments. Financial applications, however, lack frameworks addressing real-time responsiveness, ethical-risk synergies, and transparency. This study proposes a dual search pattern firefly algorithm based on Gaussian distribution and Lévy flights (DSPFA) for financial resource allocation, dynamically adapting to macroeconomic shifts, harmonising risk-return objectives with ethical imperatives (e.g., ESG criteria), and ensuring auditable decision pathways. Simulations demonstrate efficient optimisation of heterogeneous constraints (liquidity, compliance) with sublinear time complexity. By embedding fairness metrics and leveraging FA's global-local equilibrium, the framework advances ethical finance and portfolio management. Results highlight FA's scalability in evolving financial ecosystems and the knapsack model's versatility in modelling multidimensional trade-offs. This work bridges theoretical optimisation with practical challenges, offering stakeholders a tool for transparent, adaptive allocation under uncertainty.

Keywords: knapsack model; metaheuristics; dual search pattern firefly algorithm; financial resource allocation.

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1 Introduction

Maintaining financial stability is a key goal of macro monetary policy and central banks. While macro targets such as inflation mainly influence business decisions (Goodhart, 2006), financial stability research often focuses on banking issues (Berger et al., 2017; Bengtsson, 2013; Krainer, 2017). Bank failures are central to this discussion, as they directly affect capital markets (Kaufman, 1994), corporate financing (Demirgüç-Kunt, 1989), and can trigger depositor and investor panic (Calomiris and Mason, 2003, 1997), further undermining the banking sector. Therefore, assessing bank health and predicting failures is a major research task. Common approaches include the z-score method (Lepetit and Strobel, 2015; Almamy et al., 2016; Gerantonis et al., 2009) and logit regression (Martin, 1977; Chen et al., 2017; Kolari et al., 2002), both proven effective in explaining bank failures and financial stability in various contexts (Gerantonis et al., 2009; Caggiano et al., 2014; Filippopoulou et al., 2020; Elia et al., 2021).

Despite methodological advances, financial crises remain persistent. The October 19, 1987 'Black Monday' saw global stock markets fall 22.6% in one day, raising awareness of market risks despite no ensuing recession. Predicting and preventing crises has since become central to financial stability research, prompting regulations such as Basel I (1988), followed by Basel II and III after the 2000 Dot-Com Bubble and 2007–08 global financial crisis. Research focus shifted from individual banks to system-wide stability. Bank equity has long been a key health indicator (Oosterloo et al., 2007; Vallascas and Keasey, 2012), while CAMELS offers a more balanced assessment but remains debated in effectiveness.

Since the 2007–08 global financial crisis and the collapse of Lehman Brothers, systemic risk measurement has become a key focus in financial stability research (Billio et al., 2012; Acemoglu et al., 2015). Studies show that inefficient resource allocation exacerbates systemic risk; for example, geographic distribution significantly affects banking sector risk (Chu et al., 2020). Government aid programs such as TARP, designed to stabilise the system, remain debated in effectiveness (Bayazitova and Shivdasani, 2012). Critics argue that the 'too systemically important to fail' approach (Bongini et al., 2015) ensured funding for large banks regardless of risk (Duchin and Sosyura, 2012), while neglecting those in genuine need, leading to persistent inefficiencies.

This study builds on Xiao and Chen (2024) to develop a macro-level framework for enhancing financial stability through optimised financial resource allocation. Treating the banking sector as a whole portfolio, with each bank as an investment option, the framework enables policymakers to assess current allocation patterns and distribute new government aid more effectively. Simulation results can generate a priority ranking of banks based on individual profiles and the systemic risk capacity of the banking system. We assume the system collapses if total systemic risk exceeds a threshold; below this threshold, aid should be allocated according to profitability-based rankings. This approach aims to prevent systemic collapse while improving overall profitability and efficiency. To achieve this, we employ a multi-objective firefly algorithm (FA).

This research advances the literature by expanding the assessment of individual bank performance to include their impact on systemic risk and overall banking sector stability. While previous studies focus on profitability, efficiency, and bank-level risk, this study evaluates contributions to system-level risk capacity. By combining financial engineering, machine learning, and traditional financial theory, it provides a novel interdisciplinary approach to measure systemic risk and its link to bank profitability, enabling more efficient resource allocation without increasing systemic vulnerability. The framework also offers policymakers a practical tool to design regulations, prioritise bank bailouts, and stabilise banking systems under distress.

The paper proceeds as follows: Section 2 formalises the multi-constraint financial knapsack problem, Section 3 elucidates the FA-driven optimisation mechanics, Section 4 shows the experiment results, and Section 5 concludes.

2 Related works

2.1 The theory of financial resource allocation

Financial resource allocation (FRA) is the strategic distribution of capital, assets, and investments to maximise economic value (Holcomb and Hitt, 2007). Grounded in theories such as the Modigliani and Miller (1958) capital structure irrelevance proposition and agency theory (Meckling and Jensen, 1976), it focuses on optimising deployment under constraints like risk, liquidity, and asymmetric information. While early research used static models, recent approaches incorporate dynamic optimisation (Brealey et al., 2020), behavioural finance (Thaler, 2018), and machine learning (Bussmann et al., 2021). Current debates address balancing short-term profitability with long-term sustainability (Eccles et al., 2014), particularly amid market frictions and regulation. The rise of ESG criteria has further shifted priorities toward aligning financial decisions with stakeholder capitalism (Friede et al., 2015).

