Library Progress International *Print version ISSN 0970 1052*
Vol.44 No.3, Jul-Dec 2024: P. 21763-21771 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

An Emerging Optimal System using Fraudulent Transaction Detection System using block chain

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How to cite this article: Sowmiyasree.S, Ranganayaki.T (2024) An Emerging Optimal System using Fraudulent Transaction Detection System using block chain. *Library Progress International,* 44(3), 21763-21771.

ABSTRACT

A Block chain technology works well in a variety of problem domains is the bat-inspired algorithm (BA). Modified with Enhanced Bat Algorithm (M-EBA) transaction system to overcome the original BA's optimal limitation. In order to improve convergence speed to the optimal solution and avoid local optima trapping, it takes into account the frequency and velocity of the current best solution. The results show that the M-EBA algorithm performs noticeably better than competing algorithms. Additionally, M-EBA analyzes the effects of various parameters to identify the optimal combination of parameter values in the context of numerical optimization and successfully solves a real-world assignment problem which is typically solved using linear programming techniques, with satisfactory results. To detect the fraudulent transaction system in future directions for forthcoming developments are proposed, including the use of BA in large-scale, dynamic, robust, multi-objective optimization as as well as improve BA performance by utilizing election mechanisms, tuning parameters, structure population .

Keywords—Bat Algorithm, Naïve Bayes,, Deep Learning Algorithm, Feature Selection, M-EBA,

I. INTRODUCTION

The main goal of the Bat method, an optimization method that mimics bat echolocation behavior, is to identify the best choice variables in order to achieve the lowest or highest value as defined by the objective function [1, 2, 3, 4]. Every optimization algorithm has methods or strategies to look at the problem's search area and try to find the best solution [5, 6]. When the procedure for optimization starts, a few factors need to be meticulously considered, including the function's objective, parameter values, and limitations [7]. The search space region being searched cannot be exploited by these methods, but they are successful in locating potential regions inside the search space [8]. One common kind of optimization technique is the M-EBA algorithm as population-based methods [9, 10]. The goal function, parameter settings, and constraints are some of the factors that should be regarded as the optimization process starts [7]. These methods work well for finding potential regions in the search space, but they don't work well for taking use of the search space region that is being investigated [8]. M-EBA methods are a typical class of optimization techniques.

A bat optimization algorithm with random trend perturbation and modest ideal orientation is suggested in order to increase the bat algorithm's convergence speed and optimization accuracy. To maintain a high diversity of bat populations, the method incorporates a nonlinear variation factor into the velocity update formula of the global search stage. This enhances the system's capacity for global exploration. Meanwhile, the position update equation is modified during the local search period, and a slightly optimal value-oriented approach is employed to enhance the algorithm's capacity for local search for deep mining. The updated technique increases the diversity of the bat population by adding a nonlinear variation component to the global search stage's velocity update equation.

To increase the bat algorithm's speed of convergence and accuracy of optimization, a bat optimization algorithm with random trend perturbation and modest ideal orientation is suggested. The algorithm's ability to examine the world is improved by adding a nonlinear variation factor to the velocity update formula of the global search stage, which keeps bat populations very diverse. In order to enhance the algorithm's capacity for local search for deep mining, the position update equation is modified during the local search phase, and a marginally optimal value is targeted. To enhance the diversity of the bat population, the newly developed algorithm adds a nonlinear variation element to the global search stage's velocity update equation. A bat optimization algorithm with random trend perturbation and modest suitable orientation is suggested in order to increase the bat algorithm's[4] convergence speed and optimization accuracy. The nonlinear variation factor is added to the global search stage's velocity update formula by the algorithm to preserve a high degree of bat population variability, which improves the algorithm's capacity for global exploration. Simultaneously, the position update equation is modified during the local search phase, and a slightly optimal value-oriented approach is employed to enhance the algorithm's capacity for local search for deep mining. To increase bat population variety, the updated algorithm adds a nonlinear variation element to the global search stage's velocity update equation.

