Memetic Algorithm with adaptive Local Search for Capacitated Arc Routing Problem

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***Abstract*—The Capacitated Arc Routing Problem (CARP) is a challenging combinatorial optimization problem with wide real world applications. Since CARP is NP-hard, many heuristic and meta-heuristic approaches have been applied to solve CARP. In this paper, a novel extension memetic approach, named MAENS-Pls is proposed to improve the state-of-the-art algorithm—Memetic Algorithm with Extended Neighbourhood Search (MAENS) for CARP, in which using an adaptive probability to optimize the frequency and depth of local search. Based on the parameter optimization on all the 8 instances, experimental studies show that the proposed algorithm can significantly improve the average performance of MAENS, and there is an increase in the robust stability and convergence reliability. Furthermore, 4 new best known solutions are found by the proposed algorithm.**

Keywords—Capacitated Arc Routing Problem (CARP), Memetic Algorithm, Extended Neighbourhood Search, Adaptive Probability, Frequency and Depth of Local Search.

I. INTRODUCTION

The Capacitated Arc Routing Problem (CARP) was first put forward by Golden and Wong in 1981 [1], and it is a classical combinatorial optimization problem, which has a number of applications in the real world, such as salting route optimization or winter gritting, garbage collection [2], postal delivery, inspection of gas pipeline lines, electric power lines [3], and network and vehicle routing problem [4-6], etc. In basic CARP, each edge is modeled as a two-way street, and each arc as a one-way street. A fleet of identical vehicles with the same capacity limitation is organized at the only depot node. Each edge/arc can be traversed any times, and only a deadheading cost (the cost of traversing the edge/arc without serving it) is counted, the edges/arcs required services are called tasks, they have two attributes: demand and serving cost. The CARP is to identify the minimum cost routing plan of vehicles, and it must be subject to three constraints: 1) the starting and ending node for each route are both the depot; 2) each required edge is served exactly once in a single route, 3) the total demand processed by one route does not exceed the vehicle capacity [7].

Since CARP is NP-hard, it is difficult for the exact methods to solve the problem in reasonable time, and the computational cost is extraordinary large when refer to the large-scale instances. Many problem specific heuristics have been proposed for solving the CARP. These classical algorithms include the improved path scanning methods, Ulusoy's tour splitting [8], and a new constructive and improvement heuristic [9]etc. Among all the meta-heuristic and intelligent algorithms[10][11], Memetic Algorithm (MA) [12] has attracted more attention recently. MA is a hybrid algorithm combining local search with Evolutionary Algorithm (EA), which can strike a balance between global search (e.g., crossover) and local search heuristics, and thus get a better trade-off between exploration and exploitation. Memetic Algorithm with Extended Neighborhood Search (MAENS) proposed by Tang et al. [13] is a kind of improved memetic algorithm for CARP, which achieves excellent performance in the experiments, however, it is of high computational cost, for which several improvements has been researched. Besides the main limitations stated above, we notice one point which has not been considered for MAENS so far, i.e. the probability for local search is set as a constant, which limits the flexibility and adaptability for local search.

Therefore, in this paper, an adaptive probability is developed to perform better control for local search frequency. the details for the algorithm modification and parameter optimization will be conducted, and the corresponding numerical experiments and evaluation will be presented based on the benchmark set: egl [14], which is one kind of middle-sized benchmark data set for CARP as used in MAENS.

The rest of the paper is organized as follows. First, the preliminary background of this research is given, including the formal definition of CARP, the general overview of MA, and the base algorithm−MAENS. Section III describes the improved algorithm MAENS-Pls, and corresponding parameter optimization are conducted in section IV. Section V presents the experimental evaluation and solution visualization. At last, conclusions are drawn.

II. Model and Algorithm

In this section, the strict definition for basic CARP is presented, and the introduction of memetic algorithm and MAENS are described in order to provide the research foundation for the proposed algorithm.

