Application of teaching-learning-based cuckoo search (TLCS) on vehicle

**Abstract.** Vehicle Routing Problem is a problem in determination of vehicle’s route that employed to serve customers by utilising more than one vehicle to obtain a route with minimum possible distance without violating its capacity constraints. The route start and end up on a depot. The number of uses of vehicle routing problem has resulted in it being one of the many research problems. In this paper, a new hybrid algorithm named teaching-learning-based cuckoo search (TLCS) is proposed to solve vehicle routing ploblem. The TLCS combines the Lévy flight on cuckoo search and teaching-learning process on TLBO, then for solutions to be abandoned in the cuckoo search will perform Lévy flight generate new solutions, while for other better solutions, the teaching-learning process is used to improve the local searching ability of the algorithm. Experimental results are examined with some problems (small, medium and large data) and show that TLCS obtains some solutions better than their original algorithm such as cuckoo search (CS) and teaching-learning-based optimization (TLBO).

Keywords: Cuckoo search (CS), Teaching-learning-based optimization (TLBO), TLCS, Vehicle Routing Problem (VRP).

1. Introduction

The system of transporting and shipping goods is one of the most important factors in the distribution of logistics in a company. In running an item distribution system, it is necessary to save expenses for the company. One way to save expenditure costs can be done by minimizing the travel routes taken in the distribution process of the goods. The problem of distributing goods aims to minimize costs on several distribution targets by assuming that all vehicle routes must depart and return to the center of the facility. The problem of minimizing goods distribution routes with limited vehicle capacity is usually referred to as the Vehicle Routing Problem (VRP). Vehicle Routing Problems (VRP) can be described as a problem designing optimal delivery. The VRP usage system begins with the departure of the vehicle goods from the depot to deliver goods to several customers, then return to the depot. There are several methods have been used to solve this problem, such as genetic algorithm, tabu search, simulated annealing, etc. In this paper, a new hybrid algorithm named teaching-learning-based cuckoo search (TLCS) is proposed to solve vehicle routing ploblem.

Hybrid teaching-learning-based optimization (TLBO) with cuckoo search (CS) is called TLCS. The cuckoo search (CS) was recently proposed by Yang and Deb [1], the algorithm is based on the obligate brood parasitic behavior of some cuckoo species in the flight behavior of some birds and fruitflies. Another algorithm, Teaching-learning-based optimization (TLBO) algorithm was originally introduced by Rao et al [2] in 2011, and it is inspired from the philosophy of teaching-learning processes in a classroom and mimicsteacher's influence on the output of learners. Similar to other SWARM intelligence algorithms (SIs), TLBO is apopulation-based heuristic stochastic optimization algorithm, but it does not require any algorithm-specificparameters. Due to TLBO's simple concept, without algorithm-specific parameters, rapidconvergence and easy implementation yet effectiveness, it has been extended successfully and widely applied to solutions from diverse fields of science and technology.Thus, in this paper, the proposed TLC is used to solve vehicle routing problems and the results of the TLCS experiment will be compared with the original algorithm, such as cuckoo search (CS) and teaching-learning-based optimization (TLBO).

1. Vehicle Routing Problem (VRP)

Vehicle Routing Problem (VRP) is a problem related to determining the route of a vehicle that visits a number of customers where the route formed must begin and end at the depot. In VRP, each customer can only be visited exactly once by one vehicle and the capacity possessed by each vehicle is limited so that the total customer demand on one route may not exceed the capacity of the vehicle serving the route [3]. According to Toth and Vigo [4], the purpose of VRP completion is:

1. Minimize the cost of shipping goods, based on the total mileage or travel time of the vehicle, where each customer is served just once by one vehicle.
2. Minimizing the number of vehicles used to serve all customers.
3. Minimize travel routes through travel time and vehicle load

Mathematically, the Vehicle Routing Problem (VRP) is expressed as a complete graph G, for example with is a set of points that represent the location of the customer and is a set of lines expressing the connecting location of the customer's location. Point "" is a depot, which is a place to store vehicles used for distribution and is a place to start and end a route. The number of vehicles owned by the depot is a number of with total capacity of each vehicle is . Each customer has a demand of 𝑞𝑖. In order to minimize the cost of travel or distance VRP is modeled in the following form :

Decision variable :

with constraints:

1. Every customer is visited exactly once by one vehicle :
2. Every vehicle that visits a customer, after serving will leave the customer :
3. There are vehicles that start from the depot :
4. The total demand from each customer in the route traveled by each vehicle must not exceed the vehicle's load capacity :

