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Optimal selection method of financial market investment portfolio based on monarch butterfly optimization algorithm

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ABSTRACT

This paper ofers a novel technique fbr optimizing financial market portfolios making use of the Monarch Butterfly Optimization set of rules (MBOA). The have a look at starts with a complete evaluation of the significance of portfolio optimization in economic markets, losing mild at the inadequacies of traditional methodologies. In the end, the MBOA is delivered, elucidating its standards and enumerating its benefits over conventional optimization techniques. The proposed methodology is then meticulously elaborated, encompassing a thorough problem description, elucidation of implementation steps, and delineation ofparameter settings specific to the Monarch Butterfly set of rules. Through rigorous experimentation on real-worldwide financial marketplace datasets, the efficacy ofthe proposed technique is tested. The experimental consequences display the functionality of the proposed approach to exactly optimize investment portfolios, yielding advanced returns whilst mitigating dangers. Moreover, the talk section deliberates at the implications of the experimental findings and delineates ability avenues for future studies endeavors. In essence, this have a take a look at contributes to the burgeoning location ofmonetary market optimization thru introducing a novel technique grounded in the MBOA. The findings underscore the set of rules's efficacy and capability applicability in addressing the complexities inherent in portfolio optimization.

Keywords: MBOA, Financial Markets, Portfolio Optimization, Global Search, Risk Management

1. Introduction

In contemporary financial markets, portfolio optimization stands as a pivotal project [1-3]. It seeks to properly allocate finances during diverse belongings, aligning with an investor's objectives and danger tolerance to acquire gold standard returns and danger management. But, the tricky and

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unsure nature of economic markets [4-6] poses massive traumatic conditions to portfolio optimization.conventional optimization techniques regularly stumble upon severa constraints and drawbacks, impeding their efficacy in addressing those demanding situations. As a result, there is a urgent need to discover novel and greater effective optimization methodologies in the monetary domain.

Conventional optimization methodologies commonly encompass mathematical programming-based totally techniques such as the Markowitz model [7-8] and capital asset pricing model [9-10], along heuristic set of rules-based strategies inclusive of genetic algorithms(GA) [11-13], simulated annealing algorithms [14-16], amongst others. Regardless of their partial success in addressing portfolio optimization, those methods show off sure limitations. as an instance, the Markowitz version's idealized assumptions concerning asset go back charges forget market irrationality and uncertainty, at the same time as heuristic algorithms frequently fighting with high-dimensional problems and susceptibility to nearby optima.

To address those challenges, bio-stimulated algorithms have received large traction and alertness in the monetary realm in current years. Among these, the MBOA [17-19], as an rising optimization approach, boasts robust global search skills and flexibility to nonlinear troubles, thereby demonstrating promising capability in economic marketplace portfolio optimization.

MBOA is rooted in the foraging behavior of butterflies in nature and embodies a heuristic approach. In nature, monarch butterflies vibrate to find the most suitable food sources. In nature, monarch butterflies vibrate to find the most suitable food sources. In science, researchers have abstracted this behavior into an optimization framework for finding a final solution in the path-finding space. The researchers used computer simulations to simulate the monarch butterfly's behavior and iterated to find the best solution.The number one intention of MBOA, which is to maximise returns while reducing dangers, is to optimize portfolio allocation in the economic area. Moreover, MBOA has a gorgeous deal of capability for adoption in the financial industry. Although it would not completely cope with the disruptive instances of conventional portfolio optimization, it does increase to other sectors of the economy, such as danger manipulate and asset pricing. The sophisticated worldwide seek capabilities provided by using MBOA make it extra suitable for managing the complexity and unpredictability of financial markets than fashionable optimization strategies.Therefore, the combination of MBOA has important theoretical and practical significance to solve the problem of portfolio optimization in financial markets.

To sum up, economic market portfolio optimization is a challenging research direction, and traditional optimization strategies show certain limitations when dealing with the complexity and uncertainty of economic markets.MBOA, as an emerging heuristic rule set, has good international optimization capabilities and adaptability to nonlinear problems, and has broad application prospects in the monetary domain. Therefore, incorporating it into solving financial market portfolio optimization problems will bring important innovations and progress in economic research and practice.

