Local Intensity in Memetic Algorithm: Case Study in CARP

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ABSTRACT

he research in capacitated arc routing problems (CARPs) is getting more and more attention for its wide applications in reality. Memetic algorithms (MAs) are promising in solving CARPs, but the intensity of local search (LS) in MAs should adapt to the evolution of the population for achieving the maximal effectiveness. In this paper, a novel MA based on adaptive adjustment of LS intensity (LIMA) is proposed. LIMA dynamically adjusts the probability of LS according to the distance between the individual of the population and the solution lower bound for further deepening the LS depth of potential solutions. It makes the algorithm spend as much time as possible on more potential solutions, so as to shorten the computation time and speed up the convergence. Experimental results show that LIMA has faster convergence speed and better global search ability than traditional MAs. Adaptively tuning the LS intensity of a MA has high potential for solving complex problems.[1]

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**; *Search methodologies*

KEYWORDS

Capacitated arc routing problem, memetic algorithm, local search, optimization

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1 INTRODUCTION

CARP [1] is a classical combinatorial optimization problem with constraints. It is a conceptual model of a variety of application problems, such as garbage collection, post-delivery, sprinkler route planning, and it has become more and more important in logistics, supply chain design, and routing problems [1-3]. However, the CARP is a NP-hard problem with constraints of capacity. It is difficult for exact algorithms to solve the problem in an acceptable time when the problem scale increases.

Heuristic and metaheuristic algorithms have been proposed to solve CARPs, e.g. tabu search [4], simulated annealing, evolutionary algorithm (EA) [5], and memetic algorithm (MA) [6-7], etc. By adding LS operations into an EA, a MA with extended neighborhood search for CARP, termed MEANS, was proposed [6]. It combines an EA with LS operations such as single insertion, double insertion, swap, and a series of merge and split steps. The research of MAs in recent years has been extended to solve CARPs with multiple depots, large scale, and dynamic and uncertain situations [7-8], etc.

The core of a MA is its LS operations, which coordinate with the evolution operations, i.e. crossover and mutation, during the evolution process. Different from the global search behavior of evolution operations, LS focuses on a small range with limited alterations. However, LS has been shown to be an effective way to accelerate the speed for searching optimal solutions. Based on our previous study, LS is quite important in solving CARPs. However, traditional MAs generally used a constant rate for LS, neglecting that the appropriate LS intensity was mutative.

Therefore, a memetic algorithm with adaptive LS intensity, termed LIMA, is proposed to address the problem. The proposed LIMA takes MEANS as the basic algorithm in this paper, but it can be altered into the other kinds of MAs. The proposed method dynamically adjusts the probability of LS based on the distance between individuals of the population and lower bound, so that the algorithm can spend more time searching potential solutions, and reduce the time if the target solution is not good. Numerical experiments have been made on medium scale CARPs. The results show that fine tuning the LS intensity of MA during the evolution process is effective, and the appropriate LS intensity becomes higher as the evolution goes on.

2 PROBLEM DEFINITION

In a CARP, given a directed graph $G = (V, E)$, some arcs need to be served and have their respective amount of required goods. A vehicle is loaded with the required goods and starts from the depot to serve the required arcs. Since the capacity of a vehicle is limited, the vehicle may need to turn back to the depot and start a new delivery several times. The optimization objective of a CARP is to find the minimal cost travel circuits that satisfy the capacity

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constraint of a vehicle in each circuit and traverses all the demand arcs. The formal definition of the CARP can be referred to [5].

3 ALGORITHM

Since the traditional MA uses a constant rate for LS, it is not only difficult to ensure diversity and convergence of the population, but also wastes a lot of time on some poor potential solutions. We therefore propose a method to change the LS rate based on adaptive adjustment, by setting different search frequencies and search depths for individuals with different potentials in the population. Potential individuals will perform LS steps as much as possible. The LS rate of individual i is computed as follow

$$P_i^{(LS)} = \begin{cases} \alpha \exp(\beta(1 - f_i / \delta_{LB})), & \text{if } r < \theta \\ \alpha \exp(\beta(1 - f_{\text{best-so-far}} / \delta_{LB})), & \text{otherwise} \end{cases} \tag{1}$$

where r is a uniform random number in the range (0,1), θ is the threshold for calculating the LS based on the objective value f_i of the individual i, or the optimal value $f_{\text{best-so-far}}$ found so far during the evolution of the algorithm. α controls the upper limit of the rate, β is for the adjustment of the probability. δ_{LB} is the lower bound of the problem. Because δ_{LB} is generally unknown beforehand, its value can be replaced by a near lower bound value and updated if a smaller value is found. f_i / δ_{LB} denotes the distance between the individual i and the lower bound. The first equation in (1) mean is that the LS intensity is determined by the distance from the current individual to the lower bound, whereas the second equation demonstrates that the intensity is referred to the distance from the current best individual to the lower bound of the problem.

It can be observed that the LS intensity in LIMA increases as the individual approaches the lower bound of the problem. The LS depth of the more potential solutions is thus expanded. The LS operation comprises a series of single insertion, double insertion, swap, and merge and split steps. Finally, stochastic ranking is used to sort the individuals of the population, and update the best-so-far solution. The flowchart of the proposed LIMA is illustrated in Fig. 1, where *ps* is the population size for LS.

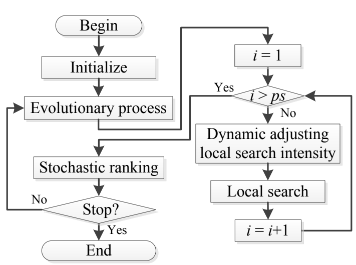

Figure 1: Flowchart of LIMA.

4 EXPERIMENATAL RESULTS

The numerical experiments are performed by using the *egl* set, which is a medium scale CARP benchmark. The proposed LIMA is implemented based on the structure of MEANS [6], and its performance is compared with the MEANS using the constant LS rate 0.2. According to the results, the local intensity in LIMA alters in the range of 0.7 to 0.8, so the constant LS values 0.6, 0.7, 0.8 by MEANS are also compared. The five methods use the same maximum function evaluations as the termination condition, thus their computation time are similar. In the tested 24 instances, the mean cost values of the five algorithms have been compared. For the same instance, the results are sorted, and the algorithms are marked with the ranking number. For example, the results of the five algorithms for egl-e1-B are 4500.37, 4498.9, 4498.9, 4499.5, 4498.53, respectively, and thus their rankings are 5, 2, 2, 4, 1. The sums of rankings for the compared algorithms are listed in Table 1. The proposed LIMA has the smallest rankings among the five algorithms.

Table 1: Sum of Rankings of the Mean Cost of the Algorithms

Egl Cases	MEANS				LIMA
	0.2	0.6	0.7	0.8	
Sum rankings	87	73	63	51	42

5 CONCLUSIONS

This paper proposed a memetic algorithm based on adaptive adjustment of LS intensity (LIMA) for solving CARPs. LIMA dynamically adjusts the probability of LS according to the distance between the individual of the population and the solution lower bound. The target of the adjustment is to increase the probability of LS to promising solutions and further deepen the LS depth of the more potential solutions. Results showed that LIMA has the best performance compared with the state-of-the-art algorithms. A more sensible method for adapting the LS intensity of the MA is our future work in solving complex problems.

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