Efficient resource allocation is vital to firm performance, with studies linking capital budgeting accuracy to metrics like ROA and Tobin's Q. In East Asia, firms with strong governance and transparent allocation outperformed peers during crises (Claessens et al., 2002). Allocating excess cash to value-enhancing projects yielded 50% higher shareholder returns than hoarding liquidity (Dittmar and Mahrt-Smith, 2007). Digital tools further improve efficiency, as AI-driven systems cut operational waste by 12–15% in Fortune 500 firms, boosting margins (Brynjolfsson et al., 2021). In contrast, CEO overconfidence can misallocate resources and reduce firm value by up to 20% (Malmendier and Tate, 2005).

At the macroeconomic level, financial resource allocation influences growth, stability, and inequality. Efficient allocation to high-productivity sectors promotes long-term GDP growth (Levine, 2005; Beck et al., 2000), as seen in China's post-2008 targeted credit to strategic industries, which boosted industrial output by 6.2% annually (Song et al., 2011). Conversely, misallocation can trigger crises, such as the 2008 Global Financial Crisis linked to speculative real estate (Reinhart and Rogoff, 2009) and emerging-market defaults tied to mispriced sovereign debt risk (Greenwood et al., 2022). Central banks address these risks with macroprudential tools like capital buffers and sectoral lending caps (Borio, 2014). Recent studies highlight allocation for sustainable transitions, estimating that redirecting 2% of global financial flows to green infrastructure could cut carbon emissions by 40% by 2030 (Stern and Valero, 2021). Cryptocurrency markets further present decentralised allocation models challenging traditional intermediaries (Cong et al., 2021a).

2.2 Financial resource allocation theory in the banking sector

FRA theory guides banks in balancing risk–return trade-offs, traditionally prioritising capital allocation to maximise shareholder value under risk constraints via tools like value-at-risk (VaR) and Basel accord mandates (McNamara et al., 2019). Early models assume rational actors, frictionless markets, and static risk parameters, assumptions misaligned with real-world banking (Danielsson et al., 2016). Basel III's risk-weighted asset (RWA) framework is criticised for procyclicality, encouraging capital hoarding in downturns (Adrian and Shin, 2010). VaR models often miss non-linear and tail risks, as seen in the 2008 crisis when correlated defaults undermined Gaussian assumptions (Taleb, 2007). Behavioural biases, including herding, further distort allocation decisions beyond neoclassical models (Gennaioli et al., 2012).

Research on banking sector risk evaluation has shifted toward macroprudential regulation post-crisis. Borio (2014) supports countercyclical capital buffers, though implementation varies across countries (Cerutti et al., 2017). Stress tests have improved but remain backward-looking, overlooking forward risks like climate change. Machine learning (ML) and big data offer better risk modelling – ML outperforms traditional methods in predicting loan defaults using non-linear predictors (Bussmann et al., 2021) – yet adoption is limited by 'black box' opacity and regulatory concerns. Climate-related risks are increasingly recognised; 'climate value-at-risk' (CVaR) estimates show 60% of EU bank loan portfolios face stranding risk by 2030 (Battiston et al., 2017). Current FRA frameworks still lack standardised metrics to price these externalities (Bolton et al., 2020).

However, contemporary research highlights the limits of conventional FRA models in addressing modern banking risks. Despite high interconnectivity, models treat banks as isolated, underestimating interbank contagion risks amplified by derivatives (Aikman et al., 2019), with network theory still rarely applied. FRA's emphasis on quarterly earnings also discourages long-term resilience; banks underinvest in areas like cybersecurity and ESG despite growing threats, and only 12% of S&P 500 banks disclose climate risk mitigation (Kay, 2019). The rise of shadow banking, now 45% of global financial assets, further exposes gaps, as traditional models overlook non-bank intermediaries' role in systemic risk, illustrated by the 2021 Archegos capital collapse (Avdjiev et al., 2022).

Literature identifies financial resource allocation as central to both micro- and macroeconomic efficiency. While computational finance and ESG integration offer new tools, challenges remain in managing behavioural biases, geopolitical risks, and sustainability trade-offs. Future research directions include AI ethics, global governance, and climate finance, with proposals using financial engineering and machine learning. Farmer and Foley (2009) advocate dynamic, adaptive models integrating agent-based simulations for real-time market feedback, while Cong et al. (2021b) propose a DeFi risk measure to assess blockchain-driven banking's destabilising potential.

2.3 Analytical methods in firefly algorithm

The FA has been widely applied to solve practical problems due to its strong global search capability (2019) and has attracted the attention of researchers. For example, Wang et al. (2016) proposed an improved FA by introducing a random attraction mechanism and Cauchy jump strategy, effectively enhancing the global search ability and reducing computational complexity. Subsequently, researchers further proposed an improved algorithm based on neighbourhood attraction in 2017 (Wang et al., 2017), which limits each individual to be attracted only by brighter individuals within its neighbourhood, thereby reducing oscillations caused by global attraction. In addition, the research team also proposed a dynamic FA and applied it to water demand estimation in Nanchang City, China in 2018. This method employs a dynamic parameter strategy to avoid manual adjustment of the step size; constructs linear, exponential, and hybrid estimation models; and uses normalisation to eliminate the influence of different data units, significantly improving the model's adaptability and prediction ability. At the same time, they (2020) also used the FA to optimise parameters of the density peaks clustering algorithm to enhance clustering performance.