BA's ease of use, conceptual simplicity, flexibility and adaptation, consistency, soundness, and completeness are only a few of its many notable properties. It has strong operators that employ the natural selection principle by using the survival-of-the-fittest rule in the intensification phase, which is attracted to the local-best solution. Next, we emphasize the several BA versions that correspond to the complexity of optimization problems: binary, modified, hybridized, and multi-objective[3][4]. The individual user is at the center of the custom modes concept. Choose one phrase to define your vocal expression or let your creativity run wild. It also discusses the critical evaluation of BA's drawbacks and restrictions. To create a rich BA review, the open-source BA code is provided.

By presenting a review of the bat algorithm (BA), the review paper seeks to provide the M-BAT optimization methods. The points that follow illustrate the study's substance

- An overview of the main concept of basic BA’s to highlight the main strengths, weaknesses, and procedures of the algorithm.
- Illustrates the related works of BA and classifies them into variants such as Binary BA, Discrete BA, and Modified BA. As well as, the recent applications of the BA such as Banking design. and image Processing, Medical fields and Engineering Design.
- M-EBA obtains the potential guidance using BA for future studies;
- Its efficiency is evaluated in comparison to other algorithms in the literature.

II) LITERARURE SURVEY

1. Blum C, Roli A (2003) The field of metaheuristics for the application to combinatorial optimization problems is a rapidly growing field of research. This is due to the importance of combinatorial optimization problems for the scientific as well as the industrial world.. We outline the different components and concepts that are used in the different metaheuristics in order to analyze their similarities and differences.

2. Velho L, Carvalho P, Gomes J, Figueiredo LD (2008) This is a subfield of Optimization in mathematical field that consists of finding an optimal object from a finite set of objects where the set of solutions is feasible and discrete can be reduced to a discrete set.

3. Mashwani WK, Haider R, Belhaouari SB (2021) optimization plays an important role in many decision-making problems are constrained and various real-world applications. In the last two decades, various evolutionary algorithms (EAs) were developed and still are developing under the umbrella of evolutionary computation.

4. Gharehchopogh FS, Gholizadeh H (2019) According to WOA applications that are used to solve optimization problems in various categories. The best solution has been determined to make something as functional and effective as possible through the optimization process by minimizing or maximizing the parameters involved in the problems.

5. Biswas A, Mishra KK, Tiwari S, Misra AK (2013). Natural phenomenon can be used to solve complex optimization problems with its excellent facts, functions, and phenomenon. This algorithm is done to show how these inspirations led to the solution of well-known optimization problem.

6. Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic algorithm, mimicking the improvisation of

music players, has been developed and named Harmony Search (HS). The performance of the algorithm is illustrated with a traveling salesman problem (TSP), a specific academic optimization problem, and a least-cost pipe network design problem.

7. Osmani, Mohamad, et al. (2020) introduce the Relevance Vector Machine (RVM), which evaluates a small set of fixed basis functions from a large dictionary of potential candidates to create efficient classification and regression models. However, the computational complexity of RVM—O(M3) in time and O(M2) in space, where M represents the size of the training set—makes it impractical for handling very large datasets

8. Qingquan, H. (2021) notes that with the increasing use of digital applications, tools like MapReduce are used for data preprocessing. However, MapReduce's structure is rigid, which can cause inefficiencies during data preparation, such as tilting. While reducing this issue is possible, it often comes at a cost

9. Li, X., Jiang, P., Chen, T., Luo, X., and Wen, Q. (2020) describe how supply chain management systems help firms by enabling data sharing and analysis. However, data discrepancies between organizations complicate planning algorithms, making it difficult to rely on accurate data

10. Naheem, M.A. (2019) proposes an alternative encoding strategy based on blockchain technology, where data from activity sequences and corresponding machines are combined in an activity node and linked with other nodes to form an activity list, utilizing the technology

III PROPOSED METHODOLOGY

This study proposes the Modified with Enhanced Bat Algorithm (M-Eba) as an enhancement of transaction system to address the local optimal limitation observed in the original BA. M-Eba incorporates the frequency and velocity of the current best solution, enhancing convergence speed to the optimal solution and preventing local optima [5][6]entrapment. The demonstrate of outcomes the M-Eba significant superiority over other algorithms. In addition, M-Eba successfully addresses a real-world assignment problem (call center problem), traditionally solved using linear programming methods, with satisfactory results. analyze the impact of different parameters on the EBat algorithm and determine the best combination of parameter values in the context of numerical optimization.

