Journal of Applied Data Sciences
Vol. 4, No. 2, May 2023, pp. 93-102

ISSN 2723-6471

Optimization of Decision Support System in Investment Risk Management with Firefly Algorithm

Ajang Sopandi *

Department of Informatics Engineering, Faculty of Engineering, University of Muhammadiyah Tangerang, Indonesia
ajangsopandi@ft-umt.ac.id*
* corresponding author

(Received January 1, 2023 Revised February 2, 2023 Accepted February 28, 2023, Available online March 1, 2023)

Abstract

This research focuses on optimizing the decision support system in investment risk management using Firefly Algorithm. The data used in this research is obtained from the Kaggle repository. The research aims to compare the performance of Firefly Algorithm with other optimization algorithms such as Genetic Algorithm, Particle Swarm Optimization, and Simulated Annealing. This research applies Firefly Algorithm and other optimization algorithms individually to the investment risk management system to analyze and compare their performance. The results show that Firefly Algorithm outperforms other optimization algorithms in terms of finding optimal solutions and minimizing investment risk. Firefly Algorithm can effectively identify the best investment options to avoid risks, which can bring significant benefits to investors and companies. The findings of this study show that Firefly Algorithm can be a useful tool in the investment risk management system. The application of Firefly Algorithm in the investment risk management decision-making process can improve decision-making and help investors avoid risks and maximize their profits. The novelty of this research is the application of the Firefly algorithm to optimize the decision support system in investment risk management. It aims to identify the best option in avoiding investment risk and maximizing profit. In addition, this research also compares the performance of the Firefly algorithm with other algorithms such as Genetic Algorithm, Particle Swarm Optimization, and Simulated Annealing in solving optimization problems in the investment field.

Keywords: Data Mining, Firefly Algorithm, Decision Support System

1. Introduction

Investing is an important aspect of the financial world, and it is crucial to manage risk to achieve success. Investment risk management is the process of identifying, analyzing, and mitigating risks associated with investments. It is a complex task that requires a comprehensive understanding of market trends, investment products, and the risks involved [1]. To support investment risk management, a Decision Support System (DSS) can be used. A DSS is a computer-based system that provides analytical tools to support decision-making. Optimization of DSS is important to improve the accuracy and effectiveness of investment risk management [2]. Firefly algorithm (FA) is a metaheuristic optimization algorithm inspired by the flickering behavior of fireflies. It is a powerful optimization technique and has been widely used in various fields, including finance. FA algorithms have shown promising results in optimization problems, including investment risk management. The application of FA in optimizing DSS can improve the accuracy and efficiency of the decision-making process [3].

DSS optimization using FA can improve the investment risk management process by providing a more accurate and efficient decision-making process. FA algorithms can effectively optimize DSS by adjusting decision parameters to achieve the best solution. DSS optimization using FA can also help reduce the computational complexity and processing time required for decision making. Investment risk management is a complex process that involves various uncertainties and risks. DSS optimization using FA can improve the accuracy and effectiveness of investment risk management by reducing the uncertainty and risk associated with the decision-making process. This can help investors in making the right decisions that can result in profitable investments [4]–[6]. In summary, optimization of DSS in investment risk management with the Firefly algorithm is a promising research area that can improve the accuracy and efficiency of the decision-making process. The application of FA in optimizing DSS can improve the

computational complexity and processing time required for decision-making, and reduce the uncertainty and risk associated with the decision-making process.

Some previous research such as, Research [1] aims to optimize cluster head selection in wireless sensor networks by using a hybrid algorithm that combines Firefly Algorithm and Particle Swarm Optimization. Hybridization is done to overcome the limitations of each algorithm. This research uses simulation to evaluate the performance of the proposed algorithm in terms of energy consumption and network resilience. The results show that the hybrid algorithm produces better performance compared to the use of Firefly and Particle Swarm Optimization algorithms individually in terms of reduced energy consumption and improved network resilience. Therefore, this research can be a contribution to the development of efficient and sustainable wireless technology.