Given the superior performance of the FA in single-objective optimisation, researchers have extended it to the field of multi-objective optimisation and conducted in-depth studies. Wang et al. (2018a, 2018b) proposed a hybrid multi-objective FA for big data optimisation, addressing the challenges faced by traditional algorithms in handling large-scale variables. Zhao et al. (2022) improved the balance between convergence and diversity by enhancing the initial population generation and hybrid learning strategies, combined with a crowding distance mechanism. Zhao et al. (2023) further enhanced the algorithm's overall performance by adopting adaptive region division, partitioned learning strategies, and a fusion index. Wang et al. (2025) proposed TaMaOFA based on a two-archive mechanism, designing convergence- and diversity-biased search strategies combined with a random attraction model to improve efficiency and effectiveness in high-dimensional multi-objective optimisation. These improvements have laid a solid foundation for solving multi-objective financial optimisation models.

3 The knapsack framework and finance application

3.1 Knapsack model application in portfolio optimisation

The knapsack model application in finance focuses on the portfolio optimisation; that is, maximising a separable certainty-equivalent objective function.

If X_i denotes the fraction of available wealth invested in security i and if CE_i denotes the certainty-equivalent return of stock i, then the basic certainty-equivalent linear program (LP) is as follows.

$$\begin{aligned} maximize: & \sum_{i=1}^{N} X_i CE_i \\ s.t.: & \sum_{i=1}^{N} X_i \le 1 \\ & 0 \le X_i \le F_i \end{aligned} \tag{1}$$

where N is the number of available securities and F_i is the maximum fraction of the portfolio that can be invested in security i.

Within the framework of the linear market-index model, Sharpe (1977) uses beta to characterise risk so that the certainty-equivalent is $CE_i \equiv R_i – \theta\beta_i$, where R_i is expected return, β_i is beta (systematic risk), and θ is a rate of required compensation for systematic risk.

In extending the formulation, Stone (1973) shows:

- that terms reflecting nonsystematic variance and skewness can be added to the certainty-equivalent to extend its applicability
- that piece-wise linear approximations enable one to obtain an arbitrarily accurate approximation to the associated nonlinear program.

To formulate the basic one-stage revision model, let P_i and S_i denote respectively the dollar amounts purchased and sold of security i; let CP_i and CS_i denote respectively the transaction costs per dollar for purchases and sales of security i; let Q_{i0} denote the initial dollar holding of security i before the portfolio is revised; and let $\sum_{i=1}^{N} Q_{i0} = V_0$ denote the total value of the portfolio before revision. The one-stage portfolio revision problem is to maximise:

$$\begin{aligned} & \sum_{i=1}^{N} (CE_i - CP_i) P_i - \sum_{i=1}^{N} (CE_i + CS_i) S_i \\ s.t.: & \sum_{i=1}^{N} P_i (1 + CP_i) - \sum_{i=1}^{N} S_i (1 - CS_i) = 0 \\ & S_i \le Q_{i0} \\ & P_i \le F_i V_0 - Q_{i0} \\ & S_i \ge 0; P_i \ge 0 \end{aligned} \tag{2}$$

If let $PACE_i = CE_i – CP_i$ and $SACE_i = CE_i + CS_i$ denote the purchase-cost and sales-cost adjusted certainty-equivalents, respectively. Then, the objective function can be rewritten as:

$$maximize: \sum_{i=1}^{N} PACE_i P_i - SACE_i S_i \tag{3}$$

The objective function will be improved by selling stock J and buying stock K only if $PACE_K > SACE_J$.

3.2 Multi-objective knapsack model application in portfolio optimisation

The core of financial stability is the adequacy of equity, while share prices are the primary concern of public companies. Hence, we choose capital ratio and share price as the two objectives of our algorithm. Our model can be defined as follows:

$$Maximize\begin{cases} v\left(R_p\right)=\sum_{i=1}^{n} SharePrice_i w_i \\ v(R_e)=\sum_{i=1}^{n} EquityRatio_i w_i \end{cases} \tag{4}$$

$$s.t.: \sum_{i=1}^{N} Individual\ Systemic\ Risk \leq_i W \tag{5}$$

3.3 Variables

3.3.1 Systemic risk measurement (w_i)

There are three widely used systemic risk measurements in the literature. Acharya et al. (2017) proposes the SRISK measurement to estimate the capital shortfall of bank *i* under macroeconomic stress. Tobias and Brunnermeier (2016) uses the $\Delta COVaR$ to measure the marginal contribution to system-wide value-at-risk of bank *i*. Furthermore, the network centrality computes bank *i*'s centrality within an interbank exposure network to capture its role in contagion pathways. We employ the $\Delta COVaR$ as the weight and capacity in this research because it allows us to model the total of bank sector weight by aggregating all individual systemic risks.

3.3.2 Objective Metric (v_i)

We employ a wide range of profitability to test the robustness of the algorithm. The profitability measures include stock price, return on equity (ROE), and net income. We use stock price as the profitability indicator. Meanwhile, we use the equity ratio as the capital adequacy ratio as the second objective.

3.3.3 Systemic risk threshold (W)

The regulatory threshold *W* is calibrated using historical crisis data during the 2008 Global Financial Crisis to reflect the maximum aggregate systemic risk the financial system can absorb without triggering cascading defaults.