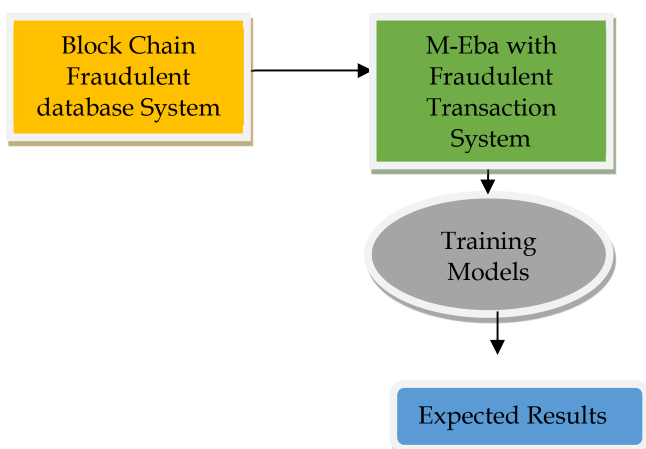

Figure 1.Proposed Study of M-Eba Algorithm

1.1. 3.1 Design of M-EBAT System

This study aims for completely detect the fraudulent detection system to assess the M-Eba performance of three sets of functions such as classical benchmark functions, Particle Swarm Optimization (PSO) and Dragonfly Algorithm (DA).

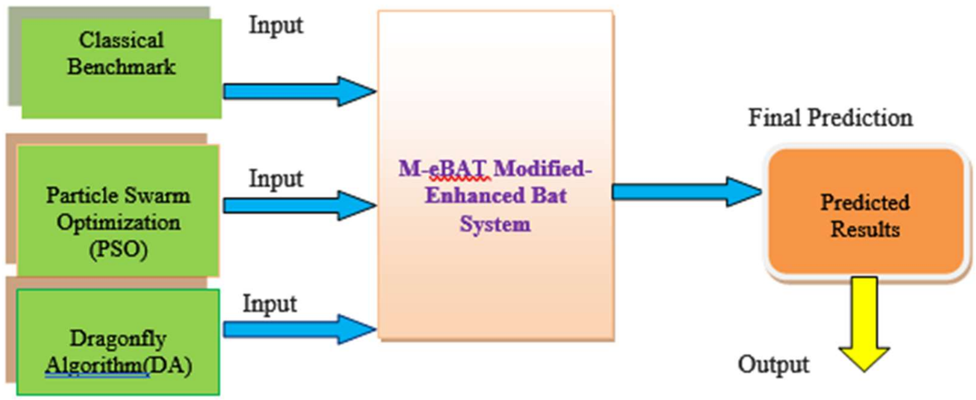

Figure 2.Structure of M-EBAT System Model for Block Chain

3.1.1 Classical Benchmark Functions

To produce this functions which have different degrees of separability, we can first randomly divide the objective variables into several groups, each of which contains a number of variables. Then, for each group of variables, we can decide to either keep them[7][8] independent or to make them interact with each other by using some coordinate rotation techniques. Finally, a fitness function will be applied to each group of variables. For this purpose, the following six functions will be used as the basic functions

a) Separable Functions

i) F1: Shifted Elliptic Function

$$F1(x) = F_{elliptrans}(z) = \sum_{i=1}^{D} (10)^{i-1/D-1} zi^2$$

Dimension: D = 1000

x = (x1, x2, · · · , xD): the candidate solution – a D-dimensional row vector

o = (o1, o2, · · · , oD): the (shifted) global optimum

z = x − o, z = (z1, z2, · · · , zD): the shifted candidate solution – a D-dimensional row vector

Properties:

1. Unimodal
2. Shifted
3. Separable
4. Scalable
5. x ∈ [−100, 100]D
6. Global optimum: x* = o, F1(x*) = 0

ii) F2: Shifted Rastrigin's Function

$$F2(x) = Frastritrans(z) = \sum_{i=1}^{D} zi^2 - [10 \cos(2\pi zi) + 10]$$

Dimension: D = 1000

x = (x1, x2, · · · , xD): the candidate solution – a D-dimensional row vector

o = (o1, o2, · · · , oD): the (shifted) global optimum z = x − o,

z = (z1, z2, · · · , zD): the shifted candidate solution – a D-dimensional row vector

Properties:

1. Multimodal

2. Shifted
3. Separable
4. Scalable
5. x ∈ [−5, 5]D
6. Global optimum: x* = o, F2(x*) = 0

b) Single-group m-non separable Function

i) F3: Single-group Shifted and m-rotated Elliptic Function

$$F1(x) = F_{mrotate}(z) =[z(p_1: p_m)] * 10 + F_{mrotatetrans}(z) =[z(p_{m+1}: p_D)]$$

Dimension: D = 1000
Group size: m = 50
x = (x1, x2, · · · , xD): the candidate solution – a D-dimensional row vector
o = (o1, o2, · · · , oD): the (shifted) global optimum
z = x − o, z = (z1, z2, · · · , zD): the shifted candidate solution – a D-dimensional row vector
P: a random permutation of {1, 2, · · · , D}

Properties:

1. Unimodal
2. Shifted
3. Single-group m-rotated
4. Single-group m-nonseparable
5. x ∈ [−100, 100]D
6. Global optimum: x* = o, F3(x*) = 0

ii) F4: Single-group Shifted and m-dimentional Rosenbrock's Function

$$F1(x) = F_{mrotateellipse}(z) =[z(P_1: P_m)] * 10 + F_{mrotatetrans}(z) =[z(P_{m+1}: P_D)]$$

Dimension: D = 1000
Group size: m = 50
x = (x1, x2, · · · , xD): the candidate solution – a D-dimensional row vector
o = (o1, o2, · · · , oD): the (shifted) global optimum
z = x − o, z = (z1, z2, · · · , zD): the shifted candidate solution – a D-dimensional row vector
P: a random permutation of {1, 2, · · · , D}

Properties:

1. Multimodal
2. Shifted
3. Single-group m-nonseparable
4. x ∈ [−100, 100]D
6. Global optimum: $x^* (P_1: P_m) = o(P_1: P_m)+1$, $x^* (P_{m+1}: P_D) = o(P_{m+1}: P_D)$,F(x*) =0

3.1.2 Particle Swarm Optimization (PSO)

It's a set of candidate solutions to the optimize defined through the parameter as a swarm of particles which flow space defining trajectories which are driven by their own [9][10]and neighbors for solving various kinds of optimization problems and by means of selected worked examples in the fields of signal warping, estimation robust PCA solutions and selection of variable in chemometric two functions :

1. A first chemometric using PSO for signal alignment
2. A second chemometric using PSO-based projection pursuit for robust PCA

$$F(x1, x2) = -20e^{-0.2} = [y(P_1: P_m)] + F(z) + 20 + e$$

3.1.3 Dragonfly Functions

It is a novel swarm intelligence meta-heuristic optimization algorithm of artificial intelligence inspired by the dynamic and static swarming behaviors. The results of this algorithm tends to find very accurate approximations of Pareto optimal solutions with high uniform distribution for multi-objective problems.

IV) EXPERIMENTAL RESULTS

The performance of the M-Eba is measured and evaluated with the existing prediction models on the considered dataset (discussed in Section 3.1). From this dataset, 75% of data instances are used for training, and the remaining 25% of data is used for testing. The evaluated existing models are Bernouli, Passive Aggressive, Logistic regression, linear SVM and SVM with RBF kernels

The metrics determined for performance evaluation are defined below.

Dataset description The performance of the proposed work is evaluated by using the Wisconsin Diagnosis Breast Cancer (WDBC) dataset (Zwitter and Soklic). This dataset includes two classes having 201 instances and 85 instances that are described by nine attributes of linear and nominal type. Table I shows the attribute information of breast cancer dataset. The WEKA tool is used for simulation purpose.