**Mathematical Representation :**

: Vehicles serve customers after visiting customers

: Distance between customer and customer

: Request from customer

: Maximum capacity of the vehicle

: Many vehicles are available at the depot

: initial customer index

: customer destination index

: vehicle index

1. The Propose TLCS

3.1 The Framework of TLCS

In the proposed hybrid algorithm, the main idea is to combine the good search ability CS and the fast convergence rate of TLBO, the proposed algorithm divide into two parts, for solution to be abandoned in the CS will perform Lévy flight to generate new solution. And for other solutions, we use TLBO to enhance the local search ability of CS. The framework of the proposed method is as in Fig. 1. For the proposed TLCS, it has strong global search ability along with a fast convergence rate [5]. As in the framework, two important ways for updating the solutions in the population are Lévy flight and the teaching-learning process. The two keys procedures are presented in the following sections.

|  |
| --- |
| **Algoritm 1 : Pseudo-code for the TLCS algorithm** |
| Define Objective function ,  Generate an initial population of solutions  **while** (Max Generation or (stop criterion)  **for** all solutions to be abandoned **do**  Perform Lévy flight from to generate new solution      **end for**  **for** all of the top solutions **do**    Student-Learning-Process      **end for**  A fraction (of worse solutions are abandoned and new ones are built  Rank the solutions and find the current best  **end while** |

Fig. 1 Pseudo code of TLCS

3.2 Lévy Flight

Cuckoo Search (CS) is one of Nature-Inspired Algorithms, based on cuckoo birds behaviour. The Cuckoo Search is inspired by the cuckoo’s reproduction behavior which consists of laying eggs in the nests of other birds [6]. In CS, when generating new solutions for cuckoo , a Lévy flight is performed :

where F and is the current best solution found among all solution at te current iteration, respectively. The first search-strategy of CS predicates on evolving all nests towards the nest that provides the best solution; i.e., the first search-strategy of CS is elitist. This strategy provides rapid access to a better solution that may be situated between a nest and the nest that provides the best solution. In this strategy, the scale factor (i.e., ) that controls the amplitude of is a random number generated by the Lèvy distribution. In this strategy, the algorithm suggested by Mantegna (Eq.(7)) has been used in order to generate F values ;

where and .

3.3 Teaching Learning Process

TLBO is a population based method. The algorithm mimics the teaching-learning ability of teacher and learners in a classroom [7]. The working of TLBO is divided into two parts, “Teacher phase” and “Learner phase.” Working of this two phases are explained below [8].

(1) Teacher phase

It is the first part of the algorithm where learners learn from the teacher. During this phase a teacher tries to increase the mean result of the class room from any value to his or her level (i.e.,. And the difference between the existing mean and new mean is given by :

Where is the teaching factor which decides the value of mean to be changed, and is the random number in the range Value of can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as :

Based on , the existing solution is updated according to the following expression :

(2) Learner phase

It is second part of the algorithm where learners increase their knowledge by interaction among themselves through group discussions, presentasions and formal communications. A learner learns new things if the other has more knowledge than him or her. Mathematically the learning phenomenon of this phase is expressed below. At any iteration , considering two different learners and where

Accept if it gives better function value.

1. Experimental results and analysis

The performance of the proposed TLCS is investigated on several data vehicle routing problems.The data used in this problem is secondary data obtained from https://www.coin-or.org/SYMPHONY/branchandcut/VRP/data/index.htm.old Data consists of data demand, and customer position. Data taken consists of 3 types, namely data from small data (18 customers), medium data (75 customers), and big data (100 customers).

For each testing problem, the parameter of the TLCS are set as follows : the population size , , Max Generation = 1000 and the TLCS is run 30 times . As the objective function , we use Eq. (1) as a fitness function and then the result will be compare with their original algorithm such as Cuckoo Search (CS), and Teaching-learning-based optimization (TLBO). The comparison of the best results with several data to solving vehicle routing problem is shown in Table. 1.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Small Data (10 Customers) | | | Medium Data (50 Customers) | | | Big Data (100 Customers) | | |
|  | TLCS | TLBO | CS | TLCS | TLBO | CS | TLCS | TLBO | CS |
|  | **235.74** | 244.406 | 263.22 | **1702.42** | 1917.65 | 1711.2 | **2381.58** | 2031.12 | 2382.79 |
| Mean | **267.661** | 267.243 | 284.133 | **1792.354** | 2048.797 | 1809.176 | **2498.167** | 2524.738 | 2500.029 |
|  | 9.065 | 12.497 | 8.3407 | 43.3587 | 34.8953 | 189.116 | **39.8498** | 269.271 | 51.654 |

Table. 1 Statistical Results of different algorithm in 30 independent run

Based on **Table 1,** it can be seen that the best solution found by TLCS is better than the best solution by other techniques. And then, the standard deviation of the results by TLCS in 30 independent runs is also very small.

1. Conclusion

In this paper , a new hybrid algorithm is applied to solve vehicle routing problem (VRP). The results are compared with the original algorithm such as teaching-learning-based optimization (TLBO), and cuckoo search (CS). Based on the overall results of the fitness function, it can be concluded that TLCS has the best solution more than the original algorithm.

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