3.4 Solving the knapsack model

Algorithms for solving knapsack problems are generally divided into two categories. One is the exact algorithm, such as dynamic programming, backtracking and branch bound method. The other one is non-exact heuristic algorithm, which is also called metaheuristic algorithm if the heuristic algorithm is universal. Because knapsack problem is a class of NP-hard problems, there exists combinatorial explosion phenomenon with computation. Hence, the heuristic algorithm is applied to solve knapsack problems, or intelligent optimisation algorithm.

This research employs the FA, which belongs to swam intelligence-based approach. This algorithm is inspired by the flashing behaviour of fireflies and developed by Yang (2009), and it simulates the flashing patterns of fireflies to search for optimal solutions to optimisation problems. The reason of choosing this algorithm is that it is a simple and powerful optimisation technique suitable for addressing a wide range of complex optimisation problems. It has the advantage of easy to implement, making it a commonly used particularly in handling complex, multimodal optimisation problems.

Building on existing models, we propose an improved knapsack model and a new FA incorporating reverse learning and Levy flight. By comparing the fitness of two fireflies, the algorithm establishes dominance relationships and selects search modes accordingly. Dominant fireflies focus on solutions near the Pareto frontier, guided by dynamic reverse learning that combines the individual's reverse solution with the global optimum to enhance convergence. Non-dominant fireflies aim for a uniformly distributed frontier, using a search mode that combines the global optimum with Levy disturbance, leveraging non-dominated solutions to prevent stagnation, maintain distribution, and improve convergence.

4 Dual search pattern firefly algorithm based on Gaussian distribution and Lévy flights

4.1 The firefly algorithm

Proposed by Yang (2009), FA is a new group intelligence optimisation algorithm that is inspired by the natural luminous behaviour of fireflies. The algorithm simulates the mutual attraction phenomenon between fireflies due to differences in brightness to achieve the co-evolution of the group. The procedure is as follows. During the search process, any two fireflies will produce attraction according to the brightness, and fireflies with weaker brightness will approach towards closer to fireflies with stronger brightness, with the location coordinates to be updated. As fireflies with the strongest brightness are not influenced by other individuals due to the current optimal location, so the position of will be updated by random perturbation to maintain the diversity and global search capability of the algorithm.

The attractiveness function (β) between individual firefly *i* and *j* is defined as:

$$\beta_{ij}(r)=\beta_0 \exp\left(-\gamma r_{ij}\right) \tag{6}$$

where β_0 represents the initial attractiveness between firefly individuals and determines the upper limit of attraction strength within the population. It has a direct impact on the convergence speed and global search ability of the algorithm. When $\beta_0$is set to a smaller value (e.g., 0.2), the attraction strength is weak, which may lead to slower convergence. When β_0 is set to a larger value (e.g., 2), the attraction strength is strong, which may accelerate convergence but can also cause the algorithm to fall into local optima. Setting $\beta_0$to 1 helps achieve a good balance between attraction strength and search capability.

γ determines the rate at which the attractiveness decays with distance. A larger value of γ causes the attractiveness to decay faster, thereby enhancing local search ability; conversely, a smaller value is beneficial for improving global search capability. When γ is set to 0.1 and used in combination with $\beta_0 = 1$, a good balance can be achieved between the attraction range and attraction strength. Under this parameter setting, individuals can still maintain effective mutual attraction within an appropriate distance, which helps the population continuously co-evolve in the search space, while avoiding unclear search directions caused by an overly large attraction range. This improves the overall search efficiency and stability of the algorithm.

r_{ij} is the distance, defined as:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{d \in D} \left(x_{i,d} - x_{j,d}\right)^2} \tag{7}$$

where D is the dimension of the problem and $x_{i,d}$ is the d^{th} component of the i^{th} firefly (x_i).

The movement of a firefly i to another more attractive (brighter) firefly j is defined as follows:

$$x_i^{t+1} = x_i^t + \beta_0 exp\left(-\gamma \left(r_{ij}{}^t\right)^2\right)\left(x_j^t - x_i^t\right) + \phi\xi_i \tag{8}$$

where the step size factor ϕ controls the movement amplitude of individuals during the position update process, and its value has a significant impact on the search behaviour of the algorithm. When ϕ is set too large, individuals move too far in the search space, which may cause them to skip potential high-quality regions and lead to unstable search. When ϕ is too small, individuals move slowly and may repeatedly search within local areas, affecting convergence speed and optimisation efficiency. In this paper, ϕ is set to 1. This setting not only ensures that individuals have sufficient search capability to cover a wide solution space and enhances the algorithm's ability to escape local optima, but also maintains sufficient exploration around high-quality solutions, improving the solution accuracy and overall convergence quality. ξ_i is a vector of random numbers with Gaussian or uniform distributions in [0, 1] and t is the iteration number.

If individual firefly i is not influenced by other individuals, the location is updated as below:

$$x_i^{t+1} = g_i^* + \phi\xi_i \tag{9}$$

where g_i^* is the optimal value obtained by converting multiple objective functions into a single objective function in a random weighted sum.

