Jurnal TEKNO
(Civil Engineeering, Elektrical Engineeering and Industrial Engineeering)
Vol. 22, No : 1, April 2025 , p-ISSN:1907-5243, e-ISSN: 2655-8416

Forensic-Based Investigation Optimization to Solving Traveling Salesman Problem

Prayoga Yudha Pamungkas[1], Umi Latifah[2], Roikhanatun Nafi'ah[3]

[1,2,3]Industrial Engineering Department, Faculty of Engineering, Bina Nusantara University, Jakarta Indonesia 11480
Email: [1]prayoga.pamungkas@binus.ac.id, [2]umi.latifah@binus.ac.id, [3]roikhanatun.nafiah@binus.ac.id

Abstract

The FBI Optimization (FBIO) represents one of the most novel metaheuristics which has been experimented with to solve Traveling Salesman Problem (TSP), demonstrating superior performance compared to tradition-al algorithms. Unlike conventional approaches that start with exploration and gradually shift to exploitation, FBIO maintains a dominant exploration phase throughout its iterations. Beginning with 100% exploration and tapering to approximately 90% dominance in exploration by the end of the process, FBIO effectively navigates the solution space, uncovering more promising routes. This exploration-centric approach enables FBIO to achieve solutions that are 8.39% closer to the near-optimal result compared to its counterparts. The algorithm's enhanced performance in TSP highlights its potential applicability to other combinatorial optimization challenges. By prioritizing exploration, FBIO offers a robust framework for addressing complex prob-lems and ensures a comprehensive search of the solution space. Its ability to deliver high quality near-optimal solutions makes FBIO a valuable tool for future research, presenting new opportunities for solving various optimization problems and advancing practical problem-solving methodologies.

Keywords: FBI Optimization, Metaheuristic, Traveling Salesman Problem

1. INTRODUCTION

The Traveling Salesman Problem is definitely a traditional optimization problem that has engaged researchers' interest over many decades indeed due to its inherent complexity and wide scope of application. More precisely, the TSP seeks the shortest possible route for a salesman to visit a set of cities and return to the origin city without repeating any city on his way. The TSP, despite being a rather simple formulation, belongs to the class of NP-hard problems, which translates to exponential running time in relation to the size of the problem. Therefore, developing solution methods in an efficient and effective way for the TSP has remained one of the major lines of research in operations research and computational optimization.

Traditional methods for solving TSP involve exact algorithms, where there are options such as branch and bound or dynamic programming. These methods give the optimal solution, but they are usually very computationally intensive to be applied to large instances. Because of this reason, heuristic and metaheuristic approaches have recently received considerable attention and are applied to obtain approximate solutions within a reasonable computational time. Methods like Genetic Algorithms, Simulated Annealing, and Ant Colony Optimization have had some degrees of success against the complexity of TSP. However, the quest for more innovative and robust metaheuristics continues.

In the last few years, nature-inspired metaheuristics have been receiving significant attention due to the powerful possibility they show in solving complex optimization problems. These algorithms are inspired by the natural process and phenomenon of events, such as the foraging behavior of ants, the flight patterns of birds, and the evolutionary process of biological species. These approaches have been able to shed new perspectives and techniques on how to deal with the intricacies of TSP and, in lieu, come up with new algorithms that come with an improved performance. Of these, Forensic-Based Investigation Optimization seems to be an exciting new entry into the metaheuristic toolbox.

In a way, FBIO is inspired by the investigative and analytical stages of the police investigation process [1]. This precisely imitates how the detectives solve crimes starting from gathering evidence, generating hypotheses, and refinement of solutions iteratively. This human-behavior-inspired approach utilizes the meticulous and strategic aspects involved in criminal investigations to navigate the search space of optimization problems. It will balance exploration and exploitation by simulating thorough and adaptive strategies of forensic investigators using the FBIO algorithm.

Similar to the case of a detective collecting clues and evidences at a crime scene, the FBIO algorithm initiates with an initial, diverse population of possible solutions. Their quality is then assessed, and more promising solutions are selected for further refinement. Much like the police investigation that follows up leads in a case, the algorithm refines these solutions iteratively. These techniques parallel hypothesis testing and cross-examination in forensic work. The process provides the basis for FBIO to adaptively improve solution quality over successive iterations and allows an overall search of the solution space.