2. Related Works

Financial market portfolio optimization is the basis of monetary research and its goal is to allocate the investment budget among various assets in order to maximize returns and reduce risks. Over the numerous years, each academia and the financial enterprise have appreciably explored this area, resulting in a plethora of methodologies and fashions.

Historically, early studies targeted on building portfolio fashions [20-22] and devising powerful funding strategies [23-25]. Markowitz Portfolio principle, proposed through using Markowitz inside the Fifties, marked a large milestone in this domain, laying the premise for current funding portfolio principle. This thought, which minimizes risk by means of decreasing portfolio variance, gives most powerful portfolio allocation below unique situations.next fashions which include the capital asset pricing model and arbitrage pricing concept also gained prominence, becoming broadly followed in monetary markets.

Regardless of their application, conventional portfolio optimization methods show off obstacles, inclusive of idealized market assumptions [26-28], oversimplified threat remedy, and oversight of nonlinear relationships. To triumph over those constraints, both academia and industry have turned to heuristic algorithms, which eschew precise mathematical assumptions in prefer of simulating natural procedures such as evolution and optimization. Those algorithms offer advanced adaptability and robustness.

Among heuristic algorithms, GA, simulated annealing, particle swarm optimization, among others, find significant software in monetary market portfolio optimization. Every set of rules possesses particular trends that beautify optimization efficiency and great. For instance, GA leverage organic evolution standards to conduct international search successfully, whilst simulated annealing sidesteps local optima by means of probabilistically accepting inferior answers.

In latest years, bio-stimulated algorithms have garnered accelerated attention in finance, with the MBOA rising as a amazing contender. Mimicking the foraging conduct of monarch butterflies, this set of rules navigates search areas via techniques like vibrating flight and desk certain durations, imparting robust global search abilities and adaptability to nonlinear problems. Consequently, it holds extensive promise for monetary marketplace portfolio optimization.

Empirical evidence underscores the efficacy of the MBOA in finance. In portfolio optimization, researchers have accomplished favorable consequences through employing the algorithm for asset allocation [29-31]. Furthermore, its utility in asset pricing and danger control fields has yielded promising effects [32-35]. Those findings underscore its ability to provide enhanced investment decision assist in economic markets.

In end, even as conventional portfolio optimization techniques have laid a stable basis, heuristic algorithms, specially bio-inspired ones just like the MBOA, preserve substantial promise. by using reviewing relevant literature, outlining optimization set of rules programs, and elucidating the MBOA's principles and advantages, this study provides precious insights and thought for future studies endeavors.

3. Problem Description

Monetary market investment portfolio optimization refers back to the allocation of confined funds to exceptional economic belongings in positive proportions, aiming to maximise investment returns beneath a given degree of threat or decrease hazard below a given level of go back. that is a traditional optimization hassle, with the objective of maximizing investor returns whilst keeping risks controllable, or minimizing risks at the same time as pursuing a predetermined go back.

The optimization problem of economic marketplace funding portfolios can be described using mathematical models. think there are n investable monetary assets, each with an expected return r, standard deviation σ_i, and investment proportion $x_i(\mathrm{i}=1,2,\ldots,\mathrm{n})$. The expected return of the investment portfolio is:

$$E\left(R_p\right)=\sum_{i=1}^{n} x_i r_i \tag{1}$$

The variance (risk) of the investment portfolio is:

$$\sigma_p^2=\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \rho_{ij}\sigma_i\sigma_j \tag{2}$$

where ρ_{ij} is the correlation coefficient between asset i and asset j .

The optimization objective can be defined as maximizing the expected return $E\left(R_p\right)$ or minimizing the variance σ_p^2 of the investment portfolio, or minimizing the variance of the investment portfolio under a given level of return. At the same time, some constraints need to be satisfied, such as:

The sum of the weights of each asset in the investment portfolio is 1, i.e., $\sum_{i=1}^{n} x_i = 1$.

There can be higher and lower limits at the funding proportions among assets.

There may be restrictions on positive property or asset categories, together with now not keeping positive particular kinds ofassets inside the funding portfolio.