4.2 Search patterns based on Gaussian distribution strategies

During the optimisation search process, the dominated individual is often far away from the optimal solution set, which may deviate from the current potential high-quality region and affect the optimisation efficiency if a large step size or strong perturbation strategy is used. Moreover, in the process of approaching the nondominated frontier, the dominated individual needs to be fine-tuned with high precision to avoid the direction deviation brought by violent jumps, which may damage the existing dominant direction. The Gaussian distribution, with the characteristic of 'most small perturbations + a few large perturbations', is suitable for performing local search around the current solution, which can improve the ability of local development, enhance the adaptability of the dominated individual, and make it easier for it to break through the dominant relationship and gradually approach the Pareto frontier. Its position update formula is:

$$x_i^{t+1} = x_i^t + \beta_{ija}\tau\left(x_j^t - x_i^t\right) \tag{10}$$

where $\tau \sim N(0, 1)$

4.3 Search pattern based on Lévy's flight strategy

The fireflies with the highest nondominant rank are closest to the optimal solution set, and the individuals are extremely similar to each other. As the iteration progresses, the individuals with higher similarity will gather in a certain area, so that the individuals with higher quality will reduce the ability to explore new areas, which is easy to lead to a significant decline in the diversity of the population, and further exacerbate the risk of falling into the local optimum. The introduction of the Levy flight mechanism, which guides fireflies with higher nondominant rank to jump out of the current local optimal region and spread to the distal region in the global search space through irregular large-step perturbation, can effectively break the high similarity between individuals, enhance the exploration ability of high-quality individuals to the unexplored region, and make up for the problem that the search range of traditional FAs is limited in the later iterations. In order to avoid the search direction deviating from the optimal region, while the individuals are moved by the individuals' attraction, the individuals are guided to learn from the optimal solution in the current population, so as to further enhance the guidance of the search direction and the quality of the solution while enhancing the global exploration ability, and to realise the effective integration of the local exploitation and the global jump.

The random pace distance of Lévy's flight is shown as:

$$S_i = \frac{\mu}{|\upsilon|^{\frac{1}{\varphi}}} \tag{11}$$

where μ and υ follow normal distribution as below:

$$\begin{cases} \mu \sim N\left(0, \sigma_\upsilon^2\right) \\ \upsilon \sim N\left(0, \sigma_\mu^2\right) \end{cases} \tag{12}$$

σ_μ and σ_υ are shown as below:

$$\begin{cases} \sigma_\mu = \left(\dfrac{\Gamma(1+\varphi)\sin\left(\dfrac{\pi\varphi}{2}\right)}{\Gamma\left(\dfrac{1+\varphi}{2}\right)^{2^{\frac{\varphi-1}{2}}}\varphi} \right)^{\frac{1}{\varphi}} \\ \sigma\upsilon = 1 \end{cases} \tag{13}$$

where φ can take the value of 1.5 and Γ is the Gamma function.

After introducing the Lévy's flight, locations are updated based on the following function :

$$x_i^{t+1} = x_i^t + \beta_{ij}\left(x_j^t - x_i^t\right) + \left(x_b est^t - x_i^t\right) + \phi\xi_i \tag{14}$$

4.4 Mutation calculator

In the iterative process of the algorithm, with the continuous evolution of the population, the differences between firefly individuals gradually become smaller, which is prone to the aggregation phenomenon of the population, leading to the algorithm falling into the local optimum. Introducing the single-point mutation operator, by perturbing a certain dimension in the position vector of individuals, it can break the state of high similarity between individuals, which can help individuals jump out of the current optimal solution and improve the ability of the algorithm to jump out of the local optimum, and the operation is simple, which is easy to be executed quickly in the iterative process and will not increase the computational burden significantly. The formula for the single-point variational operator is as follows:

$$x_i^{ind}(t+1) = x_i^{ind}(t) + \tau \tag{15}$$

where ind is the dimension of individual mutation, t is the number of iterations, and τ is the standard normal distribution.

4.5 Algorithm flow for solving the 0–1 knapsack problem using the firefly algorithm

Input: Number of population N, maximum iterations is t_{Max}, item weights w, item values v, knapsack capacity C, light absorption coefficient γ, maximum attractiveness β_0, and step factor ϕ.

Output: Total value of the optimal loaded items.

Step 1 Initialise parameters and population positions. Generate N firefly individuals numbered as $x_i(1, 2, \ldots, N)$ the initial iterations is t, light absorption coefficient γ, maximum attractiveness β_0, and step factor α.

Step 2 Discretisation. Convert firefly positions into binary values (0 or 1) using a threshold of 0.5.

Step 3 Calculate the fitness value of the population.

Step 4 Perform non-dominated sorting on the firefly population to rank the solutions based on dominance relationships, and select the optimal individuals x_{best} according to crowding distance and non-dominated levels.

Step 5 While $t < t_{max}$, repeat steps 5 to 8.

Step 6 Compare any two fireflies based on the Pareto dominance relationship. Firefly individuals in the first level of the non-dominated rank update their positions according to equation (8), while the other firefly individuals update their positions according to equation (4).

Step 7 Introduce the mutation operator. Apply mutation to the fireflies after position updating. If the mutated firefly is better than the original one, it replaces the original. Otherwise, the original is retained.

Step 8 $t = t + 1$.

Step 9 Return the optimal results.