Application of FBIO to TSP includes several key adaptations to fit into the special requirements of the problem. The first is that the representation of members of a potential TSP solution must capture the permutation nature of a TSP route. Second, the evaluation criteria of the evaluation function should accurately reflect the total travel distance. And thirdly, the domain-specific heuristics and local search methods are put into the FBIO paradigm for the performance enhancement. These adaptations ensure that FBIO is not only theoretically sound but no less practically effective in solving a TSP instance of any size and complexity.

Empirical studies and computation experiments clearly showed that the FBIO performed very well in solving the TSP. Comparative analyses done with other established metaheuristic procedures indicate that the FBIO consistently has produced high-quality solutions with competitive computational efficiency. In this context, the unique forensic-inspired strategies of FBIO indicate that it has applicability to the concerned case of TSP and to other combinatorial optimization problems. The success of the algorithm to find close-to-optimal solutions is based on the systematic exploration and exploitation of the solution space.

2. METHODS

3.1. Traveling Salesman Problem

Travelling Salesman Problem (TSP) is a problem to find best possible route of visiting all the cities with minimum travel distance [2]. TSP mathematical model is defined as follows Dantzig [3].

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ij}\, x_{ij} \tag{1}$$

Subject to

$$\sum_{i=1}^{N} x_{ij} = 1, \qquad j = 1,2,\dots,N \tag{2}$$

$$\sum_{j=1}^{N} x_{ij} = 1, \qquad i = 1,2,\dots,N \tag{3}$$

$$x_{ij} = \{0,1\}, \qquad i,j = 1,2,\dots,N \tag{4}$$

Where cij means distance of city i and city j, xij means whether the route is crossed or not. The objective function of equation (1) is to minimize the distance traveled by salesman. equation (2) and (3) means that salesman only can depart from city i once and arrive to city j once, its function to ensure that salesman only visit each city one time. Equation (4) means the route xij = 0 if not crossed and xij = 1 if crossed by salesman.

TSP can be solved using exact, heuristics, and metaheuristics approaches. Exact solution promise to optimum result such as branch & bound [4] that first discovered for discrete programming and branch & cut [5] for combinatorial optimization problem. Decades later, TSP has grown to become more complex so that solving it with an exact method is impossible in terms of computation time. Huge number of solution alternative lead to high computation time in solving medium and large scale problem [6]. Due to complexity problem and demands a short completion time, exact method is only efficient for small problem instances [7].

TSP continuous to be developed using other methods due to the limitation of exact solution. Researchers developing their methods to get good solution in reasonable time. Not like exact method that ensure the optimal results, researchers developing the methods to solve TSP in near optimal solution using metaheuristics methods. Metaheuristics is a procedure to solve complex optimization problem in good enough solution [7]. Well-known algorithms in metaheuristics are Genetic Algorthm [8], Ant Colony Optimization, and Particle Swarm Optimization [9]. Those metaheuristics have been used to solve TSP that got good-enough solution. Nevertheless, there are still a gap between optimal solution and their result.

3.2. Forensic-Based Investigation Optimization

FBI methodology, inspired by police criminal investigations, starts with identifying evidence and suspect locations within a search space [1]. The investigative team analyses suspected locations and designates the highest probability search area, while the pursuit team moves towards it following headquarters' orders. Both teams closely coordinate, with the pursuit team reporting search results so the investigative team can update information and improve assessment accuracy. This process ends when the iteration count is maximum, utilizing NP d-dimensional parameter vctors.

