An Analysis on Hybrid Brain Storm Optimisation Algorithms

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Abstract. Optimisation can be described as the process of finding optimal values for the variables of a given problem in order to minimise or maximise one or more objective function(s). Brain storm optimisation (BSO) algorithm is relatively new swarm intelligence algorithm that mimics the brainstorming process in which a group of people solves a problem together. The aim of this paper is to present hybrid BSO algorithm solutions in general, and particularly: (i) a hybrid BSO for improving the performances of the original BSO algorithm; (ii) a hybrid BSO for the flexible job-shop scheduling problem; and (iii) a feature selection by a hybrid BSO algorithm for the COVID-19 classification. The hybrid BSO algorithm overcomes the lack of exploitation in the original BSO algorithm, and simultaneously, the obtained better results prove their efficiency and robustness.

Keywords. Brain storm optimisation, dynamic parameters adjustment, job-shop scheduling problem, feature selection, classification.

1 Introduction

Optimisation can be described as the process of finding optimal values for the variables of a given problem in order to minimise or maximise one or more objective function(s). Conventional optimisation techniques are mostly based on a gradient descent to find the optimum for a given optimisation problem. This makes them highly dependent on initial solutions and most of the time it results in local optima stagnation of the algorithm. Local optima stagnation occurs when an optimisation mistakenly assumes that a local solution is a global solution. To alleviate the drawbacks of conventional optimisation techniques, stochastic algorithms were proposed. In such approaches, random abrupt or gradual change of the solutions results in a better local optima avoidance.

A metaheuristic algorithm is a search procedure designed to find a good solution to an optimisation problem that is complex and difficult to solve by optimality. It is imperative to find a near-optimal solution based on imperfect or incomplete information in this real-world of limited resources; it takes computational power and time. The emergence of metaheuristics for solving such optimisation problems is one of the most notable achievements in the last two decades in operations research. Optimisation algorithms can be divided into two classes: single-objective and multi-objective.

In 2011, a metaheuristic-based algorithm called brain storm optimisation (BSO) algorithm was developed [1]. The algorithm is motivated by the brainstorming process of humans. Brainstorming is a creative way of solving a specific problem by a group of people. In the brainstorming process, several people share their ideas with each other related to the problem that should be solved, where any idea is acceptable and criticism is not allowed. In the end, from all suggested ideas, the best possible solution is selected. Similarly, in the BSO algorithm, initially, random solutions are generated; as in any other swarm intelligence algorithm, each solution is analogous to an idea in the brainstorming process. At every iteration the idea is modified; in other words, the solution's position is updated according to the previous knowledge.

Numerous research papers [2] develop and apply the BSO algorithm. In BSO, the solutions are diverged into several clusters. One individual or more individuals are selected to generate new solutions by some genetic operators. Some multi-objective BSO algorithms [3, 4] are proposed to solve MOPs. In these multi-objective BSO algorithms, population is updated by new solutions after the solutions are clustered, which may decrease the speed of convergence.

Therefore, BSO is not only an optimisation method but it could also be viewed as a framework for the optimisation technique. The motivations for this research and new challenges for future research are interested in combining BSO with some other heuristics and metaheuristics methods to create an efficient hybrid BSO optimisation, classification, clustering, and feature selection systems. This research directly continues and expands the authors' previous research on optimisation [5]. Also, this paper, in general, continues the authors' previous research in optimisation of supply chain management, and optimisation in inventory management presented in [6–9].

The rest of the paper is organized in the following way: Section 2 provides an overview of the basic idea on brain storm optimisation algorithm. Modelling the bio-inspired hybrid systems combining BSO algorithm and metaheuristics-based algorithm is presented in Section 3. Section 4 provides conclusions and some directions for future work.

2 Brain Storm Optimisation Algorithm

Brain storm optimisation (BSO) is relatively new swarm intelligence algorithm. It is inspired by collective behaviour of human beings. It has attracted a number of researchers and has good performance in its applications for complex problems. Brainstorming is a process of collecting new ideas about a specific problem from a group of people without any prejudicing or ordering. Then, these ideas are evaluated and filtered one by one to select the best idea.