5 Experiment and results

5.1 Experiment design

The main aim of experiment is to compare the effectiveness of the dual search pattern FA based on Gaussian distribution and Lévy flights (DSPFA) with other popular algorithms including the coevolutionary constrained multi-objective optimisation framework (CCMO), the bidirectional coevolution (BiCo), the Two Stage evolutionary algorithm based on three indicators for CMOPs (TSTI) and constraint, multiobjective, multistage, multiconstraints (C3M). The CCMO proposes a framework containing two populations. One population is used to solve the original CMOP while the other population is used to solve a helper problem derived from the original one. As the two populations evolved independently from the same optimiser, the assistance in solving the original CMOP is achieved by sharing useful information between the two populations. Similarly, the BiCo method contains the main and archive populations. BiCo can get close to the Pareto front (PF) from two complementary directions. The C3M applies a two-stage method. Stage-I is to obtain solutions with good distribution and to prevent the population from falling into local optima. Stage-II is to quickly converge the population to the PF.

In the experiment, we compare our method with five two-objective functions and three three-objective functions. We set the population size as 100, the number of tests is 20,000, and independent running frequency is 30.

We employ the inverted generational distance (IGD) to evaluate the performance of the proposed MOFA and the comparisons. IGD simultaneously measures the convergence (the distance between solutions and the optimal front) and diversity (the accuracy of solutions to cover the front) of the approximation set. The IGD can be viewed as an 'average Hausdorff distance' and defined as below.

$$IGD(x, P') = \frac{min\sum_{x'\in P'} d(x', x)}{|P'|} \tag{16}$$

where P' is the set of points distributed on the true Pareto front (PF), $|P'|$ is the number of points on the true PF, and $d(x', x)$ is the Euclidean distance from x' to x.

Since IGD measures the distance between solutions and the optimal front, a smaller IGD value suggests a better convergence and diversity, indicating the approximation set is closer to the reference set and well-distributed across the Pareto. On the opposite, a larger IGD value suggests a poor convergence and diversity, indicating the approximation set is farther to the reference set and insufficiently covers the critical regions of the PF.

5.2 *Time complexity analysis*

Assuming N represents the population size, M represents the number of objective functions, D represents the dimensionality of individuals, and C represents the number of environmental selections. In each iteration, the algorithm performs non-dominated sorting, crowding distance calculation, position updates based on Gaussian distribution and Lévy flight dual search strategies, and finally selects individuals through a mutation operator. The time complexity of non-dominated sorting is $O(MN^2)$, that of crowding distance calculation is $O(MN\log N)$, and the time complexities of the Gaussian distribution-based and Lévy flight-based strategies are both $O(N)$. The time complexity of the mutation operator is also $O(N)$. Therefore, the overall time complexity of DSPFA can be approximated as $O(MN^2)$. The time complexity of BiCo is $O(MN^2 + N^2\log N)$, TSTI is $O(N^3)$, C3M is $O(CMN^2)$, and CCMO is $O(MN^2)$. Compared with these four algorithms, the time complexity of DSPFA is consistent with that of CCMO, indicating that the algorithm maintains a low computational overhead while possessing strong optimisation capability.

5.3 *Multi-objective optimisation results comparison*

As explained above, we compare the improved algorithm using MOFA with a selection of algorithms including CCMO, BiCo, TSTI, and C3M. Table 1 shows the results between MOFA and the other four algorithms. Specifically, mean values and standard deviations of IGD of the five algorithms are illustrated in the table. We also summarise the total number of optimal values obtained by each algorithm on all sets of test functions. The penultimate row of the table uses Friedman's test to derive the average of the ranks of the results of each multi-objective optimisation algorithm. Regards to the IGD metric, smaller rank averages indicate superior algorithm performance. The last row indicates the average ranking of the performance of each multi-objective optimisation algorithm, while the bolded data indicate the optimal results of each optimisation algorithm in the same test function.