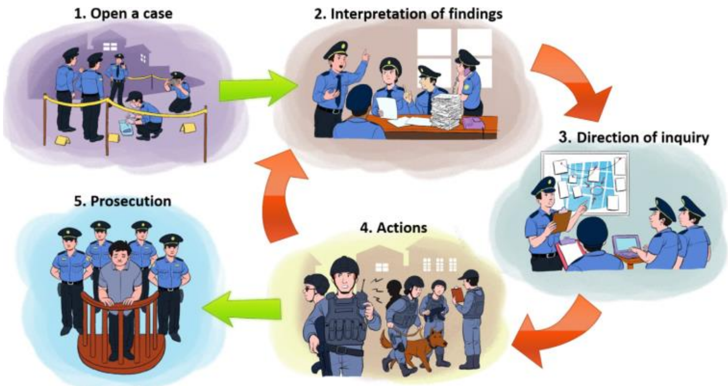

Figure 1. FBI Optimization Scheme

In optimizing FBI investigations, a structured five-stage process helps enhance overall effectiveness and resource allocation. The first stage, opening a case, involves determining whether the incoming information warrants a full investigation, essentially setting the problem scope. During the interpretation of findings, agents analyze data to pinpoint critical insights and prioritize leads, akin to identifying variables and constraints in an optimization problem. This leads to the direction of inquiry, where specific investigative strategies are formulated based on the interpreted data, similar to determining the best possible paths or solutions in an optimization model. The actions stage then implements these strategies, aligning resources and efforts to maximize investigative efficiency, much like applying optimization algorithms to achieve the best outcome. Finally, in the prosecution stage, the focus shifts to ensuring that the optimized strategy translates into a strong legal case, ensuring that evidence is presented effectively to secure a conviction. This optimization approach streamlines the investigative process, ensuring that each stage contributes to the overall goal of solving and prosecuting the case efficiently. In general, FBI Optimization operates on 2 team: the first one is investigation team to open a case, findings the clue, and direction; the second is pursuit team to conduct an action and prosecution.

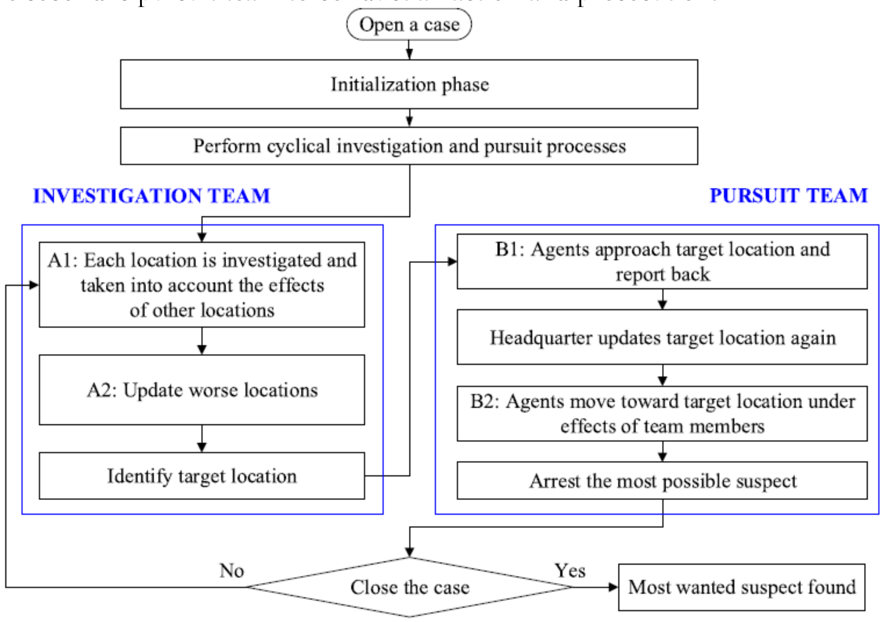

Figure 2. FBI Optimization Methodology

2.2.1 Opening a case

The investigation starts when the police receive information about a criminal incident. The first responding officer at the crime scene gathers essential preliminary information, forming the investi-gative team's foundation to begin their inquiry. Standard procedures are followed to secure the crime scene, assess the victim's condition, identify potential suspects, and collect relevant back-ground information. Additionally, investigators seek out eyewitnesses and conduct interviews to gather testimonies that could help further investigation.

2.2.2 Interpretation of Findings

After collecting initial information, the investigative team conducts an in-depth analysis of all evidence and data obtained. During routine team meetings, they share collected information to build a common understanding of the case. This stage involves critically evaluating the information and connecting various elements found to the initial impressions and hypotheses about the incident. This interpretation helps identify who might be involved and how the crime was committed. Mathematically this step is given by:

$$X_{A1_{ij}} = \frac{X_{A_{ij}} + \left((rand - 0.5) \cdot 2\right)\left(\sum_{a=1}^{a_1} X_{A_{aj}}\right)}{a1} \quad (5)$$

Where,

- X_{A1_i} is inferred from X_{A_i}
- X_{A_i} is new suspected location.
- j = 1,2,...,D; D is the number of dimensions.
- $((rand - 0.5) \cdot 2)$ is random number in the range (-1,1).
- $rand$ is random number in the range (0,1).
- $a1 \in$ {1, 2, ..., n-1} indicating the number of individuals affecting the movement of $X_{A_{ij}}$
- a = 1, 2, …, $a1$.
- $a1$ = 2 yielded the optimal outcome within a brief computational period.
- p_{A_i} is the objective value of locations X_{A1_i} (i.e., $p_{A_i} = f_{objective}(X_{A_i})$).