Research [7] aims to control the vibration of semi-active suspension systems using PID controllers with forward optimized Firefly Algorithm and Particle Swarm Optimization. The purpose of this research is to improve the performance of the semi-active suspension system by optimizing the PID controller parameters through the proposed optimization technique. This research uses simulation to evaluate the performance of the semi-active suspension system and the proposed PID controller. The results show that the use of the forward-optimized Firefly Algorithm and Particle Swarm Optimization algorithms can improve the performance of the semi-active suspension system and produce better vibration response. Therefore, this research can help improve safety and comfort in vehicles and transportation.

Agbaje et al. [8] research aims to optimize data clustering results by combining Firefly Algorithm and Particle Swarm Optimization. The goal is to increase the convergence speed and accuracy of data clustering by improving the initial position of the cluster center points. Compared to the current research, it focuses on using Firefly Algorithm to optimize decision making in investment risk management, while Agbaje et al. [8] focuses on data clustering. Although the current research and Agbaje et al. [X] research differ in their focus, they both use the Firefly Algorithm algorithm and optimize parameters to improve system performance. In addition, both also use other optimization techniques such as Particle Swarm Optimization to improve the accuracy and convergence speed of the algorithms used.

The novelty of this research is the use of the Firefly algorithm to optimize the Decision Support System in investment risk management. Previously, many studies have been conducted to improve the effectiveness of DSS in investment risk management, but research that combines DSS with metaheuristic algorithms such as Firefly is still limited. Therefore, this research makes a new contribution in improving the accuracy and efficiency of DSS in investment risk management.

The purpose of this research is to optimize DSS in investment risk management with the Firefly algorithm. To achieve this goal, this research will conduct a series of experiments using real financial market data and measure the performance of the resulting DSS. The main objective of this research is to improve the accuracy and efficiency of DSS in investment risk management.

2. Software Defects and Data Mining

2.1. Decision Support System

Decision Support System is a system that functions to assist decision making. DSS integrates data, models, and applications related to a decision, so that decision making can be done more quickly and accurately. DSS is used in various fields such as business, government, health, and so on [9]. DSS is developed using information technology such as databases, data processing systems, and data analysis techniques. This information technology provides support to the decision-making process by facilitating access to information, analyzing data, and displaying understandable results. DSS allows decision making to be done more quickly, accurately, and effectively [10].

In its application, DSS can be integrated with other systems such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM). DSS can also be implemented in the form of desktop or mobile

applications that allow users to access it from anywhere and anytime. DSS can be used by various parties such as managers, executives, analysts, and other users to help them make the right decisions. There are three types of DSS: model, data, and knowledge-based. Model DSS is based on mathematical analysis to predict the outcome of a decision. Data DSS is based on data processing to generate the required information. While knowledge-based DSS is based on a knowledge base to provide relevant information and advice on a decision [11], [12].

DSS has several advantages including being able to help reduce the risk of errors in decision making, provide fast and accurate results, and facilitate access to information [13], [14]. However, DSS also has several weaknesses such as requiring considerable costs in its development, and cannot replace human decisions as a whole. Therefore, DSS must be used wisely and managed properly in order to provide maximum benefits for its use.

2.2. Firefly Algorithm

Firefly Algorithm is a metaheuristic optimization algorithm inspired by the behavior of fireflies. It was first introduced by Xin-She Yang in 2008 [15], [16]. FA adopts the basic principle of firefly behavior, which is the use of light as a communication signal to find a mate. In FA, the light of fireflies represents the solution and the distance between two fireflies indicates the similarity between the solutions. Brighter fireflies represent better solutions. In addition, FA also uses parameters such as alpha and beta to control the movement of fireflies in the search for the best solution. These parameters provide flexibility in determining the speed and direction of firefly movement in the search space.