A. The Capacitated Arc Routing Problem Model

In order to define CARP in a mathematical way, firstly, the mathematical notations are given as below [13]:

TABLE I. Mathematical notations

Notation	Description
G	Graph G (V, E, A) on which CARP is defined.
V	Vertex set, among which dep is a central depot vertex dep ∈ V, where a set of vehicles are based.
E ER	Edge set. the set of edge tasks, which are required to be served, ER ⊆ E.
A AR	Arc set (i.e., directed edges). the set of arc tasks, which are required to be served, AR ⊆ A.
t	Task ID, which has five features: tail (t), head (t): the tail of head vertices of task t; sc (t): serving cost of task t; dc(t): dead heading cost of task t; dem(t): demand of task t.
inv (t)	The inversion of edge task t. Each edge in ER is assigned two IDs, i.e. t and inv (t), while each arc in AR is assigned a unique ID.
dummy task	It is used to separate different routes in a solution, the ID of dummy task is 0, and tail(0) =dep or head(0)=dep.
S	Solution to CARP, it can be represented by an ordered sequence of tasks (IDs), i.e. S=(S1,S2,.....Slength(S)) , where Si is the ith task of S, and length(S) stands for the length of S.
m	number of routes in S.
Ri	route i in S, Sik denotes the kth task in route Ri
$\mathrm{TC}(S)$	the total cost of S
$\mathrm{app}(S_i)$	Count for the times that task S_i appears in S
$\mathrm{load}(R_i)$	The total demand of route R_i

As Table I shows, the solution to CARP can be represented by an ordered sequence of tasks (IDs), and each route for one vehicle is separated by the dummy task. Based on that, the mathematical formulation for CARP can be given as follows:

$$\min_{S} \mathrm{TC}(S) = \sum_{i=1}^{\mathrm{length}(S)-1} [\mathrm{sc}(S_i) + \mathrm{dc}(S_i + S_{i+1})] \tag{1}$$

$$\text{s.t.} \qquad \mathrm{app}(S_i) = 1, \forall S_i \in A_R; \tag{2}$$

$$\mathrm{app}(S_i) + \mathrm{app}(\mathrm{inv}(S_i)) = 1, \forall S_i \in E_R; \tag{3}$$

$$m \leq \mathrm{nveh}; \tag{4}$$

$$\mathrm{load}(R_i) = \sum_{k=1}^{\mathrm{length}(R_i)} \mathrm{dem}(S_{ik}) \leq Q.\ (i = 1,2, \ldots m) \tag{5}$$

Since it is a minimization problem, the goal is to minimize the total cost $(\mathrm{TC}(S))$, which can be calculated as the summation of serving cost of each task $(\mathrm{sc}(S_i))$ and the deadheading cost of the shortest paths between two consequent tasks Si and Si+1 $(\mathrm{dc}(S_i + S_{i+1}))$. (1) stands for the objective of the optimization problem, and the constraints presented in (2)-(5) are corresponding to the constraints described above.

B. Memetic Algorithm with Extended Neighborhood Search

Memetic Algorithm was first proposed by Pablo Moscato [12], it can be seen as a hybrid algorithm which combines EA and local search. The general framework [**Error! Bookmark not defined.**12] of MA is as follows:

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Initialization: Generate an initial population
while stopping criteria are not satisfied do
        Evaluate all individuals in the population
        Evolve a new population using evolutionary operators
        for each individual do
              Perform local search around it with probability Pls ;
        end
end
```

Fig. 1. General Framework of MA

The superior performance of MA is mainly credited to its local search operators, which distinguishes MA from EA. Therefore, a number of researches focus on the local search procedure to try to bring incremental development for MA. The typical questions for MA to consider are the frequency and depth of local search. These two factors control the balance between exploration and exploitation, thus have a direct influence on the optimum we get. For example, too much local search may lead to being quickly stuck in the poor quality local optima, or it is likely that the same local optimum will be rediscovered. Besides, the population diversity may get lost as we always focus on improving the neighbours around current solution [16]. The probability for local search Pls can be viewed as one indicator for the frequency of local search, and the runtime for local search can reflect the search depth.

Memetic Algorithm with Extended Neighborhood Search (MAENS) proposed by Tang et al [13] is an effective method to solve CARP, in which a novel local operator with large search step size is applied with combination of traditional operator in local search, thus the search procedure become more efficient and less likely to be trapped in local optima. The process of MAENS can be divided in to four phases [17] : Initialization , Crossover, Local search, Stochastic ranking.

The probability for local search is just set as 0.2, which can be modified and improved, the details will be presented in next section.

III. Adaptive Local Search Probability for MAENS

In this section, we first propose the adaptive probability of local search for MAENS (MAENS-Pls), then focus on the parameters in MAENS, parameter optimization is conducted, which lay the foundation for the evaluation and application.

A. *MAENS-Pls*

Since the computational resources are mainly occupied by local search, it is not efficient to apply the same local search frequency to every individual, so here we design an adaptive probability which increases with fitness of the individual, i.e. MAENS-Pls. The mathematical definition is as follows:

$$\mathrm{Pls} = \rho 1 * \exp(\rho 2 * (1 - \frac{\mathrm{LB}}{\mathrm{total\ cost}})) \qquad (1)$$

$\frac{LB}{total\ cost}$ is the normalized total cost, which range between (0, 1), the closer $\frac{LB}{total\ cost}$ to 1, the lower total cost is, i.e. the higher fitness the solution has. While $\rho 1$ and $\rho 2$ are two parameters for Pls, $\rho 1$ sets the upper bound of Pls, while $\rho 2$ controls the speed with which the Pls changes. Below is the illustration of adaptive Pls, in which $\rho 1$ and $\rho 2$ are set as 0.8 and 2, respectively. The black line is Pls in the base algorithm MAENS, which is set as a constant as 0.2.

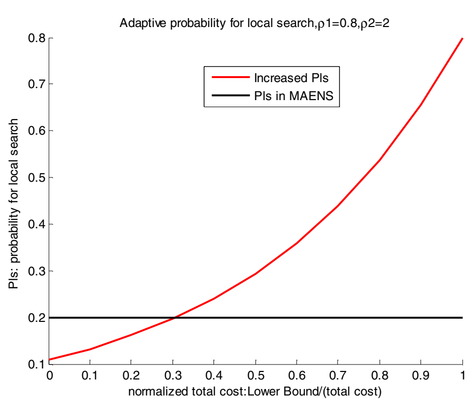

Fig. 2. Illustration adaptive Probability for Local Search

In Fig 2, the x axis is the normalized total cost ($\frac{LB}{total\ cost}$), the closer it gets to 1, the lower the total cost of the individual has, i.e. the higher fitness the solution has. Due to this fact, we can first conclude that it performs more local search to the good individuals, which have larger probability to be selected into next generation, thus the improvements on good individuals can be maintained. Besides, as the search proceeds, the fitness level of whole population will increase, so the adaptive Pls also varies towards the end of a run.

To sum up, by applying MAENS-Pls, the algorithm can allocate limited resources to improve good individuals which have large probability to be selected into next generation; and conduct more exploitation towards the end to locate the optimal precisely. As a result, the balance between exploration and exploitation seems to be improved.

B. *Parameter Optimization for MAENS-Pls*