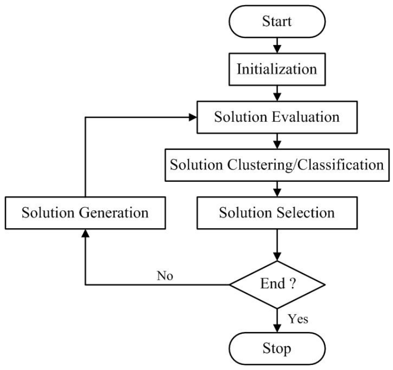

Fig. 1. The process of brain storm optimisation algorithms

The general description of BSO flowchart is displayed in Fig. 1. The basic steps of BSO are summarized by the pseudo code revealed in Algorithm 1.

Algorithm 1 *The basic procedure of the* ***brain storm*** *optimisation algorithm*

Begin

- ***Step 1:*** ***Initialization.*** Randomly generate ***n*** individuals (potential solutions), and evaluate the ***n*** individuals;
- ***Step 2:*** ***While*** *not find "good enough" solution or not reach the pre-determined maximum number of iterations* **do**
- ***Step 3:***   ***Solution clustering/classification*** *operation: Diverge* ***n*** *individuals into* ***m*** *groups by a clustering/classification algorithm;*
- ***Step 4:***   ***New solution generation*** *operation: Select solution(s) from one or two groups randomly to generate new individual (solution);*
- ***Step 5:***   ***Solution selection*** *operation: Compare the newly generated individual (solution) and the existing individual (solution) with the same individual index; the better one is kept and recorded as the new individual;*
- ***Step 6:***   *Evaluate* ***n*** *individuals (solutions);*
- ***Step 6:*** ***end While***
- ***Step 7:*** *Post-processing the results and visualization;*

End.

In a BSO algorithm, the solutions are separated into several clusters. The best solution of the population will be kept if the new generated solution is not better. New individual can be generated based on one or two individuals in clusters. The exploitation ability is enhanced when the new individual is close to the best solution found till that moment. The exploration ability is enhanced when the new individual is randomly generated, or generated by individuals in two clusters.

2.1 Solution Clustering

The aim of solution clustering/classification is to converge the solutions into small regions. Different clustering algorithms can be utilized in the brain storm optimisation algorithm. In the original BSO algorithm, the basic *k*-means clustering algorithm is utilized. The clustering strategy has been replaced by other convergence methods.

2.2 New Solution Generation

A new individual generation can be generated based on one or several individuals or clusters. In the original brain storm optimisation algorithm, a probability value is utilized to determine a new individual being generated by one or two “old” individuals. Generating an individual from one cluster could refine a search region, and it enhances the exploitation ability. On the contrast, an individual, which is generated from two or more clusters, may be far from these clusters.

2.3 Selection

Selection strategy plays an important role in an optimisation algorithm. The aim of the selection strategy is to keep good or more representative solutions in all individuals. The better solution is kept by the selection strategy after each new individual generation, while clustering strategy and generation strategy add new solutions into the swarm to keep the diversity for the whole population. The selection strategy determines the lifecycle of individuals. Individuals can only do one of the three things in selection strategy: be chosen, be kept, and be replaced. In other words, individuals are born, live, and die in the optimisation process by the selection strategy. Different selection strategies in genetic algorithms, such as ranking selection, tournament selection, and other selection schemes, are analysed in [10].

2.4 Variants of BSO Algorithms

The brain storm optimisation algorithm is not only an optimisation method but also can be viewed as a framework for the optimisation technique. The process of BSO algorithm could be simplified as a framework with two basic operations: the converging operation and the diverging operation. These two basic operations in BSO algorithms are shown in Fig. 2.

Some variants of BSO algorithms have been proposed to improve the search ability of the original BSO algorithm. The solutions get clustered after a few iterations and the population diversity decreases quickly during the search, which are common phenomena in swarm intelligence. A definition of population diversity in BSO algorithm is introduced to measure the change of solutions' distribution. According to the analysis, different kinds of partial re-initialization strategies are utilized to improve the population diversity in the BSO algorithm [11].

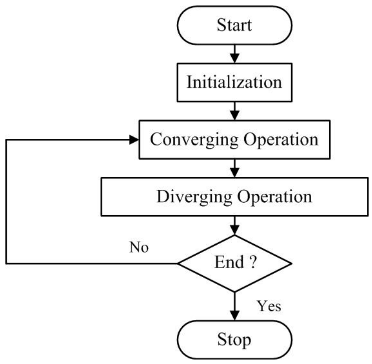

Fig. 2. Two basic operations in brain storm optimisation algorithms [11]

Under similar consideration, chaotic predator-prey brain storm optimisation was proposed to improve its ability for continuous optimisation problems. A chaotic operation is further added to increase the diversity of population.