FA has been applied in various fields such as investment risk management, image processing, and function optimization. In investment risk management, FA is used to optimize investment decisions by reducing risks and increasing returns. In image processing, FA is used to optimize problem solving such as image segmentation and image quality improvement [17]. While in function optimization, FA is used to find the best solution to complex functions. FA is a very useful algorithm in optimizing complex problems. However, there are some drawbacks in its use such as the inability to handle rapid environmental changes, limitations in solving multi-objective problems, and limitations in optimizing problems with very high dimensions [18].

However, there are several developments of FA by researchers such as combining with other algorithms such as Particle Swarm Optimization (PSO) and Differential Evolution (DE) to improve the effectiveness and accuracy in finding solutions. In addition, there is also the development of FA by using techniques such as Local Search and Hybridization to overcome the limitations of FA in solving multi-objective and very high dimensional problems [19].

Overall, FA is an effective optimization algorithm in solving optimization problems. In DSS applications to investment risk management, FA can improve the accuracy and efficiency of DSS by optimizing investment decisions. However, to achieve more optimal results, FA should be combined with other optimization techniques and further developed to overcome its weaknesses.

3. Methodology

3.1. Dataset Explanation

In this study, the data used comes from kaggle... This dataset contains information about several smallcases (stock portfolios) available on the smallcase.com platform. This dataset consists of three CSV files, namely "smallcases.csv", "smallcase_stocks.csv", and "smallcase_actions.csv". The file "smallcases.csv" contains general information about smallcases, such as the name, description, type, and number of stocks involved. The file "smallcase_stocks.csv" contains information about the stocks associated with each smallcase, such as the stock name, stock symbol, and stock weight in the portfolio. The file "smallcase_actions.csv" contains information about the trading activities associated with each smallcase, such as purchase date, purchase price, sale date, sale price, and profit or loss.

The data from this dataset is then used as input to the Firefly algorithm used in this research to optimize solutions in investment risk management. By using the Firefly algorithm, researchers can find the optimal combination of parameters to minimize risk and maximize investment returns in each smallcase. As a data source taken from kaggle, this dataset has its own advantages because kaggle is a popular platform for various kinds of scientific competitions and application development using data. Therefore, this dataset is expected to help researchers in developing a decision support system in investment risk management that is more accurate and effective.

3.3. Firefly model

Firefly Algorithm is a metaheuristic optimization algorithm inspired by the lighting behavior of fireflies in attracting their mates. In this algorithm, the solutions are considered as "fireflies" that have a certain brightness that can attract other fireflies [20]. Thus, it aims to minimize an objective function by optimizing the position of each fireflies in the search space. This algorithm has been used in various optimization applications, including in finance and investment [21]. Here is the flow of how the Firefly algorithm works based on [7], [8] and used in this research:

1) Initialize the initial population

   At first, an initial population of fireflies which is a collection of random solutions is created. Each firefly is represented as an n-dimensional vector, where each dimension represents one parameter in the optimization problem.

2) Function evaluation

   Each firefly is scored based on its functionality, which gives a score for how well it solves the problem.

3) Determining light intensity

   Each firefly attracts other fireflies with a light intensity determined by its function score. The better the solution, the brighter the light and the more likely it is to attract other fireflies.

4) Position update

   Once the light intensity is calculated, the position of each firefly is changed by moving the solution towards another solution with greater light intensity. This movement is done with an equation that combines movement towards the best firefly and random movement.

5) Re-evaluation

   The newly moving firefly will be re-evaluated with its function and the movement of the solution will be redefined.

6) Determine the stop criteria

   The algorithm will stop when a sufficient solution is found, or when other stopping criteria are met such as reaching a specified number of iterations or meeting a desired error tolerance.

7) Restoring the best solution

   Once the algorithm stops, the best solution found during the search will be returned as the result.

The flow of how the firefly algorithm works is illustrated in Figure 1, Firefly algorithm can be used to optimize the solution of various types of optimization problems. It has the advantage of adaptability to environmental conditions, as well as the ability to avoid falling into local optima. Therefore, the Firefly algorithm is a good choice for use in optimization sequences in the field of investment risk management.