The investigators compare the probability pA1i of the new suspect's location with the current one. The area with the higher probability will be kept, and the other discarded.

$$X_{A1_{ij}} = X_{A_{ij}} + \left((rand_1 - 0.5) \cdot 2\right) \cdot \left(X_{A_{ij}} - \frac{\left(X_{A_{kj}} + X_{A_{hj}}\right)}{2}\right) \quad (6)$$

Where,

- $k, h,$ and i are 3 suspected locations.
- $\{k, h, i\} \in \{1,2, \dots, NP\}$, k and h are chosen randomly.
- j = 1, 2, ..., D, D is the number of dimensions.
- $((rand - 0.5) \cdot 2)$ is random number in the range (-1,1).

$rand$ is random number in the range (0,1).

2.2.3 Direction of Inquiry

The investigative team formulates various hypotheses and scenarios from the initial findings, exploring motives and outlining paths. This fluid stage allows new discoveries to alter the investigation's direction. The team continuously reviews and tests hypotheses, adjusting strategies based on new information. Investigators compare the probabilities of suspected locations to identify the most likely one for further investigation, focusing on minimization optimization. In the realm of mathematics, this step is articulated as below:

$$Prob\left(X_{A_{ij}}\right) = \frac{(p_{worst} - p_{A_i})}{(p_{worst} - p_{best})} \quad (7)$$

Where,

- p_{worst} represents the lowest possibility.
- p_{best} represents the highest possibility.

Other suspected locations influence the update of a search location, but only random directions are changed to diversify. X_{A_i} movement is affected by the best and random individuals. Step A2 is similar to step A1, using the formula as below:

$$X_{A2_i} = X_{best} + \sum_{b=1}^{a_2} a_b \cdot X_{A_{bj}} \quad (8)$$

Where,

- X_{best} is the best location.
- $a2 \in$ {1, 2, ..., n-1} indicating the number of individuals influencing the movement of X_{A2_i}
- b = 1, 2, …, $a2$.
- a_b is the effectiveness coefficient $(a_b = [-1,1])$ of the other individuals to the move.

Numerical experiments set a2 at 3. The new suspected location $X_{A2_{ij}}$ is generated with Eq. (5), and its possibility is calculated to determine if it should be updated.

$$X_{A2_{ij}} = X_{best} + X_{A_{dj}} + rand_5\left(X_{A_{ej}} - X_{A_{fi}}\right) \quad (9)$$

Where,

- X_{best} is the best location in step A1.
- $d, e, f,$ and i are four suspected locations.
- $\{d, e, f, i\} \in \{1,2, \ldots, NP\}$, $d, e,$ and f are chosen randomly.

2.2.4 Actions

After setting priorities, the investigative team plans arrests or searches to gather more information and strengthen evidence. These actions are reviewed to assess their impact, with continuous adjustments based on new field information. Once the investigation team reports the best location, all pursuit agents must coordinate to arrest the suspect. Mathematically this step is given by:

$$X_{B1_{ij}} = rand_6 \cdot X_{B_{ij}} + rand_7 \left(X_{best} - X_{B_{ij}}\right) \tag{10}$$

Where,

- X_{best} is the optimal location identified by the investigation team.
- $rand_6$ and $rand_7$ are two random numbers in the range [0, 1].
- j = 1, 2, ..., D, D is the number of dimensions.

When police agents move, they report the new location probabilities to headquarters. Headquarters updates the location and directs the pursuit team to approach it. Each agent B_i coordinates with others, moving toward the best location and influenced by agent B_r's probability p_{B_r}.

$$X_{B2_{ij}} = X_{B_{rj}} + rand_8 \left(X_{B_{rj}} - X_{B_{ij}}\right) + rand_9 \left(X_{best} - X_{B_{rj}}\right) \tag{11}$$

If p_{B_i} is better than p_{B_r}, it is expressed as the following equation:

$$X_{B2_{ij}} = X_{B_{ij}} + rand_{10} \left(X_{B_{ij}} - X_{B_{rj}}\right) + rand_{11} \left(X_{best} - X_{B_{ij}}\right) \tag{12}$$

Where,

- X_{best} is the best location provided in Step B1002E
- $rand_8$, $rand_9$, $rand_{10}$, and $rand_{11}$ are random numbers in the range [0, 1].
- r and i are two police agents.
- $\{ r, i \} \in \{1, 2, ..., NP\}$, and r is chosen randomly.
- j = 1, 2, ..., D, D is the number of dimensions.