In real financial markets, funding portfolio optimization faces many demanding situations and constraints. Firstly, the uncertainty and volatility of financial markets often make it hard to exactly are expecting asset returns and dangers, increasing the difficulty of portfolio optimization. Secondly, numerous complex constraints exist inside the market, along with prison guidelines, traders' danger preferences, and marketplace liquidity, which restriction the selection area of investment portfolios. Additionally, the high complexity and non-linear traits of monetary markets additionally increase the complexity of optimization problems, making it difficult for classic optimization techniques to address these troubles.

In end, economic market investment portfolio optimization is a complex and essential problem, aiming to gain the nice investment returns by way of reasonably allocating property below given constraints. but, there are many challenges and constraints in actual monetary markets, along with market uncertainty, various constraints, and market complexity. Therefore, locating effective optimization strategies to clear up this problem is of super theoretical and sensible significance.

4. Method

MBOA is a nature-stimulated metaheuristic algorithm that mimics the foraging conduct of emperor butterflies to solve optimization problems. This algorithm is primarily based at the commentary of the way emperor butterflies utilize a dissimilation of seek strategies to efficiently discover food resources in their natural habitat. underneath, i'm able to element the standards of MBOA, give an explanation for the way it simulates the flight behavior of emperor butterflies to look for most advantageous solutions, and discuss its characteristics along with global search capability and adaptability to nonlinear troubles. Fig. 1 suggests the glide chart ofthe MBOA.

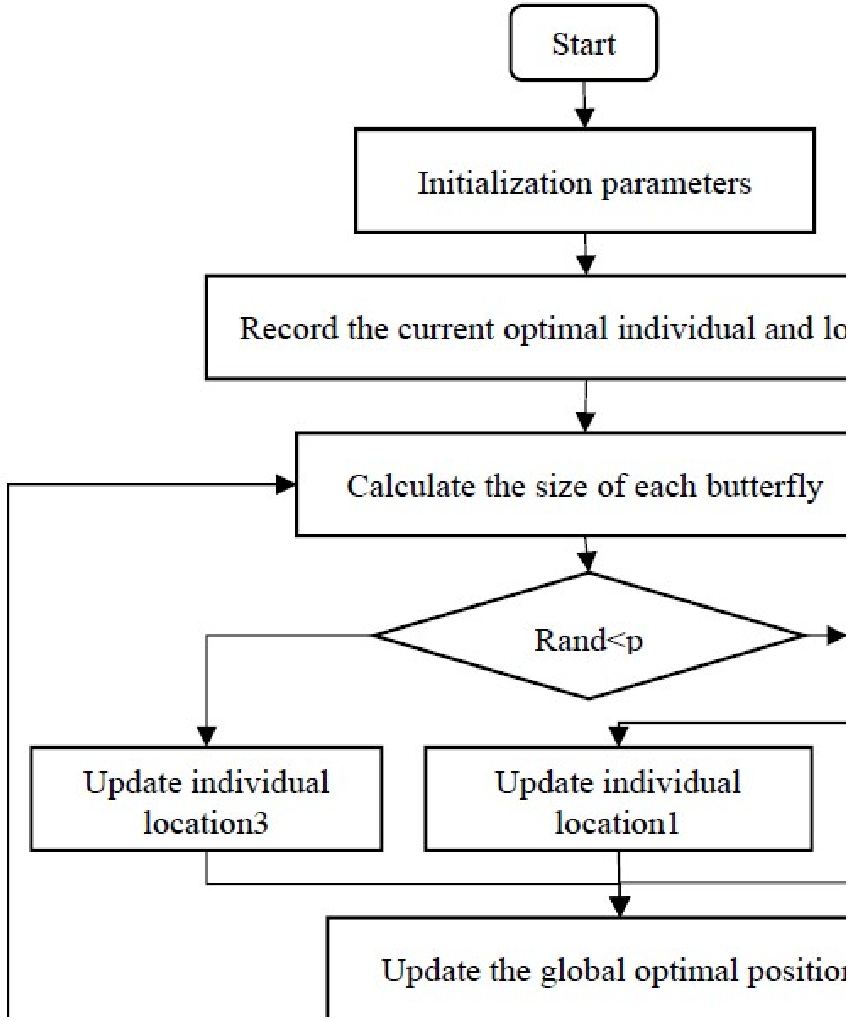

Fig. 1. MBOA flow chart

4.1. Principles of MBOA

MBOA is inspired by the foraging behavior of emperor butterflies, which involves a combination of exploration and exploitation strategies to efficiently locate food sources. The important thing concepts of MBOA encompass