- Performance metrics : The metrics used for evaluating the performance of the proposed work are described below
- Correctly Classified Instances : It is the amount of cells that are correctly classified as normal or cancerous cells.
- Incorrectly Classified Instances : It is the amount of normal cells that are wrongly
- Statistics: It measures the agreement of prediction with the true class. If the kappa value is 1, there is a complete agreement with the true class.

Table 1 Comparison of different results at various levels in fraud detection models

Metrics	Bernouli Naves	Linear Regression	Proposed (Linear Regression)
Performance metrics	**87.45**	**94.45**	**94.23**
Correctly Classified Instances	**85.12**	**95.12**	**96.23**
Incorrectly Classified	**85.85**	**85.89**	**98.23**
Statistics	**85.58**	**90.25**	**90.23**

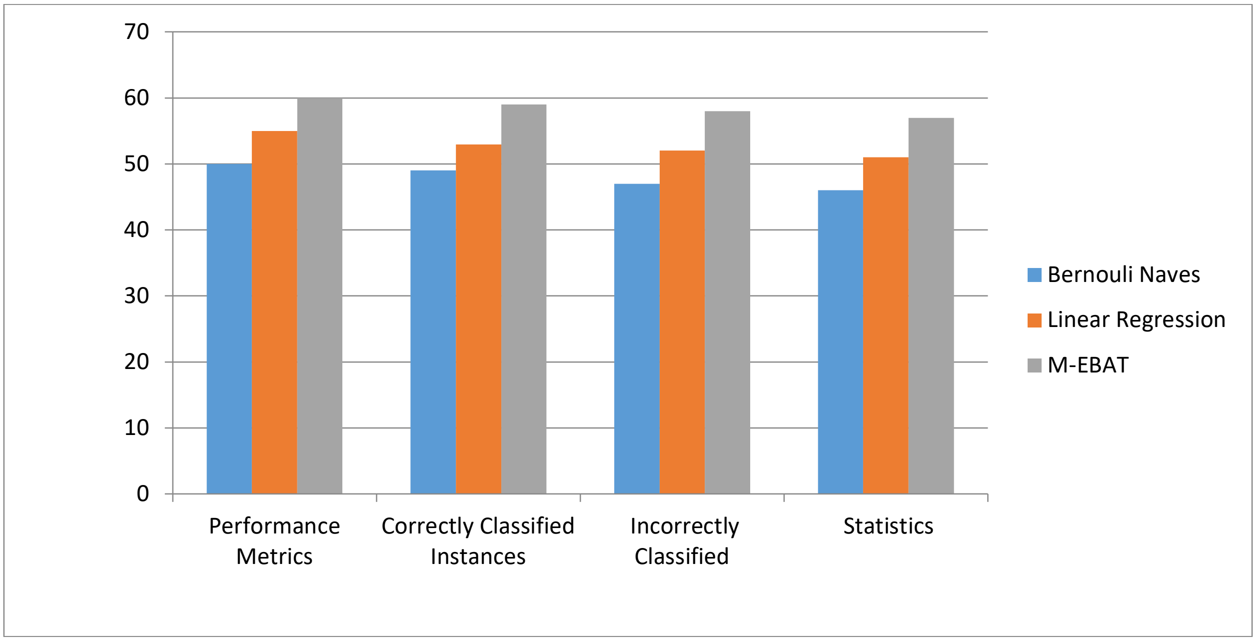

Figure 2. Assessment of Different fraud transaction detection Models

In Figure 2 plots the results of various fraud transaction models in our local area in Tamilnadu. It is noted that the Performance metrics as precision, correctly classified instances, Incorrectly classified instances and statistics of bernouli Naves performed better than Linear Regression models, respectively.

Table 2 presents the results for various fraudulent transaction system models of data recorded in Tamilnadu.