2.2.5 Prosecution

The final stage of the investigation is to bring the case to the legal process. After a thorough investigation, when the investigative team has gathered sufficient evidence and identified the main suspect, they present the case to the prosecutor. The prosecutor reviews all the evidence and decides if there is a solid basis to file legal charges. This process continues to court, where the collected evidence will be presented to prove the suspect's guilt and achieve justice for the victim. In conclusion of the FBI Optimization algorithm can seen through figure 3.

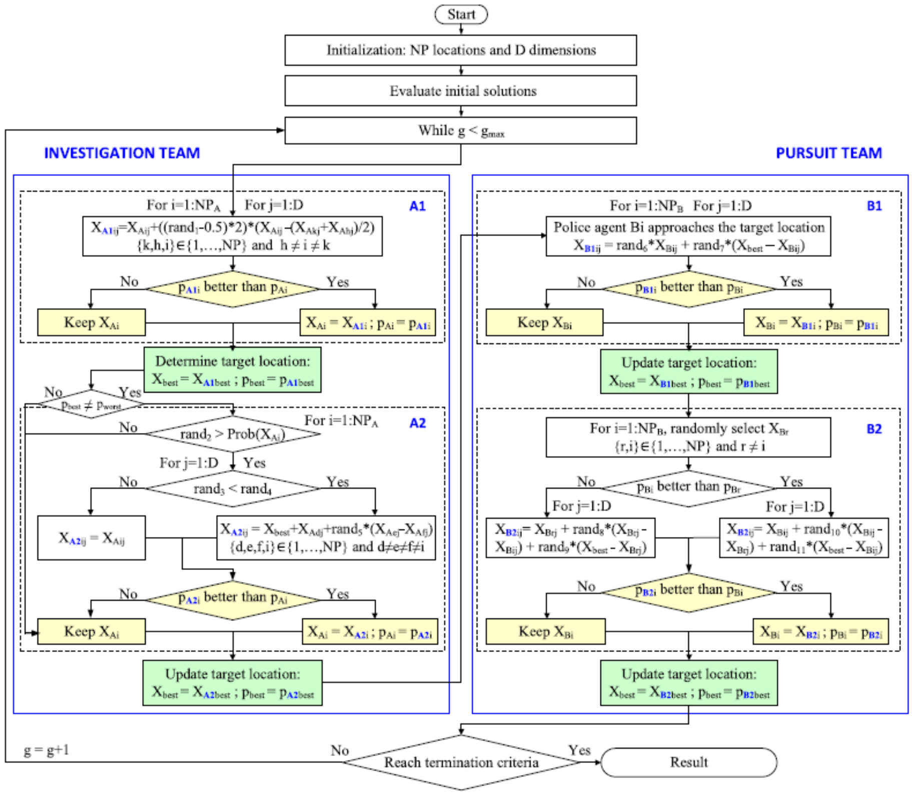

Figure 3. FBI Optimization Methodology

3. RESULTS AND DISCUSSION

3.1. Instance Dataset

In this work, the dataset used is the Burma14 TSPLib instances [10]. The library of test problems is very famous and in wide use within the operations research community for the benchmarking and comparing of different algorithms that have been developed to solve the TSP. Inclusion of the Burma14 dataset in this study shows its importance and usefulness as one of the tools toward exploring optimization techniques. Being small and simple, this 14-node dataset, in an academic sense, has proved to be very useful in testing preliminary algorithms.

Table 1. Coordinates of burma14 instance

Node	Coordinate

	X	Y
0	16.47	96.10
1	16.47	94.44
2	20.09	92.54
3	22.39	93.37
4	25.23	97.24
5	22.00	96.05
6	20.47	97.02
7	17.20	96.29
8	16.30	97.38
9	14.05	98.12
10	16.53	97.38
11	21.52	95.59
12	19.41	97.13
13	20.09	94.55

3.2. Existing Metaheuristics

Table 2 gives the current performance for some of the well-known metaheuristics including Genetic Algorithms (GA) [8], Simulated Annealing, and Particle Swarm Optimization [9]. These algorithms are very often deployed because they have the ability to solve a lot of optimization problems. In spite of the effectiveness of metaheuristics in optimization problems, there exist gaps in the solution toward the optimum solution. Therefore, it gives a very good opportunity for developing new algorithms that decrease the solution gap toward near the optimum value.

Table 2. Existing metaheuristic solution value on burma14 instance.