Exploration and Exploitation: Emperor butterflies appoint a balance among exploration (searching for new meals assets) and exploitation (exploiting acknowledged meals assets) to maximize their probabilities of locating highest quality food. In addition, MBOA continues a diverse population of answers to explore the search space efficaciously whilst additionally exploiting promising regions for top-quality solutions.

Verbal exchange and Cooperation: Emperor butterflies speak with every other thru pheromone trails, which facilitates them share statistics about the area of food sources. In MBOA, solutions trade information via a verbal exchange mechanism, allowing cooperative search behavior that courses the whole populace toward promising areas of the search area.

Variation and Evolution: Emperor butterflies adapt their flight behavior based on environmental conditions and the provision of food sources. Similarly, MBOA includes mechanisms for adaptive adjustment of search parameters, allowing the algorithm to dynamically respond to modifications inside the optimization landscape and enhance solution excellent over iterations.

4.2. Simulation of Emperor Butterfly Flight behavior

MBOA simulates the flight behavior of emperor butterflies via a hard and fast of predefined rules and strategies:

Random Exploration: much like how emperor butterflies explore their environment randomly to discover new meals sources, MBOA continues a diverse population of answers and employs random search operators to discover uncharted areas of the hunt area.

Nearby seek: Emperor butterflies exhibit localized search conduct around acknowledged food resources to make the most their surroundings correctly. In MBOA, local seek operators are implemented to promising solutions in the populace to make the most their neighborhoods and refine the answers.

Verbal exchange and Cooperation: Emperor butterflies speak data about food resources thru pheromone trails, guiding other butterflies in the direction of promising regions. In MBOA, answers percentage statistics thru a conversation mechanism, permitting the populace to collectively guide the hunt toward superior areas of the hunt area.

Adaptive Adjustment: Emperor butterflies adapt their flight patterns based totally on environmental cues and food availability. Further, MBOA carries adaptive mechanisms to adjust seek parameters dynamically, making sure that the algorithm can respond effectively to adjustments inside the optimization panorama and hold exploration-exploitation balance.

4.3. Characteristics of MBOA

International seek functionality: MBOA well-knownshows sturdy worldwide seek functionality owing to its numerous population initialization and exploration strategies. by means of retaining a various set of solutions and using both random and guided search operators, MBOA can efficiently explore the whole search area and find optimal solutions in complicated landscapes.

Adaptability to Nonlinear troubles: MBOA is properly-proper for nonlinear optimization troubles owing to its adaptive nature and ability to dynamically modify search parameters. Nonlinear optimization landscapes regularly include multiple neighborhood optima, and MBOA's stability between exploration and exploitation allows it to break out neighborhood optima and converge closer to international optima efficiently.

In precis, MBOA attracts concept from the foraging conduct of emperor butterflies to resolve optimization issues. by simulating the exploration, exploitation, communication, and adaptation strategies of emperor butterflies, MBOA exhibits sturdy global seek capability, adaptability to nonlinear issues, and effective convergence residences.

Emperor Butterfly's role update Equation:

The position of each butterfly (answer) within the seek area is up to date based totally on its modern position and velocity. This equation consists of both exploration and exploitation additives, allowing butterflies to navigate the quest space effectively.

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

where

$x_i(t)$ is the position of butterfly i at time t.

$v_i(t+1)$ is the velocity of butterfly i at time $t+1$.

Emperor Butterfly's speed replace Equation:

the rate of every butterfly is updated to adjust the exploration and exploitation conduct. This equation balances the inertia of the butterfly's movement with the impact of attractive food assets determined via different butterflies.