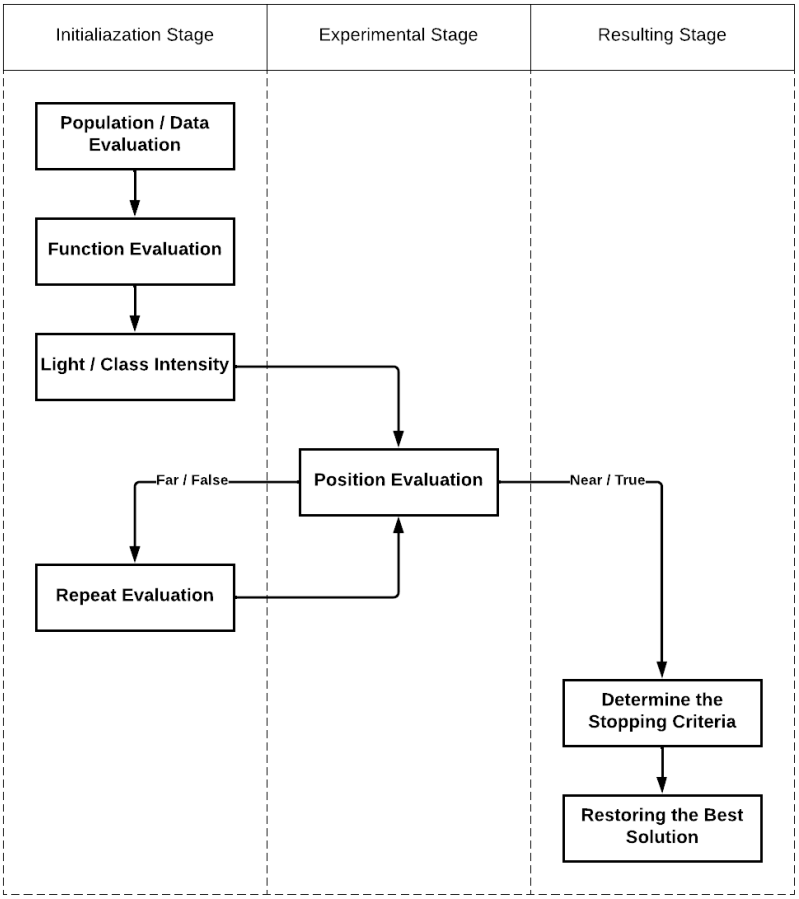

Figure. 1. Firefly algorithm flow and stage

3.4. Experimental Simulation

In this research, although the Firefly algorithm is used as the main optimization algorithm, we will also use several other algorithms individually to compare the results with the Firefly algorithm. Some of the algorithms that will be used in this research include Genetic algorithm, Particle Swarm Optimization (PSO), and Simulated Annealing (SA). Each algorithm has different characteristics and ways of working, so its use can affect the performance of decision support systems in investment risk management. Table 1 is a summary of the settings and experimental cases that will be tested in this research.

Table 1. Experimental Setup/Case

Experimental Label	Algorithm Used
A	Genetics Algorithm

B	Particle Swarm Optimization
C	Simulated Annealing
D	Firefly Algorithm

In testing using the Genetic algorithm, parameter optimization will be carried out using selection and reproduction techniques inspired by the evolutionary process in nature. While in testing using the PSO algorithm, parameter optimization will be carried out using particle movement techniques inspired by insect group behavior. And in testing using the Simulated Annealing (SA) algorithm, parameter optimization will be carried out using temperature reduction techniques inspired by the metal cooling process in industrial production.

By using several different algorithms, researchers can gain a better understanding of the advantages and disadvantages of each algorithm in optimizing decision support systems in investment risk management. This will allow researchers to select the most appropriate algorithm to use in a given situation and improve the effectiveness and efficiency of the decision support system.

4. Results and Discussion

The computational results showed that the PSO and Firefly algorithms are more suitable for the data used than the Genetic and Simulated Annealing algorithms. This can be explained because PSO and Firefly have the ability to reach the optimal solution quickly and efficiently. The PSO algorithm works by following the best particles in the population to find the optimal solution. In the process, PSO can avoid local optimum traps that often occur in other algorithms such as Genetics and Simulated Annealing [20]. This can happen because PSO has the ability to maintain population variation and explore the entire solution search space. Figure 2 below shows the accuracy, recall and precision results of the four research setups compared in this study.