Methods	Total Distance	Gap (%)
Optimum Solution	30.87	-
Genetics Algorithm	33.96	9.97%
Particle Swarm Optimization	35.37	14.5%
Simulated Annealing	34.98	13.27%

In table 1 presents an analysis of the Burma14 instance dataset, it found that the optimal solution is 30.87. In contrast, popular metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) produced results of 33.96, 35.37, and 34.98, respectively. This indicates a performance gap, with the smallest deviation from the optimal solution being 9.97%. These performance gaps underscore the inherent difficulties in approximating the optimal solution using metaheuristic approaches. Metaheuristic reflect the fundamental trade-offs between solution quality and computational efficiency. To tackle these complex optimization challenges, it becomes clear that continuous research and development are essential. By refining our algorithmic strategies, we can strive for solutions that are not only closer to the optimal value but also feasible in terms of computational resources.

3.3. Constructed Algorithm

The developed FBI Optimization algorithm is all-inclusive since it involves five critical stages that guarantee thorough case handling and successful prosecution. Open a Case is a systematic initiation of an investigation where all the necessary details are recorded carefully to form a strong base. This is followed by the Interpretation of Findings where the collected evidence is rigorously analyzed for meaningful insights and patterns. The Direction of Inquiry is the third stage and involves tactical direction of investigation based on hypothesizing the findings and establishing possible leads that can be followed. Investigative activities during this stage entail actions aimed at surveillance, interviews, and the gathering of evidence in proof of the case. The final stage, Prosecution, wraps up the process by piecing this strong case for prosecution together with all the gathered evidence and investigative effort, by making sure everything is in its place to secure a successful prosecution. Since this is an algorithmic approach, it builds up operational efficiency at the FBI, hence improving the effectiveness of criminal investigations.

Algorithm Forensic-Based Investigation Algorithm

Require: N_{iter}, N_{pop}, D and boundaries of variables.
Ensure: Fitness function $f(P)$ is defined.

Initialize the population Xi (i = 1,2, …, NP)
$X_A = X_{B_i} = X_i$
while (g < maximum iterations) #Start the cyclical investigation and pursuit processes#
    for i = 1 : NP #Step A1 – Interpretation of findings#
        for j=1:D, where D = dimension of the problem
            Generate new location $X_{A1_{ij}}$ by using Eq.2
        end for
        Calculate p_{A1_i} (objective value of location X_{A1_i})
        Update X_{A_i} and p_{A_i}
    end for
    update best location $X_{best} = X_{A1_{best}}$ and global best $p_{best} = P_{A1_{best}}$
    if $P_{best} \neq P_{worst}$ #Step A2 - Direction of inquiry #
        for i = 1:NP
        Calculate probability $Prob(X_{A_i})$ by using Eq.3
            if $rand_2 > Prob(X_{A_i})$
                for j = 1:D
                    if $rand_3 < rand_4$
                        Generate new location $X_{A2_{ij}}$ by using Eq.5

end if

end for

Calculate P_{A2_i}

Update X_{A_i} and P_{A_i}

end if

end for

Update best location $X_{best} = X_{A2_{best}}$ and global best $p_{best} = p_{A2_{best}}$

end if

for I = 1:NP #Step B1 - Actions#

for j = 1:D

Generate new location $X_{B1_{ij}}$ by using Eq.6

end for

Calculate p_{B1_i}

Update X_{B_i} and p_{B_i}

end for

Update best location $X_{best} = X_{B1_{best}}$ and gloval best $P_{best} = P_{B1_{best}}$

for i = 1:NP #Step B2 - Prosecution#

Randomly select X_{B_r}

if PBr better than P_{B_i}

for j = 1:D

Generate new location $X_{B2_{ij}}$ by using Eq.7

end for

else

for j = 1:D

Generate new location $X_{B2_{ij}}$ by using Eq.8

end for

end if

Calculate P_{B2_i}

Update X_{Bi} and P_{B_i}

end for

Update best location $X_{best} = X_{B2_{best}}$ and global best $P_{best} = P_{B2_{best}}$

end while

FBI Optimization consists of 2 parameters to solving optimization problem, number of population and number of evaluations. Number of population in FBIO metaphorically aligns with the number of initial theories or leads that investigators consider at the beginning of an investigation. These are parameters used to tune for efficiency in the solving of TSP. Table 3 details the specific

Vol. 22, No : 1, April 2025, p-ISSN:1907-5243, e-ISSN: 2655-8416

parameters used in this study. Table 3 identifies the specific parameters used in this research.

Table 3. FBI Optimization Parameter Setting.