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot \left(p_{best} - x_i(t)\right) + c_2 \cdot r_2 \cdot \left(g_{best} - x_i(t)\right) \tag{4}$$

where: w is the inertia weight controlling the influence of the previous velocity. c_1 and c_2 are the cognitive and social coefficients controlling the influence of personal and global best positions, respectively. r_1 and r_2 are random values sampled from the uniform distribution between 0 and 1.

p_{best} is the personal best position of butterfly i. g_{best} is the global best position among all butterflies.

Objective Function Evaluation Equation

The objective function is evaluated to determine the fitness ofeach butterfly's position in the search space.

$$f\left(x_i\right) \tag{5}$$

where $f\left(x_i\right)$ is the objective function value at position x_i.

Fitness Evaluation Equation

$$Fitness\left(x_i\right) = \frac{1}{1 + f\left(x_i\right)} \tag{6}$$

where Fitness $\left(x_i\right)$ is the fitness score of butterfly i .

$f\left(x_i\right)$ is the objective function value at position x_i.

International exceptional update Equation the global first-rate position amongst all butterflies is up to date primarily based on their health scores. This equation tracks the satisfactory solution determined with the aid of any butterfly for the duration of the optimization technique.

$$g_{best} = \arg\max\left(Fitness\left(x_i\right)\right) \tag{7}$$

where g_{best} is the global best position.

$\arg\max\left(Fitness\left(x_i\right)\right)$ Returns the position with the very best fitness rating among all butterflies.

These equations govern the movement, exploration, exploitation, and convergence of butterflies in the MBOA, facilitating effective search for optimal solutions in complex optimization landscapes.

As shown in Table 1 is the MBOA pseudo code.

Table 1. The pseudocode of the MBOA

Algorithm: MBOA
Input: Objective function $(f(x))$, Population size (N), Maximum number of iterations (Max_Iter), Search space boundaries, Parameters: (w), (c_1), (c_2)
Output: Optimal solution $(x^{\wedge *})$
1. Initialize a population of butterflies with random positions and velocities. 2. Initialize personal best positions and fitness values for each butterfly. 3. Initialize global best position and fitness value. 4. for $(iter=1)$ to (Max_Iter) do 5. for each butterfly (i) in the population do 6. Update velocity of butterfly (i) using Equation. 7. Update position of butterfly (i) using Equation. 8. Evaluate fitness of butterfly (i) using the objective function $(f(x))$. 9. Update personal best position and fitness of butterfly (i) if necessary. 10. Update global best position and fitness if a better solution is found. 11. end for 12. Update inertia weight (w) (optional). 13. end for 14. return Global best position $(x^{\wedge *})$

5. Experiment Results

5.1. Data set

When conducting experiments and analyzing results, it is essential to select appropriate financial market datasets to evaluate the performance ofthe MBOA andcompare itwithGA, particle swarm algorithms(PSO), and ant colony algorithms(ACO). In this study, stock prices are chosenas the financial market dataset, whichcanbe acquired from financial data providers or research institutions. The dataset should span a sufficiently long period to assess algorithm performance under diverse market conditions. The selected algorithms are applied to the same financial market dataset, and common evaluation metrics are employed for performance comparison. Techniques such as cross-validation and parameter tuning are utilized to ensure the accuracy and reliability of experimental results.

Evaluation metrics include accuracy, recall, and precision, which are calculated using the following formulas:

$$Acc=\frac{TP+TN}{TP+TN+FP+TN} \tag{8}$$

$$\mathrm{Re}\,c=\frac{TP}{TP+FN} \tag{9}$$

$$\mathrm{Pr}\,e=\frac{TP}{TP+FP} \tag{10}$$

5.2. Experiment Results

On this section, we generally compare the overall performance of the MBOA with GA, PSO, and ACO.