Table 2 Comparison of different results at various levels in fraud detection models

Metrics	Bernouli Naves	M-EBATAlgorithm	Proposed (M-EBAT Algorithm)
Performance metrics	87.45	94.45	94.23
Correctly Classified Instances	85.12	95.12	96.23
Incorrectly Classified	85.85	85.89	98.23
Statistics	85.58	90.25	90.23

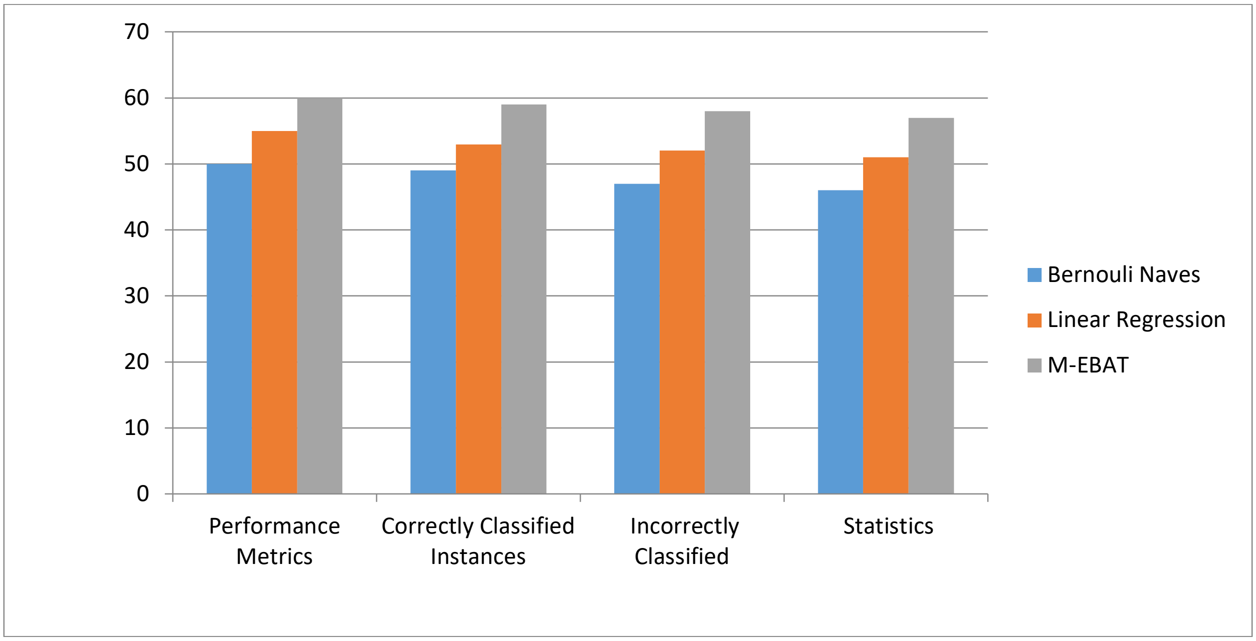

Figure 2. Assessment of Different fraud transaction detection Models

Figure 3 plots the results of various fraud transaction models in our local area in Tamilnadu. It is noted that the Performance metrics as precision, correctly classified instances, Incorrectly classified instances and statistics of M-EBAT is performed better than bernouli Naves, and Linear Regression models, respectively.

V) Conclusion and Future Works

When solving the M-EBAT optimization problems with non-convex, nonlinear, multi objective, multi-variable, and constrained characteristics, the standard version of the bat-inspired algorithm (BA) has demonstrated effective performance. Several uses including binary, discrete, permutation discrete, continuous, and structural search spaces have been successfully handled by the M-EBAT. The optimization structure of the BA has changed as a result of the complexity of the optimization problems. Consequently, a number of BA variants have been put forth by including additional elements taken from effective optimization techniques. The results were merged and fed to the bootstrapped M-EBAT for the final prediction To enhance its performance in other trials, the BA is hybridized with other heuristic or meta heuristic-based algorithms. Additional M-EBAT variations are suggested to meet the multi objective optimization issues under consideration. Finally, extensive experiments demonstrated that the M-EBAT has an improved the high level accuracy level compared to the other block chain prediction models.

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