Parameter	Value
Number of Population	50
Number of Evaluation	1,000

3.4. Computational Result

The FBI Optimization for TSP was written in the Python language and run on a computer system running with an AMD Ryzen 5 5600H CPU and 16GB of memory. This setting offered a proper environment for analyzing the algorithm's efficacy and efficiency. It sets the parameters of the FBI Optimization to enable it to work on the Traveling Salesman Problem, while the performance of the algorithm is optimized with a lot of exploration. Finally, the implementation of FBIO using the parameters above was very effective in making the algorithm create a solution for the TSP. The result is route traced its way starting from node 12 and ended to node 10 before come back to initial departure in node 12. This returned a total distance of 33.46, thereby justifying the efficiency of the algorithm in arriving at the best solution for any combinatorial, intricate optimization problem. Details of constructed route written in table 4 that shown how salesman must depart from which node and continue to which node so can take the shortest distance without missing a single node.

Table 4. The order of nodes the salesman should go to

Constructed Route	Total Distance
12 - 13 - 2 - 3 - 4 - 5 - 11 - 6 - 7 - 0 - 1 - 9 - 8 - 10 -12	33.46

The convergence rate depicted on Fig. 4 is the process the FBIO solves TSP through the objective value over 1,000 iterations. At the start of the chart, a high objective value can be viewed at roughly 43, gradually decreasing through the first 50 iterations. By the 400th iteration, the solution value had stabilized at more than 34 and dropped for the last time in the iteration 400s, maintaining the total distance until the end of the iteration with the final solution value of 33.46. This steep drop at early iterations thus indicates that the FBIO works very effectively in rapidly exploring and finding the solutions.

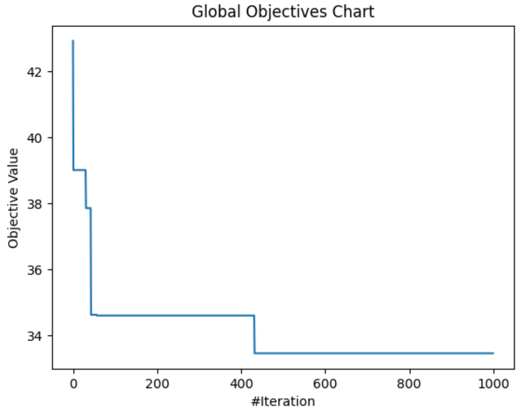

Figure 4. Convergence rate of FBIO in solving TSP

Figure 5 illustrates the exploration and exploitation percentages over 1000 iterations of the FBIO algorithm for solving the Traveling Salesman Problem (TSP). Throughout the entire run, the exploration percentage remains significantly higher than the exploitation percentage, starting near 100% and slightly decreasing but staying above 80%. This indicates a strong emphasis on exploring new potential solutions over refining existing ones. The stable rates after an initial adjustment period suggest consistent behavior in the algorithm's exploration and exploitation dynamics. Unlike many metaheuristic algorithms where an initial exploration phase transitions to exploitation, FBIO maintains high exploration throughout, highlighting its design to continually search the solution space. This continuous high level of exploration is due to FBIO's inspiration from forensic investigations, which emphasize thorough exploration to mimic the investigative process of gathering and analyzing evidence comprehensively.

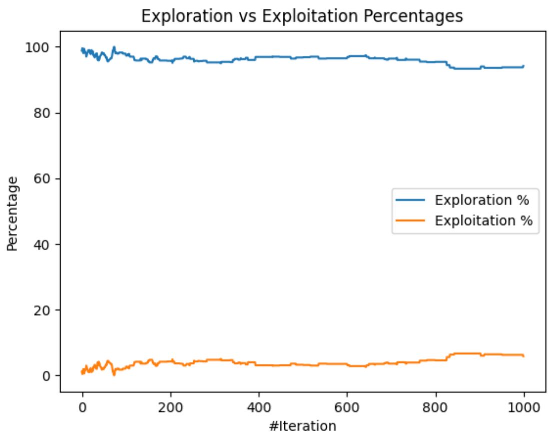

Figure 5. Exploration and exploitation movement for each iteration

This continuous high exploration level can be beneficial for avoiding local optima and ensuring a thorough search for near-optimal solutions. However, it also suggests that the algorithm might benefit from increased exploitation to enhance solution quality through refinement. Balancing exploration and exploitation is crucial for efficient optimization, and the current implementation leans heavily toward exploration. Adjusting parameters such as the refinement rate or incorporating adaptive mechanisms could shift the focus towards more exploitation as iterations progress.