Determine two illustrates the accuracy ofthe MBOA algorithm as itvarieswiththe wide variety of iterations (see Fig. 2). Initially, it's far located that because the quantity of iterations increases, the general accuracy famous a slow upward fashion. This phenomenon means that the monarch optimization set of rules gradually complements its accuracy at the dataset in the course of the iteration procedure, indicating a convergence closer to a more greatest answer. But, fluctuations and oscillations also are substantial within the accuracy curve. Those fluctuations may additionally arise from the algorithm oscillating around neighborhood ideal solutions or from noise gift within the seek area. Such occurrences are commonplace in optimization algorithms, particularly for complicated troubles or datasets with tremendous noise interference. No matter these fluctuations, it is noteworthy that the general accuracy charges show off an upward trajectory. Moreover, the accuracy curve has a tendency to stabilize after reaching a certain range of iterations. This stabilization suggests that the algorithm has converged to a exceptionally quality answer, with further iterations yielding minimum impact on accuracy. This stable conduct is ideal in realistic applications of the algorithm, indicating that it has attained an appropriate level of overall performance.

In summary, the accuracy of the MBOA at the dataset beneath attention demonstrates characteristics of slow improvement, fluctuation, and stable convergence with changing generation numbers. This progression displays the algorithm's convergence and performance in addressing particular issues and offers insights and guidance for in addition optimization of the algorithm's parameter settings and overall performance evaluation.

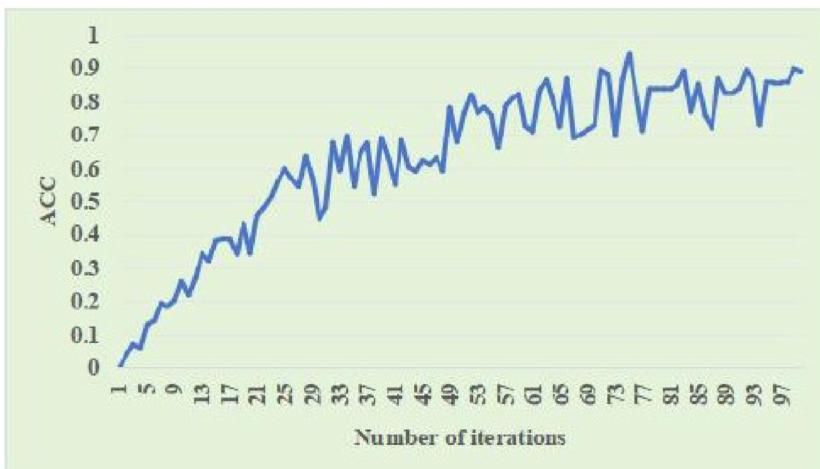

Fig. 2. The accuracy of MBOA set ofrules changes with the number of iterations

As depicted in Figure 3, the loss fee ofthe MBOA at the dataset fluctuates with the range of iterations. The loss cost serves as a metric to quantify the disparity among the model's prediction and the actual price. A decrease loss fee shows closer alignment among the model's prediction and the real statistics. To begin with, it is located that these loss values show off fluctuations all through the new release system. Such fluctuations can stem from the inherent randomness of the algorithm, in addition to noise or uncertainty present within the dataset. Typically, with an growth inside the wide variety of iterations, the loss cost must gradually decrease, signifying development inside the version's ability to healthy the statistics throughout the learning manner. However, it's far referred to that now not all loss values show off a monotonic lower, suggesting that the algorithm may also come across nearby ideal solutions in sure iterations or be prompted by means of different factors. Moreover, the changing trend ofthe loss price with the quantity ofiterations is likewise determined. The loss price tends to stabilize in the later levels of iteration, indicating that the version has either converged to an top-quality answer or reached a factor where in addition performance improvement is restrained.

In summary, the fluctuations in the loss values of the MBOA at the dataset highlight the algorithm's dynamic studying process and potential challenges encountered at some point of optimization. The located traits offer insights into the convergence conduct of the set of rules and its potential to efficiently adapt to the dataset. These findings make a contribution to a deeper understanding of the set of rules's performance characteristics and provide valuable steering for in addition refinement and optimization.