In order to seek the optimal parameter combination in MAENS-Pls ($\rho 1$ and $\rho 2$) and MAENS on the considered benchmark set egl, it is desirable to evaluate and compare algorithms with as many different parameter settings as possible; however, the number of required experiments may be very large in order to obtain the complete picture of their performance. Therefore, in this section, we adopt the method of racing algorithm [18] to reduce the computational costs of large scale experiments.

According to some preliminary experiments, we first try to give the range of each parameter. For $\rho 1$, we set the range of [1,0.8,0.5,0.2], and for $\rho 2$, we set [1,2,4,8]. Both $\rho 1$ and $\rho 2$ have 4 candidate values, so there are 16 combinations totally. Here, the combination of $\rho 1$ and $\rho 2$ is regarded as one factor, and there are total 16 candidate parameter settings in this case.

TABLE II. Results of Racing Algorithm [18] for MAENS-Pls

The third and fourth columns show the results or p-value obtained with Kruskal-Wallis test and Mann-Whitney U-test

No	Instance	p-value	Mann-Whitney U-test	Candidate parameter settings remained
1	E3B	p=9.334e-08	(1, 4), (0.2, 1), (0.2, 8), (0.5, 4), (0.8, 1), and (0.8, 8) are significantly worse than others	10 (6 parameter settings are removed)
2	E4B	p=0.5023	-	10 (none is removed)
3	S3B	p=0.1998	-	10 (none is removed)
4	S4B	p=4.332e-12	(0.8, 2) is significantly better than others	1 (9 are removed, only (0.8, 2) survived)

After running the racing algorithm on four instances, only one combination survived, so the racing algorithm terminates. The final result is that only the combination of ρ1=0.8 and ρ2 = 2 survives the racing test on eight instances(TABLE II), which means the optimal parameter combination of adaptive Pls with Heuristic 1 is ρ1=0.8 and ρ2 = 2 in the considered situation for all the eight instances.

C. Parameter Optimization for MAENS

The probability for local search (Pls) is set as 0.2 in MAENS. For the sake of fairness, we should also perform parameter optimization for Pls in MAENS. We try to define the range of Pls as [0.15, 0.2, 0.35, 0.5], and firstly we apply the racing algorithm on S4B, the null hypothesis is assumed as there is no significant difference between algorithms with different parameter settings. From racing algorithm results on S4B, we can see that the algorithm with Pls =0.35 is significantly better than others, since there is only one parameter setting left, so there is no need to continue to conduct racing algorithm on other instances. So Pls= 0.35 will be applied in evaluation.

IV. EVALUATION AND SOLUTION VISUALIZATION

In this section, we will evaluate MAENS-Pls with the optimal parameters setting. First, comparisons on all the eight instances are given, including the total cost and runtime; then statistical analysis are applied to present a more refined analysis; last, application and solution visualization are presented by plotting different routes with distinct colours based on the coordinates of the nodes in the dataset. More details will be provided below.

A. Experimental Studies

Based on the results of parameter optimization above, experimental studies are conducted and the algorithms are run for 30 times on each instance.

The comparison is carried out with the tuned parameters on all the eight instances, namely E1B, E2B, E3B, E4B, S1B, S2B, S3B, and S4B. The metrics used for evaluation are described in Table IV, namely Average, Standard Deviation, Number of Successful runs, Best result among 30 runs, and Runtime. The Wilcoxon Signed-Rank test [19] has been used to perform a statistical test between MAENS and MAENS-Pls, The following table and figures report the details of the results. For Table V, the high lightings in blue indicate the results are significantly better than MAENS. In particular, yellow means that the results are better or equally good comparing with MAENS and numbers in red represent the new best known solutions found by our methods. The last few rows calculate the average performance over all the eight instances considered.

TABLE III. METRIC DESCRIPTION

Metric	Description
Average	The average of total cost over 30 independent runs.
Std	The standard deviation of total cost over 30 independent runs, which can be defined as the convergence reliability in our experimental study.