3 Modelling the Hybrid Brain Storm Optimisation Algorithms

Two main processes in any metaheuristic algorithms are intensification and diversification. Often, the algorithm has one of these two processes more enhanced: one of the approaches for making the right balance between these two phases is by hybridizing two or more algorithms.

3.1 A Hybrid BSO for Improving the Performances of the Original BSO

Intelligence algorithms play an increasingly important role in the field of intelligent control. Brain storm optimisation (BSO) is a new kind of swarm intelligence algorithm inspired by emulating the collective behaviour of human beings in the problem-solving process. To improve the performance of the original BSO, many variants of BSO are proposed.

In the research paper [12], an improved BSO algorithm with a dynamic clustering strategy (BSO-DCS) is proposed as a variant of BSO for global optimisation problems. To reduce the time complexity of the original BSO, a new grouping method named dynamic clustering strategy (DCS) is proposed. The aim was to improve the clustering method in the original BSO. To verify the effectiveness of the proposed

BSO-DCS, it was tested on 12 benchmark functions of CEC 2005 with 30 dimensions. Experimental results demonstrated that DCS was an effective strategy to reduce time complexity, and the improved BSO-DCS performed greatly better than the original BSO algorithm.

As a novel swarm intelligence optimisation algorithm, brain storm optimisation (BSO) has its own unique capabilities in solving optimisation problems. However, the performance of a traditional BSO strategy in balancing exploitation and exploration is inadequate, reducing the convergence performance of BSO. To overcome these problems, in the research paper [13], a multi-strategy BSO with dynamic parameters adjustment (MSBSO) is presented. In MSBSO, four competitive strategies based on the improved individual selection rules are designed to adapt to different search scopes, thus obtaining more diverse and effective individuals. In addition, a simple adaptive parameter that can dynamically regulate search scopes is designed as the basis for selecting strategies. The proposed MSBSO algorithm and other state-of-the-art algorithms are tested on CEC 2013 benchmark functions and CEC 2015 large scale global optimisation (LSGO) benchmark functions, and the experimental results prove that the MSBSO algorithm is more competitive than other related algorithms.

3.2 A Hybrid BSO for the Flexible Job-Shop Scheduling Problem

The Job-Shop Scheduling Problem (JSSP) is a common and difficult problem in resource allocation whereby various jobs are assigned to physical resources or machines at a given time. The research paper [14] presents the hybrid BSO algorithm with an updating strategy as a solution to the flexible job-shop scheduling problem (FJSSP). With the aim to improve the global search of the BSO algorithm, a new updating strategy is proposed to adaptively perform several selection methods and neighbourhood search operations (BSO_US).

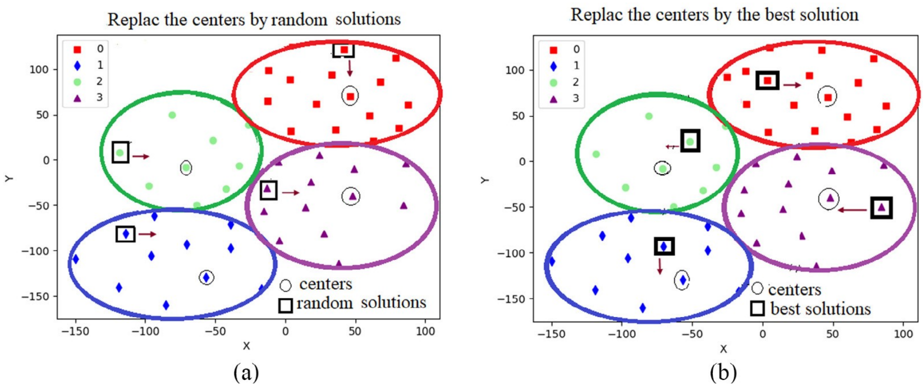

Fig. 3. BSO clustering algorithm with updating strategy [14]

The Flexible Job-Shop Scheduling Problem (FJSSP) is a generalisation of the traditional JSSP whereby every operation is processed by several machines which are chosen from a candidate machines subset. This has been identified as an NP-hard problem [15, 16]. However, FJSSP is considered to be more challenging and complex, since it needs to select the machines properly from a group of machines, as well as balance the machines' workload.