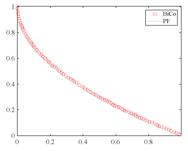
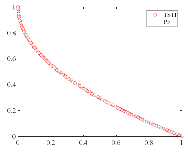
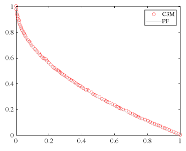
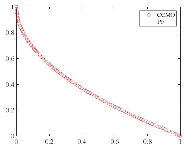
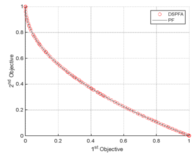
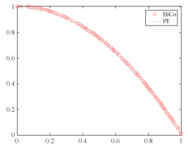
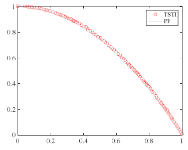
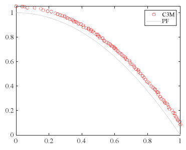
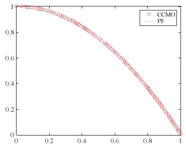
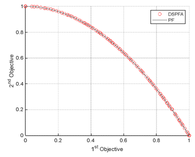
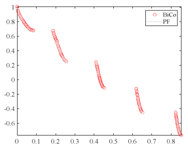
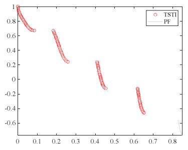
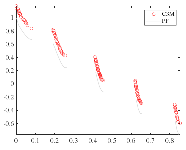
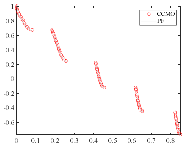
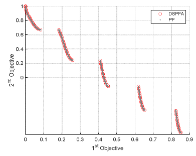
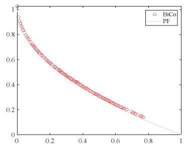
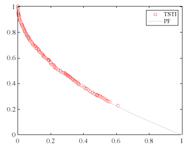
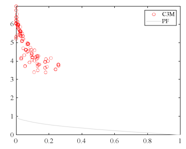
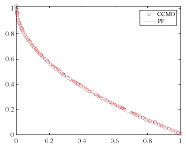
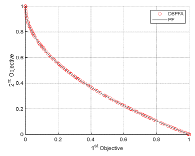
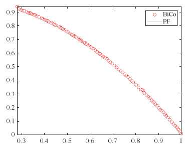
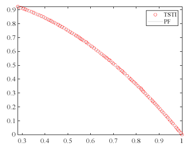
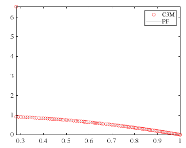
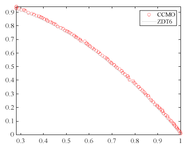
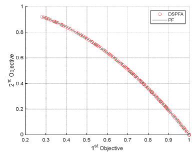
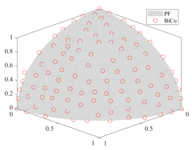
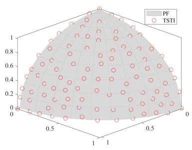
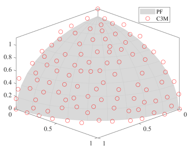
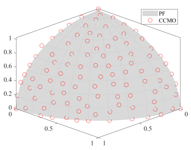
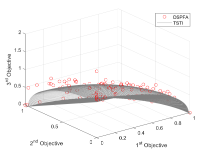
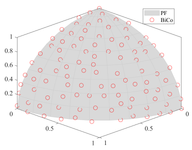
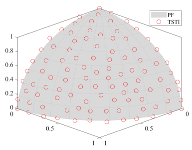
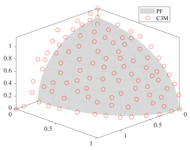
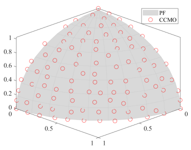
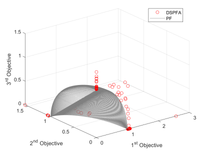
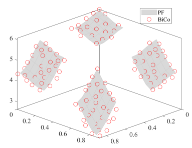
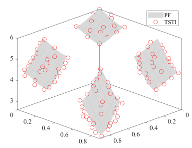
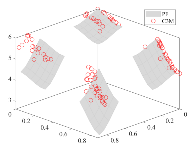
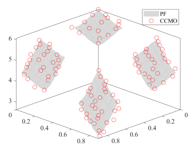
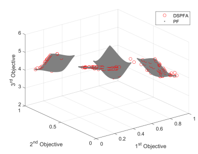
Table 1 IGD values of DSPFA, CCMO, BiCo, TSTI, and C3M

Problem	*Results*	*BiCo*	*TSTI*	*C3M*	*CCMO*	*DSPFA*
ZDT1	Mean	5.03e-3	8.76e-3	1.04e-2	5.01e-3	*4.54e-3*
	Std	3.69e-4	1.07e-2	5.72e-3	4.21e-4	*1.21e-4*
ZDT2	Mean	5.38e-3	2.41e-2	1.15e-2	5.43e-3	4.76e-3
	Std	5.09e-4	3.09e-2	3.70e-3	5.09e-4	*1.18e-4*
ZDT3	Mean	6.33e-3	2.12e-2	2.41e-2	7.51e-3	*5.11e-3*
	Std	5.32e-3	3.34e-2	1.80e-2	7.52e-3	*1.53e-4*
ZDT4	Mean	8.12e-2	9.96e-2	2.96e-1	2.43e-2	*4.56e-3*
	Std	6.42e-2	7.60e-2	2.79e-1	2.83e-2	*1.14e-4*
ZDT6	Mean	1.15e-2	6.55e-3	*3.13e-3*	6.33e-3	3.44e-3
	Std	5.64e-3	2.42e-3	*3.66e-5*	1.98e-3	1.28e-4
DTLZ2	Mean	5.44e-2	*5.43e-2*	6.66e-2	5.45e-2	8.33e-2
	Std	5.57e-4	*4.64e-4*	1.58e-3	6.45e-4	6.20e-3
DTLZ4	Mean	1.65e-1	*5.47e-2*	7.63e-2	1.36e-1	2.83e-01
	Std	2.35e-1	*6.14e-4*	3.07e-3	1.84e-1	3.52e-02
DTLZ7	Mean	7.27e-2	3.07e-1	1.42e-1	*6.17e-2*	9.31e-2
	Std	5.22e-2	2.09e-1	8.97e-2	*1.98e-3*	4.09e-2
Total		0	2	1	1	4
Ranking		2.875	3.500	3.750	2.500	2.375
Final rank		3	4	5	2	1

It can be seen that the dual search pattern FA based on Gaussian distribution and Lévy flights (DSPFA) obtained the IGD optimal means on ZDT1, ZDT2, ZDT3, and ZDT4, respectively. It means the proposed algorithm obtained 4 IGD most means on 8 test problems, which is the highest number of optimal values among all compared algorithms. Additionally, The TSTI algorithm achieved two best IGD optimal means among all test problems, while CCMO and C3M algorithms achieved one. BiCo algorithm showed zero IGD optimal mean. Based on the Friedman test, results are kept consistent with the IGD results. DSPFA has the lowest ranking, followed by CCMO, BiCO, and TSTI. C3M has the highest ranking. Overall, it means the DSPFA algorithm shows the best overall result.