Best	The solutions with lowest cost obtained among the 30 runs, it can be interpreted as the ability of global optimization.
NS	A relative metric, indicating the number of successful runs among 30 runs; a run is successful if the total cost obtained by this run is not worse than that of MAENS, it can indicate the robust stability of the algorithm.
Run time	The executing time

In terms of the metric of Average, MAENS-Pls outperforms MAENS in all situations, The average total cost decreases the average total cost from 9703.9 to 9666.7.

As for Standard Deviation of total cost, MAENS-Pls represents an improvement with respect to MAENS, decreasing it from 28.7 to 22.5. The improvement in terms of Standard Deviation can be interpreted as the improvement of convergence reliability, which can be defined as the range of fluctuation between the results to the average in our research. The smaller the fluctuation is, the better convergence reliability will be. In the following analysis, the term of convergence reliability is used in this meaning as a corresponding qualitative factor for standard deviation.

The metric of Best Solutions, it can be explained as the ability of global optimization. 4 new best known solutions are found by MAENS-Pls. It is noticeable that on average over eight instances, MAENS-Pls find the new best known solutions of 9619.9, comparing to 9658 of MAENS.

Number of Successful runs, it can be regarded as the indicator of robust stability of the algorithms. On average over eight instances, it is expected that MAENS-Pls has a superior result (27.63 out of 30) in the metric of NS again. The reason for that can be explained by the emphasis of local search in MAENS-Pls , as it is easier to carry out more stable results during 30 independent runs.

From the Average Runtime over 30 independent runs (Fig 3), it is reasonable to see that MAENS-Pls is the more time consuming than MAENS, since it performs more local search, which is more expensive than that in MAENS. However, the time consuming is still with a acceptable range, considering the improved performance.

B. Statistical Analysis

The Wilcoxon Signed-Rank test is used to perform a statistical test on the average total cost over 30 runs for each instance between MAENS and MAENS-Pls. The null hypothesis is that there is no significant difference between MEANS and the considered method. The results are as follows, and the significant level is set as 0.05.

For the paired statistical test between MAENS and MAENS-Pls, the V statistic is 36, and the P value is 0.01415, so we can reject the null hypothesis, and conclude that MAENS-Pls are significantly different from MAENS. In order to have a clear understanding for each instance in statistical view, unpaired statistical test are performed on the results for 30 runs for each instance, the result shows that MAENS-Pls brings significant improvements on all the eight instances. The performance of MAENS-Pls is predictable, since local search is especially emphasized, which improves the solution quality directly.

C. Solution Visualization

The solution to E4B and S3b is plotted as an example (Fig 4,5). The task numbers are marked on the task arcs, the depots are marked on the maps. Different line colors and styles are used to distinguish different routes. Since each route is separated by dummy task, which means each route starts and ends both at depot (node 1), and the tasks within each route are connected with shortest distance, so in this representation the connection between each task is not plotted, and only the tasks are presented.

In E4B, all the edges are required to be served, and 14 vehicles are needed. In S3B, 159 out of 190 edges marking with different colors are required to be served; 22 vehicles are needed, and the dotted lines indicate the edges that do not need to be served.

From the solution visualization, more intuitive understanding of this optimization problem can be gained. However, since the limitations of the figures, more details could not be presented, which can be analyzed trough the sequences of tasks in output file in further study.

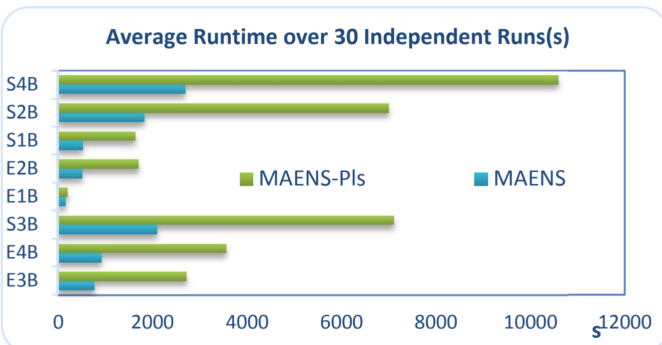

Fig. 3. Comparison of Runtime on Eight Instances

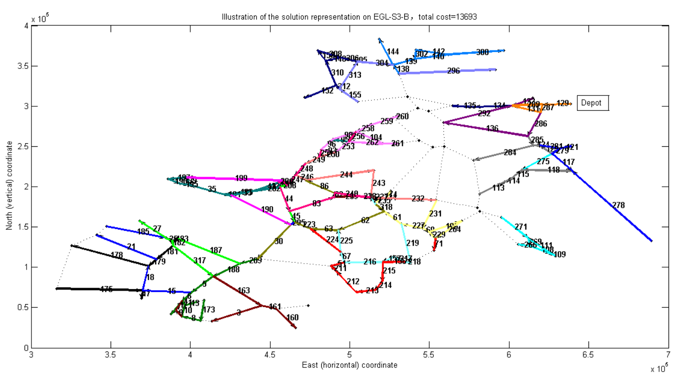