To this end, the case Burma14 was used as a reference for a comparison in order to estimate the performance of FBIO to solve TSP. In this context, this work also implemented GA, PSO, and SA to compare the performances of FBIO against these optimization techniques. The result of such a comparison is presented in Table 5, which shows the total distances reached by each algorithm along with their deviations from the optimum solution.

Table 5. Existing metaheuristic solution value on burma14 instance.

Methods	Total Distance	Gap (%)
Optimum Solution	30.87	-
Genetics Algorithm	33.96	9.97%
Particle Swarm Optimization	35.37	14.5%
Simulated Annealing	34.98	13.27%
Forensic-Based Investigation Optimization	**33.46**	**8.39%**

4. CONCLUSIONS

The FBIO algorithm makes tremendous improvements while solving TSP, improving other algorithms in bringing their solution 8.39% closer to the near-optimal result. Unlike traditional algorithms, which normally start with exploration and then shift to a phase of exploitation as iterations proceed, the FBIO algorithm runs with a dominant phase of exploration throughout its execution. Starting from 100% exploration, the FBIO automatically adjusts the emphasis on the exploration end rather than the exploitation and slowly tapers off to about 90% exploration dominance towards the end of iterations. This approach will definitely let FBIO successfully traverse the solution space to reveal more promising routes for improved overall solution quality in the solution of TSP. The results are quite astounding, improving TSPs where the solution given by FBIO comes closer to the optimum as compared to its counterparts.

The promising performance in solving the TSP indicates that FBIO has the potential to be applied to other combinatorial optimization problems. The key attributes that enable it to focus on the core of exploration throughout its algorithmic lifecycle are: providing a very strong framework for tackling complex problems beyond the TSP, ensuring not only better solution accuracy but also a very robust framework. This exploration-based strategy will ensure that a clear investigation is done within the solution space for FBIO. This would be an important tool for future research in various combinatorial fields. This has the capability to realize very near-optimal solutions with a high degree of exploration, making it an excellent candidate for further development and application in different optimization scenarios.

REFERENCES

[1] J.-S. Chou and N.-M. Nguyen, "FBI inspired meta-optimization," Appl Soft Comput, vol. 93, p. 106339, 2020, doi: https://doi.org/10.1016/j.asoc.2020.106339.

[2] R. Matai, S. Singh, and M. L. Mittal, "Traveling Salesman Problem: an Overview of Applications, Formulations, and Solution Approaches," in Traveling Salesman Problem, D. Davendra, Ed., Rijeka: IntechOpen, 2010, p. Ch. 1. doi: 10.5772/12909.

[3] G. Dantzig, R. Fulkerson, and S. Johnson, "Solution of a Large-Scale Traveling-Salesman Problem," Journal of the Operations Research Society of America, vol. 2, no. 4, pp. 393–410, 1954, [Online]. Available: http://www.jstor.org/stable/166695

[4] A. H. Land and A. G. Doig, "An Automatic Method of Solving Discrete Programming Problems," Econometrica, vol. 28, no. 3, pp. 497–520, 1960, doi: 10.2307/1910129.

[5] J. E. Mitchell, "Branch-and-Cut Algorithms for Combinatorial Optimization Problems," in Handbook of Applied Optimization, P. M. Pardalos and M. G. C. Resende, Eds., New York: Oxford University Press, 2002, pp. 65–77.

[6] E. Horowitz and S. Rajasekaran, Computer Algorithms, 1st ed. New York: W.H. Freeman, 1997.

[7] K. Braekers, K. Ramaekers, and I. Van Nieuwenhuyse, "The vehicle routing problem: State of the art classification and review," Comput Ind Eng, vol. 99, pp. 300–313, 2016, doi: https://doi.org/10.1016/j.cie.2015.12.007.

[8] W. Yang, L. Deng, Q. Niu, and M. Fei, "Improved Shuffled Frog Leaping Algorithm for Solving Multi-aisle Automated Warehouse Scheduling Optimization," in AsiaSim 2013, G. Tan, G. K. Yeo, S. J. Turner, and Y. M. Teo, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 82–92.

[9] L. Li, Y. Cheng, L. Tan, and B. Niu, "A Discrete Artificial Bee Colony Algorithm for TSP Problem," in Bio-Inspired Computing and

Vol. 22, No : 1, April 2025, p-**ISSN:1907-5243, e-ISSN: 2655-8416**

Applications, D.-S. Huang, Y. Gan, P. Premaratne, and K. Han, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 566–573.

[10] G. Reinelt, "Discrete and Combinatorial Optimization," http://comopt.ifi.uni-heidelberg.de/software/TSPLIB95/tsp.