The FJSSP is divided into two problems. The routing sub-problem is the first, in which every operation is assigned to a machine. The second sub-problem is sequencing, which consists of defining a sequence for the assigned operations - resulting from the first step - on each machine. This step aims to achieve a practical schedule to minimize the time needed for the task to be accomplished – makespan. Therefore, two sub-problems present further complexity in solving the problem.

The idea of selecting the solution to be updated comes from the original BSO algorithm. The idea is to utilize the benefit of the clustering of the population, which leads to not searching similar solutions. The selection strategies are listed below: (i) select the centre of a random cluster; (ii) select a random solution from a randomly selected cluster; (iii) select two centres from two random clusters; and (iv) select two random solutions from two random clusters.

The *neighbourhood search operators* are described as the following: (i) *Neighbourhood N1* – where a selection of jobs is random and the operations on each machine are interchanged with other machines without constraints' breaking; (ii) *Neighbourhood N2* – where an operation is selected randomly, and it is taken into account for exchange with another operation or moved to a new random and possible location; (iii) *Neighbourhood N3* – this neighbourhood is based on the critical path. The sequence of two critical operations handled by the same machine is known as the critical path, which presents the longest schedule.

Computational experience proves that the following values are more effective for the proposed hybrid method: *number of iterations* = 200; and *population size* = 50. The number of clusters was chosen based on [17].

Finally, it can be concluded that the new updating strategy is also proposed for the BSO algorithm to enhance the global search by adaptively applying different selection and neighbourhood methods. The experimental results demonstrate that the BSO_US overcomes the basic BSO algorithm. Moreover, when compared with other algorithms, it is obvious that the BSO_US algorithm displayed to be effective for the FJSSP, obtaining comparable results [14].

3.3 Feature Selection for the Hybrid BSO Algorithm for COVID-19 Classification

A large number of features lead to very high-dimensional data. The total possible number of attribute subsets is 2^n in datasets with n number of features. As the dimension of data increases, the possible feature subset increases highly. Hence, the goal in the feature selection problem is to minimize the dimension and at the same time maximize the classification accuracy of the given dataset, which is considered as an optimisation task.

The feature selection method reduces the dimension of data, increases the performance of prediction, and reduces the computation time. Feature selection is the process of selecting the optimal set of input features from a given dataset in order to reduce the noise in data and keep the relevant features. The optimal feature subset contains all useful and relevant features and excludes any irrelevant feature that allows machine learning models to understand better and differentiate efficiently the patterns in datasets. In this article, a binary hybrid metaheuristic-based algorithm for selecting the optimal feature subset is proposed. In feature selection problems, due to the exponential increase in the number of features, this kind of problem belongs to nonpolynomial-hard (NP-hard) optimisation problems, where traditional exact optimisation algorithms would fail. However, stochastic approximation algorithms, such as metaheuristic algorithms, are very successful in tackling such problems.

In the research paper [18], the brain storm optimisation (BSO) algorithm by the firefly algorithm (FA) [19] to achieve a better trade-off between the exploration and exploitation and apply it for feature selection problem by using a wrapper-based method is applied. Concretely, the BSO algorithm is hybridized by the FA and adopted as a wrapper method for feature selection problems on classification datasets. The control parameters for the proposed BSO-FA feature selection system are presented in Table 1. At the end of the BSO-FA algorithm procedure, the Sigmoid function squeezes the solution's value between 0 and 1, afterward based on the threshold value, to decide whether 0 or 1 will be assigned to the corresponding feature. If the solution's value is less than the threshold, which is set to 0.5, after applying the transfer function, the solution will be 0; otherwise, it will be 1.

Table 1. Control parameters for the BSO-FA feature selection system

Parameter	Value
BSO parameters	
One cluster selection probability p1	0.8
Total number of clusters $cluster_{number}$	5
Replacing operator probability $p_{replace}$	0.2
Probability of choosing the centre of cluster 1 $p_{1center}$	0.4
Probability of choosing the centres of clusters 2 $p_{2center}$	0.5
Step size k	20
Parameter Ω_1	0.5
Parameter Ω_2	0.5
FA parameters	
Randomization parameter α	1.0
Attractiveness parameter β_0	1.0
Bright intensity parameter γ	1.0

The proposed algorithm in [18] is evaluated on 21 datasets from UCI data repository [20], which are presented in Table 2, and compared with 11 metaheuristic algorithms. In addition, the proposed method is adopted for the coronavirus disease dataset [21]. That dataset is applied for COVID-19 patient health prediction, where the dataset has 15 different attributes (features), including the patient's location, country, gender, age, and different symptoms [22].