Fig. 4. Illustration of the solution representation on S3B, total cost =13693. Different colors indicate different routes for each vehicle, 22 routes, and dotted lines indicate the non-task edges

TABLE IV. COMPARISON OF TOTAL COST ON EIGHT INSTANCES

Highlight in yellow indicate the results which are not worse than MANES, blue indicate significantly better. Bold red fronts: the best known results found by our algorithms

Instance	|V|	|R|	|E|	LB	Index	MAENS	MAENS-Pls
Egl-E3-B	77	87	98	7704	Average	7800.4	7785.1
					Std	21.7	12.5
					Best	7775	7775
					NS		27
Egl-E4-B	77	98	98	8884	Average	9015.9	9000.6
					Std	15.1	10.2
					Best	8990	**8982**
					NS		30
Egl-S3-B	140	159	190	13616	Average	13866.6	13774.7
					Std	59.7	35.9
					Best	13758	**13689**
					NS		30
Egl-E1-B	77	51	98	4498	Average	4508.1	4501.3
					Std	12.6	8.6
					Best	4498	4498
					NS		27
Egl-E2-B	77	72	98	5305	Average	6335.2	6326.8
					Std	10.6	10.8
					Best	6317	6317
					NS		25
Egl-S1-B	140	75	190	6384	Average	6416.4	6404.8
					Std	20.5	19.7
					Best	6388	6388
					NS		22
Egl-S2-B	140	147	190	12968	Average	13248.5	13156.3
					Std	58.4	36.6
					Best	13165	**13057**
					NS		30
Egl-S4-B	140	190	190	16093	Average	16439.7	16383.6
					Std	31	45.3
					Best	16373	**16253**
					NS		30
Average on all the 8 instances					Average	9703.9	9666.7
					Std	28.7	22.5
					Best	9658	**9619.9**
					NS		27.63

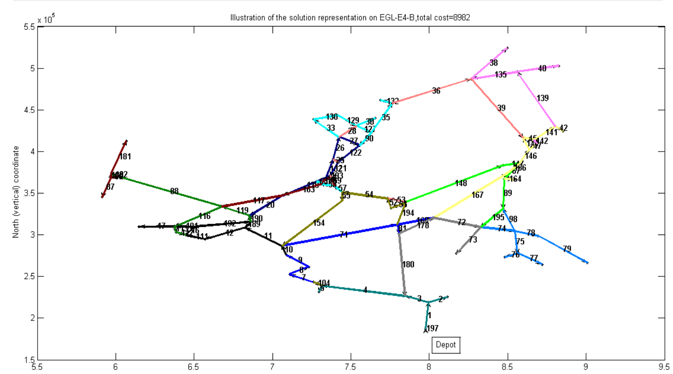

Fig. 5. Illustration of the solution representation on E4B, total cost =8982

Different colors indicate different routes for each vehicle, 14 routes

V. Conclusion

In this paper, a novel improved version to the state-of-the-art algorithm–MAENS for CARP has been proposed, which applies an adaptive probability to optimizing the frequency and the depth of local search. Based on the algorithm design and implementation above, we also perform parameter optimization to all the algorithms with racing algorithm. Besides, comparisons on five metrics between the proposed algorithms with MAENS on egl dataset have also been carried out, and statistical analysis methods are used to conduct evaluation.

A. Findings

Given the same number of generations for all the algorithms, MAENS-Pls is proved to be a novel version of MAENS which improves MAENS significantly in statistical view. The improvement can be credited to the effect of the frequency and depth of local search, which are two important issues in MA. Besides, 4 new best known solutions have been are discovered by our algorithms;and the convergence reliability, robust stability, and the ability of global optimization of MAENS-Pls appear to be better than MAENS. Last, the optimal parameter settings for MAENS-Pls, and MAENS for all the eight instances considered are optimized, it is hoped that it may be useful for further studies.

B. Limitations

The major limitation of our algorithms is the time complexity. The adaptive probability in MAENS-Pls increases the computational cost significantly. Besides, being limited to time, only a small number of parameter combinations for parameter optimization are considered, which may limit the opportunity to seek better results. In addition, this study only performs experiments on eight instances, which lacks the generalization ability for more situations. Lastly, given the same level of runtime for MAENS and MAENS-Pls, we find that MAENS-Pls do not show significant improvements over MAENS, which means adopting adaptive Pls do not contribute to improving MAENS given the same runtime.

C. Future Work

Corresponding to the limitations above, it is recommended that further research be undertaken in the following areas. First, more effective research is needed to reduce the high computational cost in MAENS-Pls. Besides, it is expected to consider more combinations of parameter settings to identify better parameter tunings for seeking the optimal solutions. In addition, for the case of running the algorithms for the same level of time, more future research is needed to analyze and understand the algorithm behaviors. Lastly, we only evaluate the proposed approaches through experiments on benchmark dataset and statistical methods, more theoretical analysis could be considered for a deeper understanding of the algorithm.

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