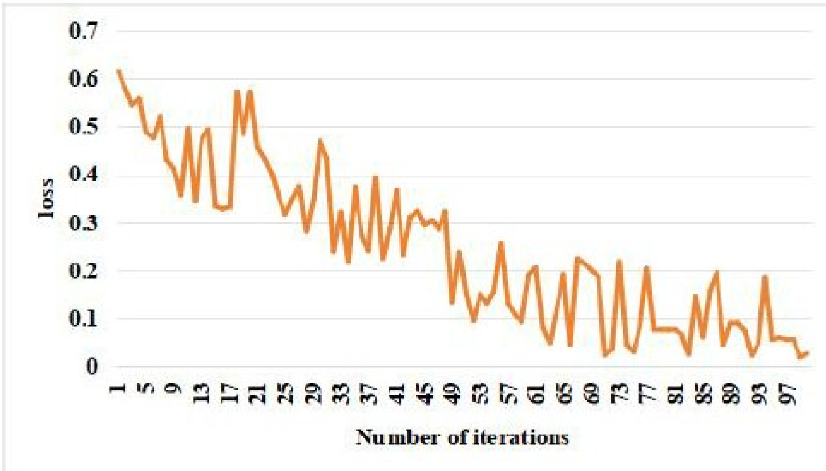

Fig. 3. Loss changes with the wide variety of iterations

As depicted in Figure 4, the overall performance of the four optimization algorithms (MBOA, GA, PSO, and ACO) is evaluated in phrases of precision and recall.

First off, regarding accuracy, MBOA reveals the highest performance, observed by PSA, ACO, and GA, in descending order. This shows that among all samples expected to belong to positive categories, MBOA achieves the highest percentage of correct classifications, while GA demonstrates the bottom accuracy. Therefore, MBOA outperforms different algorithms in predicting accuracy for advantageous categories.

Secondly, from the perspective of recall charge, the overall performance of MBOA and GAis extraordinarily comparable, with PSA barely trailing at the back of, and ACO exhibiting the bottom recall charge. This shows that MBOA and GA possess distinctly sturdy capabilities in identifying authentic nice classes, whilst ACO well-knownshows a lower recall price.

basic, although MBOA demonstrates marginally better precision in comparison to other algorithms, its recall price is comparable to GA. consequently, MBOA may be appeared as a positive preference in phrases of both prediction accuracy and the ability to discover fine classes. Even as GA lags slightly at the back ofother algorithms in precision, its performance in recall price remains rather solid, rendering it some other feasible option. Conversely, ACO's performance is exceedingly inferior, with precision and recall charges barely decrease than different algorithms, indicating the want for similarly optimization to decorate performance.

In end, the comparative evaluation of precision and recall quotes among the four optimization algorithms gives treasured insights into their respective strengths and weaknesses. MBOA emerges as a promising candidate for attaining high prediction accuracy and fantastic class detection capacity, at the same time as GA gives a strong overall performance throughout precision and recall metrics. meanwhile, ACO's overall performance falls short in assessment, warranting in addition refinement to beautify its effectiveness. those findings contribute to the appreciation of algorithmic performance in financial marketplace optimization and manual future research efforts toward optimization set ofrules improvement and refinement.

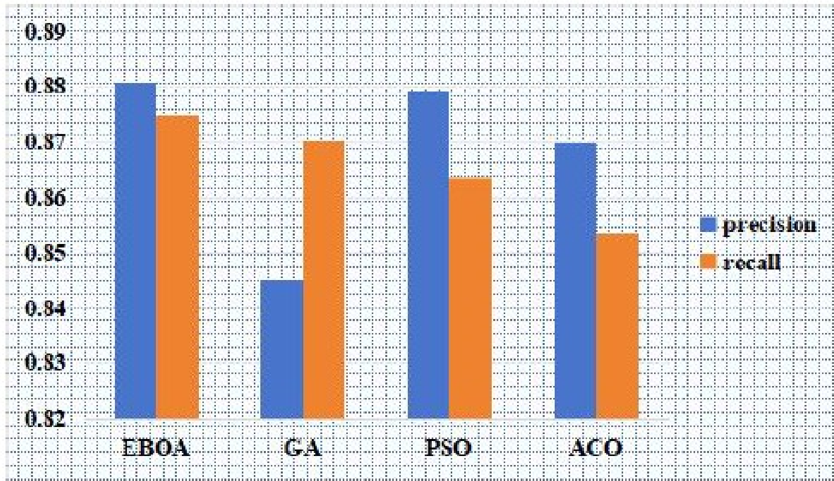

Fig. 4. Affords the field plot depicting the running time ofthe four algorithms, measured in seconds. Each algorithm's field plot illustrates the distribution of execution time across a couple of runs. Upon evaluation of the four algorithms, discernible variations in their execution times are glaring. Drastically, there are not any prominent outliers found within the container plots ofthe 4 algorithms, indicating notably stable execution instances across runs.