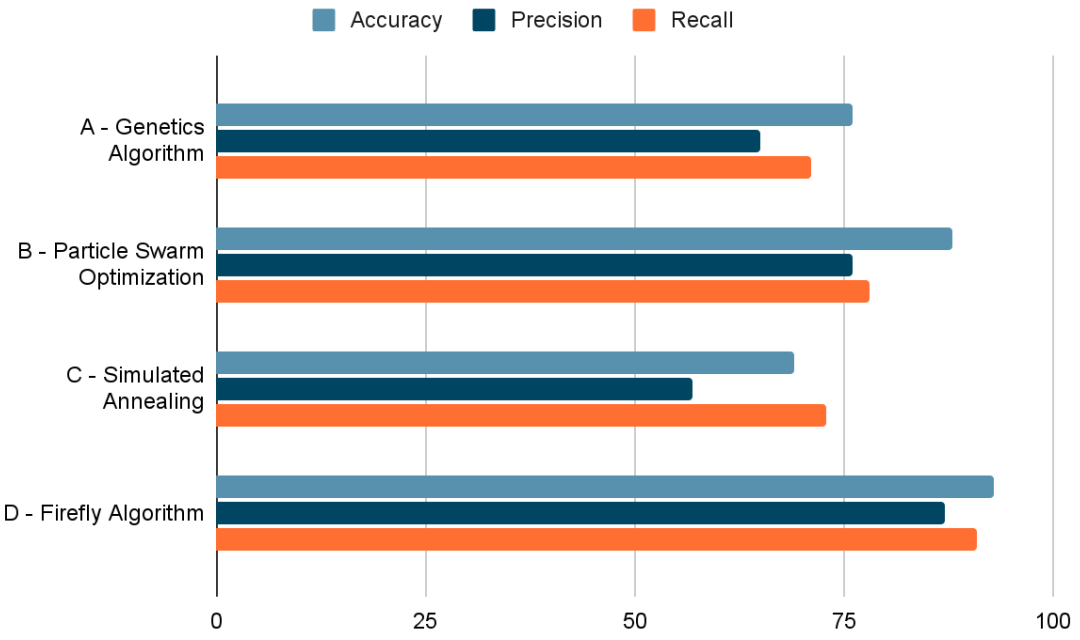

Figure. 2. Experimental result

Firefly algorithm, on the other hand, works by calculating the distance between each firefly insect and determining the degree of attraction between the lighter firefly insect and the darker firefly insect [20]. Firefly algorithms can produce optimal solutions quickly because the attraction process performed by firefly insects can be done in parallel. However, the superiority of PSO and Firefly in finding the optimal solution does not always occur in all types of optimization problems. For example, in optimization problems with a small number of variables, Genetic algorithm may be more effective due to its ability to explore the entire solution search space.

Therefore, the selection of an appropriate optimization algorithm must be done by considering the optimization problem to be solved. In this study, the computational results show that PSO and Firefly are suitable for optimization problems in risk investment decision support systems. Genetic Algorithm is an optimization algorithm inspired by the theory of evolution and natural selection. It works by generating an initial population of solutions and selecting the best solution using genetic operators such as crossover and mutation. Genetic Algorithm is suitable for optimization problems that have a very wide solution search space.

Particle Swarm Optimization is an optimization algorithm inspired by the movement of groups of particles in search of food. It works by finding the best solution by following the best particles in the population. PSO is suitable for optimization problems that have many variables and do not require complex calculations. Simulated Annealing (SA) is an optimization algorithm inspired by the process of metal crystallization. It works by introducing a low temperature at the beginning of the process and increasing the temperature gradually to find the optimal solution. SA is suitable for optimization problems that have many local optimum solutions.