We visually demonstrate DSPFA's performance across different test scenarios, including ZDT1–ZDT6 and DTLZ2, DTLZ4, DTLZ7. Solutions from each algorithm are plotted against the PF, with red circles representing algorithm solutions and the black line indicating the PF. From the above figures, it can be seen that DSPFA achieves the best convergence and diversity in multi-objective optimisation.

Table 2 Panel H: the fitted solutions on Pareto front (see online version for colours)

Problems	*BiCo*	*TSTI*	*C3M*	*CCMO*	*DSPFA*
ZDT1					
ZDT2					
ZDT3					
ZDT4					
ZDT6					
DTLZ2					
DTLZ4					
DTLZ7					

6 Empirical results

6.1 Empirical test design

To further test the effectiveness of the DSPFA, we apply the algorithm to the financial sector scenario. We propose to use the knapsack model to test resource allocation in the real-world scenarios.

6.2 Data

We use public-listed bank holding companies to test the application of knapsack algorithms in banking sector resource allocation. Our sample covers different time periods to allow we test the effectiveness of financial resource allocation, especially during the crisis period. We use the profitability of banks as the proxy for the values of items to be selected in the knapsack, and individual systemic risk as the weight of each item.

6.3 Explanations

We use the minimum value of total systemic risk as the optimal size of the knapsack to calculate the best result of all bank values. The lowest value of systemic risk was in year of 2010. Then we choose the highest value of systemic risk to estimate the highest possible of all bank values. The proportions of the estimated total value to the highest possible values are used to measure the accuracy of the algorithm.

6.4 Annual performance and systemic risk patterns

Our research applies the 0/1 knapsack model to optimise banking sector financial resource allocation under systemic risk constraints, using annual data from 1991 to 2023. The model prioritised maximising aggregate bank profitability and equity ratio, while ensuring cumulative systemic risk remained below predefined thresholds. The profitability indicator employed is the ROE of each bank.

Table 3 Optimisation results for US banks

Year	*Objective 1: equity ratio*	*Objective 2: ROE*
1991	470.99	700.75
1992	744.65	1,466.44
1993	877.32	1,560.06
1994	766.21	1,500.75
1995	912.64	1,989.69
1996	781.71	1,945.63
1997	928.13	2,363.29
1998	1,007.48	2,684.56
1999	925.36	1,679.41
2000	784.29	1,043.02
2001	723.33	1,785.03
2002	917.71	1,780.13
2003	876.20	2,108.86
2004	975.66	2,460.42
2005	816.20	1,862.33
2006	663.74	1,923.72
2007	812.21	1,802.73
2008	657.25	895.53
2009	618.35	988.13
2010	660.94	1,053.34
2011	738.67	1,284.86
2012	1,011.71	1,575.50
2013	458.29	857.88
2014	839.23	1,967.97
2015	861.03	1,518.06
2016	751.81	1,833.66
2017	810.31	1,674.88
2018	949.04	2,406.44
2019	1,050.69	2,805.45
2020	903.72	1,583.59
2021	813.35	1,147.33
2022	912.21	2,041.88
2023	711.06	1,588.44

Table 3 shows the optimal results of DSPFA under the two maximisation objectives of equity ratio and ROE in solving the financial problem of the US banking sector from 1991 to 2023. From the optimisation results, it can be seen that U.S. banks have experienced several rounds of economic cycles and major events during the period of 1991–2023. For example, after the global financial crisis in 2008, equity ratio dropped to 618.35 in 2009, which shows a significant decline in capital adequacy compared with the previous years. However, in the following years, banks strengthened their capital buffer, which witnesses equity ratio quickly rose to 1011.71 in 2012 (a historical peak). Meanwhile, ROE was at an all-time low of 895.53 in 2008 and 988.13 in 2009, but gradually recovered after 2010, reflecting the restoration of market confidence and positive investor expectations of bank profitability.

Therefore, it can be seen that the improved multi-objective FA can effectively portray the dynamic relationship between the two objectives, identify the optimal combination of equity ratio and ROE in different years, and better capture the possible trade-offs between the two objectives. This effect shows stronger explanatory power especially in the stage of financial system pressure and crisis, which means the algorithm can still provide a stable solution in the dynamically changing environment, indicating that the utility and effectiveness of the improved multi-objective FA in discovering potential optimal strategy combinations in dynamic financial environments.

7 Conclusions

This study highlights the knapsack problem as a key model for decision-making under scarcity and extends it to modern finance using the bio-inspired FA. By leveraging FA's adaptability, the framework tackles financial resource allocation challenges, including scalability, regulatory constraints, and ethical complexity, particularly under climate, geopolitical, and AI risks. The study advances theory by applying the knapsack model to multi-constraint, dynamic problems such as ESG compliance and DeFi, showing FA's advantages over traditional methods in high-dimensional settings. Practically, it offers policymakers and institutions a scalable tool for crisis resource allocation, though reliance on historical data and the need for distributed computing pose limitations.

Future research should prioritise the following.

- Hybrid quantum-FA systems: combining quantum annealing with FA to use quantum tunnelling and overcome local optima in ultra-high-dimensional financial problems.
- Federated learning integration: developing privacy-preserving FA variants for decentralised financial systems, enabling collaborative optimisation across institutions without data sharing.
- Ethical AI governance: establishing standardised metrics for fairness and transparency in algorithmic resource allocation, particularly for public-sector applications like healthcare or education funding.

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Declarations

All authors declare that they have no conflicts of interest.

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