As shown as Figure 5, reading the general trend, it appears that the PSO algorithm has a tendency to exhibit longer execution instances usual, while the GA and ACO algorithms demonstrate especially shorterexecution times. The MBOA set of rules's execution time falls anywhere between these extremes. These versions highlight discrepancies within the efficiency and stability ofdifferent optimization algorithms while tackling troubles.

In precis, the container plot analysis of going for walks times presents insights into the overall performance traits of the 4 algorithms in terms of computational performance and balance.

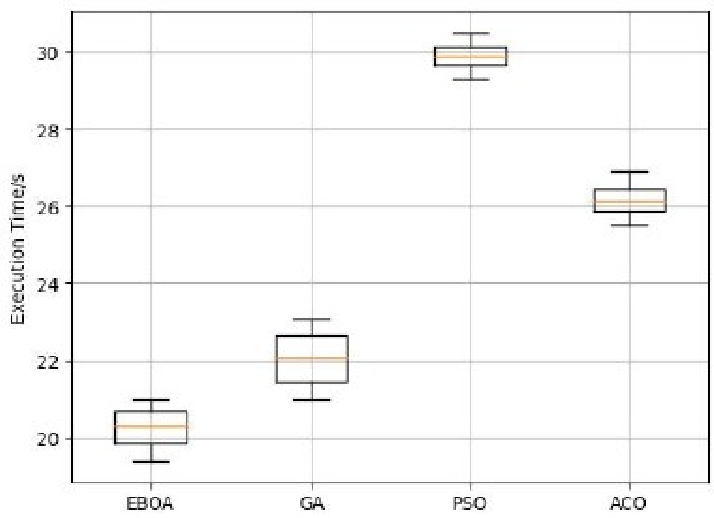

Fig. 5. Running time

6. Discussion and Outlook

The experimental effects demonstrate that MBOA well-knownshows superior overall performance in the performed experiments, outperforming GA, PSO, and the Ant Colony algorithm (ACO) in both precision and recall. This underscores the potential of MBOA in addressing economic marketplace portfolio optimization problems.

The strengths of the MBOA are mainly manifested in numerous aspects. MBOA possesses strong global search capabilities, permitting the discovery of top-quality answers within the search space, thereby facilitating the identification of potential investment portfolio answers. Given that monetary marketplace portfolio optimization problems often entail nonlinearity, MBOA, as a heuristic optimization set of rules grounded in organic ideas, demonstrates exquisite adaptability and efficacy in managing complicated nonlinear optimization challenges.

Though, the MBOA also well-knownshows positive obstacles. The overall performance of MBOA is considerably inspired through parameter choice, with exclusive parameter configurations probably yielding disparate optimization effects. For this reason, meticulous parameter tuning is critical to obtain choicest algorithmic performance.

In mild of the aforementioned barriers, destiny research directions and development techniques may additionally consist of.

Further investigation into parameter selection methods, such as adaptive parameter tuning or parameter optimization algorithms, to enhance the robustness and efficacy of the algorithm.

Extension of the MBOA to tackle multi-objective optimization problems, thereby addressing multiple objectives and constraints in financial market portfolio optimization, such as maximizing returns and minimizing risks.

Exploration of methodologies to integrate the monarch optimization algorithm with other optimization techniques to mitigate its limitations and enhance optimization outcomes. For instance, combining MBOA with local search methods or evolutionary algorithms can expedite convergence and augment the quality of optimization results.

In conclusion, the MBOA holds promising prospects for application in financial market portfolio optimization. Through continual refinement of algorithm parameters, enhancement of algorithmic design, and integration with complementary optimization methodologies, MBOA can be leveraged to achieve greater efficacy in the financial domain.

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