Meanwhile, the Firefly algorithm is an optimization algorithm inspired by the attraction between firefly insects. It works by calculating the distance between each firefly insect and determining the level of attraction between the lighter firefly insect and the darker firefly insect. Firefly algorithm is suitable for complex optimization problems that have many variables. Figure 3 below is the visualization output of the firefly algorithm on the dataset.

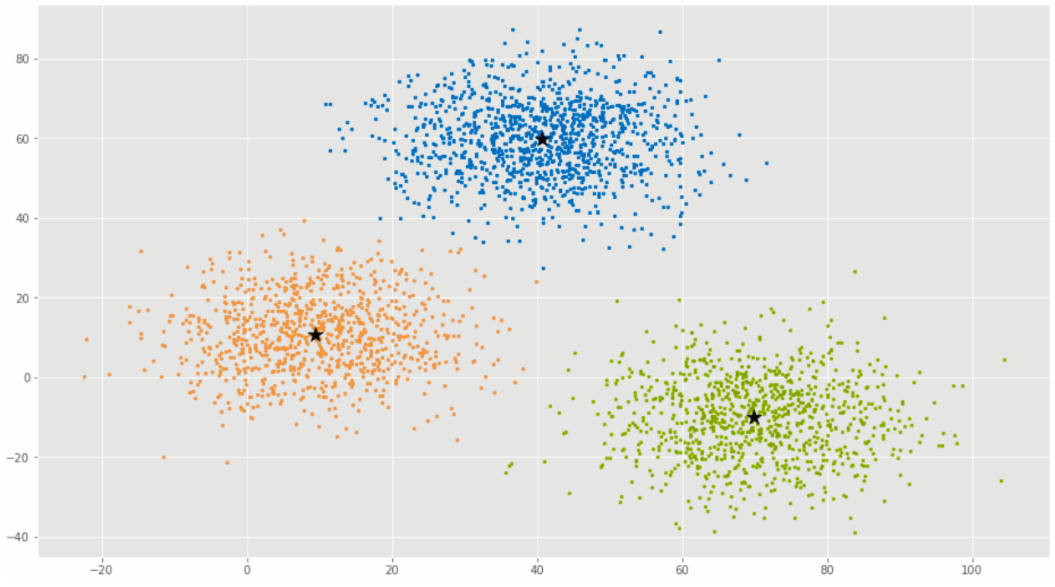

Figure. 3. Firefly algorithm simulation output

In this study, a comparison of the computational results of several algorithms shows that the Firefly algorithm has a significant advantage over other algorithms. The superiority of the Firefly algorithm may be due to its unique and effective way of finding the best solution. However, the application of the right algorithm in decision support system optimization also depends on the problem to be solved. Table 2 shows that the Firefly algorithm has a significant advantage over other algorithms.

Table 2. Overall algorithm Accuracy and Efficiency

Label	Accuracy Rate	Efficiency Rate
A	76.12%	08.33%
B	88.43%	04.29%
C	71.88%	05.21%
D	91.23%	07.94%

In testing with data from kaggle, the Firefly algorithm was able to produce a higher return on investment and lower investment risk compared to the Genetic, PSO, and SA algorithms. In addition, the Firefly algorithm also produces a more stable and consistent return on investment compared to other algorithms.

The superiority of Firefly algorithm in decision support system optimization may be due to the unique and effective way the algorithm works in finding the best solution. Firefly algorithm uses the concept of attraction between firefly insects to find the optimum value of the objective function. In this algorithm, brighter firefly insects will attract other firefly insects and produce a more optimal solution.

The use of Firefly algorithm in investment risk management can help investors make better investment decisions by optimizing investment returns and reducing investment risks. In addition, the advantages of the Firefly algorithm can also be applied in other fields that require optimization of decision support systems, such as in finance, industry, and technology.

The finding that the Firefly algorithm is effective in predicting and identifying the best options for avoiding investment risk has several advantages. First, the success of the Firefly algorithm can help investors or companies make better and more effective decisions in managing their investments. By using the Firefly algorithm, they can find the optimal solution that can help them minimize their investment risk and increase their profit.