The experimental results of the hybrid BSO-FA system are compared with other approaches, as well as with: (i) the original FA; (ii) the original BSO algorithm; (iii) whale optimisation algorithm (WOA); (iv) binary whale optimisation algorithm with Sigmoid transfer function (bWOA-S); (v) binary whale optimisation algorithm with hyperbolic tangent transfer function (bWOA-V); (vi) three variants of binary ant lion (bALO1) (bALO2) (bALO3); (vii) particle swarm optimisation (PSO); (viii) binary grey wolf optimisation (bGWO); and (ix) binary dragonfly algorithm (bDA). In addition, the proposed method is compared with three gaining-sharing knowledge-based algorithm (GSK) variants [23]: (x) V-shaped GSK-based algorithm (bGSK-V4) [24]; (xi) chaotic GSK-based optimisation algorithm (CBi-GSK1) [25]; and (xii) binary GSK-based optimisation (FS-pBGSK) [26].

Table 2. Datasets

Dataset name	No. of features	No. of samples
Breast Cancer	9	699
Tic Tac Toe	9	958
Zoo	16	101
Wine EW	13	178
Spect EW	22	267
Sonar EW	60	208
Ionosphere EW	34	351
Heart EW	13	270
Congress EW	16	435
Krvskp EW	36	3196
Waveform EW	40	5000
Exactly	13	1000
Exactly 2	13	1000
M of N	13	1000
Vote	16	300
Breast EW	30	569
Semeion	265	1593
Clean 1	166	476
Clean 2	166	6598
Lymphography	18	148
Penghung EW	325	73

The experiment is repeated in 20 runs, the maximum number of iterations = 70, and the population size is set to 8. Moreover, the binary BSO-FA approach is employed for COVID-19 and compared with other state-of-the art methods, where the proposed hybrid binary BSO-FA method is over performed by other approaches. The accuracy of bBSOFA is 93.57%, whereas the second-best performing approach is hyper learning binary dragonfly algorithm (HLBDA), with the classification accuracy of 92.21% [27].

In the case of the total selected features, both approaches selected two to three features on average. Based on the analysis of the selected features, we can draw a conclusion that specific features are not important for the prediction, and symptom4, symptom5, and symptom6 are never selected by the algorithm in the experiments.

The hybrid BSO algorithm with the FA algorithm overcomes the lack of exploitation in the original BSO algorithm. The obtained experimental results substantiate the robustness of the proposed hybrid binary BSO-FA algorithm. It efficiently reduces and selects the feature subset and at the same time results in higher classification accuracy than other methods in literature. Moreover, some other methods are employed for COVID-19 classification, such as: Gradient-based grey wolf optimiser with Gaussian walks in modelling and prediction of the COVID-19 pandemic [28], COVID-19 diagnosis on CT images with Bayes optimization-based [29], and a proficient approach to forecast COVID‑19 spread via optimized dynamic machine learning [30]. However, the comparison of different traditional methods and novelty heuristics and metaheuristics methods with different datasets is very difficult, maybe even impossible.

4 Conclusion and Future Work

The brain storm optimisation (BSO) algorithm has its own unique capabilities in solving optimisation problems, but the performance of traditional BSO strategy in balancing exploitation and exploration is inadequate. Therefore, an improved BSO algorithm with a dynamic clustering strategy, and a multi-strategy BSO with a dynamic parameter adjustment, intended to reduce the time complexity and overcome problems of the original BSO algorithm are presented in this paper.

However, the focus and the aim of this paper were to propose the hybrid new brain storm optimisation algorithms. First, the hybrid BSO for the flexible job-shop scheduling problem which combined new strategy to enhance the global search by adaptively applying different selection and neighbourhood methods in BSO algorithm was shown. Second, a feature selection by a new hybrid BSO algorithm for COVID-19 classification was presented. The hybrid BSO algorithm for feature selection combines classical BSO and firefly optimisation algorithms in classification problem. Both hybrid BSO algorithms presented in this paper have proved the better efficiency and robustness in comparison with the original BSO algorithm.

Regarding future work, it would be of interest to investigate the effect of all these modifications and improvements of the hybrid BSO algorithms for other optimisations, prediction classifications, and clustering problems, testing their performance and behaviour on broader domains, as well as experimenting with more different datasets.

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