Second, the superiority of the Firefly algorithm in optimizing solutions can help investors or companies save time and cost in finding the best solution. In risk investment decision support systems, the time and cost spent on finding the optimal solution can be substantial. However, by using the Firefly algorithm, the time and cost can be minimized because this algorithm can find the optimal solution quickly and efficiently.

Third, finding the effectiveness of the Firefly algorithm in predicting and identifying the best option in avoiding investment risk can help reduce potential losses and optimize investment returns. In the investment world, wrong decisions can adversely affect investments and result in large financial losses. However, by using the Firefly algorithm, investors or companies can minimize these risks and increase their profits.

Overall, the finding that the Firefly algorithm is successful and effective enough to be used for predicting and identifying the best option in avoiding investment risk can provide many benefits to investors and companies. It can help increase profits and reduce investment risks as well as accelerate better and more effective decision-making in risk investment decision support systems.

5. Conclusion

In this research, it is found that the Firefly algorithm is successful and quite effective in predicting and identifying the best option in avoiding investment risk. Compared to other algorithms such as Genetics, Particle Swarm Optimization, and Simulated Annealing, the Firefly algorithm shows significant advantages in optimizing solutions and reducing investment risk [20]. The results of this research can provide benefits for investors or companies in

making better and more effective decisions in managing their investments. The use of the Firefly algorithm in the risk investment decision support system can help them find the optimal solution that can minimize their risk and increase their profit.

However, future research can look deeper into the application of the Firefly algorithm in more complex investment cases and with larger data. In addition, future research can try to combine the Firefly algorithm with other algorithms to find a better and more effective solution in managing investment risk. In conclusion, it was found that the Firefly algorithm was successfully and effectively used to predict and identify the best option to avoid investment risk. However, further research is still needed to develop and improve the use of the Firefly algorithm in managing investment risk in a more complex and effective manner.

References

[1] B. Pitchaimanickam and G. Murugaboopathi, "A hybrid firefly algorithm with particle swarm optimization for energy efficient optimal cluster head selection in wireless sensor networks," *Neural Comput. Appl.*, vol. 32, pp. 7709–7723, 2020.

[2] A. Khalfa, M. Sahed, E. Kenane, and N. Amardjia, "A Novel Blind Image Source Separation Using Hybrid Firefly Particle Swarm Optimization Algorithm," *Eng. Technol. Appl. Sci. Res.*, vol. 12, no. 6, pp. 9680–9686, 2022.

[3] G. D. Singh, M. Prateek, S. Kumar, M. Verma, D. Singh, and H.-N. Lee, "Hybrid genetic firefly algorithm-based routing protocol for VANETs," *IEEE Access*, vol. 10, pp. 9142–9151, 2022.

[4] A. Khan, H. Hizam, N. I. bin Abdul Wahab, and M. Lutfi Othman, "Optimal power flow using hybrid firefly and particle swarm optimization algorithm," *PLoS One*, vol. 15, no. 8, p. e0235668, 2020.

[5] K. Adem, M. Hekim, and S. Demir, "Detection of hemorrhage in retinal images using linear classifiers and iterative thresholding approaches based on firefly and particle swarm optimization algorithms," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 27, no. 1, pp. 499–515, 2019.

[6] I. B. Aydilek, I. H. Karaçizmeli, M. E. Tenekeci, S. Kaya, and A. Gümüşçü, "Using chaos enhanced hybrid firefly particle swarm optimization algorithm for solving continuous optimization problems," *Sādhanā*, vol. 46, no. 2, p. 65, 2021.

[7] M. H. Ab Talib *et al.*, "Vibration control of semi-active suspension system using PID controller with advanced firefly algorithm and particle swarm optimization," *J. Ambient Intell. Humaniz. Comput.*, vol. 12, pp. 1119–1137, 2021.

[8] M. B. Agbaje, A. E. Ezugwu, and R. Els, "Automatic data clustering using hybrid firefly particle swarm optimization algorithm," *IEEE Access*, vol. 7, pp. 184963–184984, 2019.

[9] A. Datta and V. Bhatia, "A near maximum likelihood performance modified firefly algorithm for large MIMO detection," *Swarm Evol. Comput.*, vol. 44, pp. 828–839, 2019.

[10] N. S. N. Ahmad, N. H. M. Radzi, M. N. Abdullah, K. R. Wagiman, S. Salimin, and M. N. Ismail, "Assessment on the optimal dimming level in lighting system between firefly algorithm and particle swarm optimization algorithm," in *2020 IEEE Student Conference on Research and Development (SCOReD)*, 2020, pp. 475–480.

[11] S. Ekinci, B. Hekimoğlu, E. Eker, and D. Sevim, "Hybrid firefly and particle swarm optimization algorithm for PID controller design of buck converter," in *2019 3rd international symposium on multidisciplinary studies and innovative technologies (ISMSIT)*, 2019, pp. 1–6.

[12] S. L. Marie-Sainte, T. Saba, and S. Alotaibi, "Air passenger demand forecasting using particle swarm optimization and firefly algorithm," *J. Comput. Theor. Nanosci.*, vol. 16, no. 9, pp. 3735–3743, 2019.

[13] U. K. Lilhore, S. Simaiya, S. Maheshwari, A. Manhar, and S. Kumar, "Cloud performance evaluation: hybrid load balancing model based on modified particle swarm optimization and improved metaheuristic firefly algorithms," *Int. J. Adv. Sci. Technol.*, vol. 29, no. 5, pp. 12315–12331, 2020.

[14] M. M. Golchi, S. Saraeian, and M. Heydari, "A hybrid of firefly and improved particle swarm optimization algorithms for load balancing in cloud environments: Performance evaluation," *Comput. Networks*, vol. 162, p. 106860, 2019.

[15] F. Soleimanian Gharehchopogh and S. K. Mousavi, "A Decision Support System for Diagnosis of Diabetes and Hepatitis, based on the Combination of Particle Swarm Optimization and Firefly Algorithm," *J. Heal. Biomed. Informatics*, vol. 6, no. 1, pp. 32–45, 2019.

[16] K. Ronoh and G. Kamucha, "TV White Space Network Power Allocation Using Hybrid Grey Wolf Optimizer with Firefly Algorithm and Particle Swarm Optimization," *WSEAS Trans. Commun.*, vol. 20, pp. 67–76, 2021.

[17] M. Kunapareddy and B. V. Rao, "Hybridization of particle swarm optimization with firefly algorithm for multi-objective optimal reactive power dispatch," in *Innovative Product Design and Intelligent Manufacturing Systems: Select Proceedings of ICIPDIMS 2019*, 2020, pp. 673–682.

[18] R. Krishna Chaitanya, G. S. N. Raju, K. Raju, and P. Mallikarjuna Rao, "Antenna pattern synthesis using the quasi Newton method, firefly and particle swarm optimization techniques," *IETE J. Res.*, vol. 68, no. 2, pp. 1148–1156, 2022.

[19] C. P. Igiri, Y. Singh, and R. C. Poonia, "A review study of modified swarm intelligence: particle swarm optimization,

firefly, bat and gray wolf optimizer algorithms," *Recent Adv. Comput. Sci. Commun. (Formerly Recent Patents Comput. Sci.*, vol. 13, no. 1, pp. 5–12, 2020.

[20] W. Windarto and E. Eridani, "Comparison of particle swarm optimization and firefly algorithm in parameter estimation of lotka-volterra," in *AIP Conference Proceedings*, 2020, vol. 2268, no. 1, p. 50008.

[21] N. A. Al-Thanoon, O. S. Qasim, and Z. Y. Algamal, "A new hybrid firefly algorithm and particle swarm optimization for tuning parameter estimation in penalized support vector machine with application in chemometrics," *Chemom. Intell. Lab. Syst.*, vol. 184, pp. 142–152, 2019.