

A Novel Pareto-Based Meta-Heuristic Algorithm to Optimize Multi-Facility Location-Allocation Problem

Vahid Hajipour, Samira V. Noshafagh, and Reza Tavakkoli-Moghaddam

Abstract—This article proposes a novel Pareto-based multi-objective meta-heuristic algorithm named non-dominated ranking genetic algorithm (NRGA) to solve multi-facility location-allocation problem. In NRGA, a fitness value representing rank is assigned to each individual of the population. Moreover, two features ranked based roulette wheel selection including select the fronts and choose solutions from the fronts, are utilized. The proposed solving methodology is validated using several examples taken from the specialized literature. The performance of our approach shows that NRGA algorithm is able to generate true and well distributed Pareto optimal solutions.

Keywords—Non-dominated ranking genetic algorithm, Pareto solutions, Multi-facility location-allocation problem.

I. INTRODUCTION

NOWADAYS, among different classifications of optimization methodologies, developing multi-objective evolutionary algorithms to optimize the problems with conflicting objectives has found considerable attention. Among different classifications of discrete location-allocation models, this article attempts to find Pareto-solution of a specific location-allocation problem (LAP) within queuing framework. Current et al. [1] introduced eight basic facility location models namely p-median, p-center, p-dispersion, set covering, maximal covering, fixed charge, hub, and minisum. Moreover, several models and different solving methodologies have been proposed in [2]-[4]. As a main purpose of manufactures and service providers, customer satisfaction is mirrored as customer-desired characteristics [5]-[7].

The LAP combined with other aspects of industrial and operational management such as queuing theory has received considerable attentions in the literature. Wang et al. [8] proposed a facility location model within the M/M/1 queuing system. Berman and Drezner [9] developed facility location model within M/M/m queuing framework in which more than one server can be located at each facility. Berman et al. [10] introduced a similar model with more constraints on the lost demand in which the number of facilities is minimized. Pasandideh and Niaki [11] proposed a bi-objective facility location problem within M/M/1 queuing framework on the p-median problem. They modeled the bi-objective problem using the desirability approach and solved the model

employing a genetic algorithm. Hajipour and Pasandideh [12] proposed a multi-objective facility location problem within $M^{[x]}/M/1$ queuing framework. They also presented a genetic algorithm which integrated by Lp-metric approach to find efficient solutions. Pasandideh et al. [13] proposed two parameter-tuned meta-heuristic algorithms to solve the multi-objective facility location-allocation problem.

Besides, several evolutionary algorithms have since been developed which combine rules and randomness mimicking natural phenomena. These phenomena include biological evolutionary processes for example evolutionary algorithm [14], [15], genetic algorithm (GA) [16], [17], animal behavior [18], [19], the physical annealing process [20], and the musical process of searching for a perfect state of harmony [21]. Many researchers have recently studied these meta-heuristic algorithms to solve various optimization problems.

Recently, non-dominated ranked genetic algorithm (NRGA) as another multi-objective evolutionary algorithm is proposed by Al Jaddan et al. [22] to solve multi-objectives optimization models. While the implementation of NRGA is limited in the literature, therefore, in this paper, we presented NRGA to solve multi-objective facility location problems with competing objectives which presented by Hajipour and Pasandideh [12]. Computational results show the robustness of the NRGA method to obtain well-distributed optimal solutions.

The structure of the remainder of the paper is as follows. In the next section, the concept and definitions of the multi-objective optimization problem is illustrated. Then, next section analyzed the results and comparisons. Finally, in Section V, conclusions are made and possible future research works are suggested.

II. CONCEPT AND DEFINITION

Many real-world problems involve simultaneous optimization of several objectives. In this type of optimization problems, there is usually no single optimal solution. Hence, all objectives are considered when a set of alternative solutions are optimal in the wider sense, which no other solutions in the search space are superior to them. These solutions are known as Pareto-optimal.

In order to clarify the point, some basic multi-objective concepts are required to be reviewed [23]. Consider a multi-objective model with a set of conflict objectives as follow:

Vahid Hajipour is with Young Researchers Club ,Qazvin Branch, Islamic Azad University, Qazvin, Iran (phone: +989123829766; fax: +982813358026; E-mail: v.hajipour@qiau.ac.ir).

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1: Initialize Population  $P$ 
2: Generate random population – size  $N$ 
3: Evaluate objectives values and constraints
4: Calculate the rank of objectives values,
 $R_{f_i}, (i = 1, 2, \dots, k)$  for each solution,  $R_{f_i} \in [1 - N]$ 
5: Calculate the rank of the sum of the constraints
violation  $R_g$  for each solution
 $R_g \in [(N + 1) - (2N)]$ 
6: Convert the constrained problem to unconstrained one
using the equation (8) for each objective function, for
each solution in  $P$ 
7: Assign Rank (level) Based on Pareto dominance – sort
8: Calculate the crowding distance between members on
each front
9: Generate offspring Population  $Q$  from  $P$ 
10: {Ranked based Roulette Wheel Selection
11: Recombination and Mutation
12: Evaluate objectives values and constraints}
13: for  $g = 1$  to  $G$  do
14:   for each member of the combined population
( $P \cup Q$ )
15:     Calculate the rank of objectives values,
 $R_{f_i}, (i = 1, 2, \dots, k)$  for each solution in the combined
population  $P \cup Q, R_{f_i} \in [1 - 2N]$ 
16:     Calculate the rank of the sum of the constraints
violation  $R_g$  for each solution in the combined
population  $P \cup Q, R_g \in [(2N + 1) - (4N)]$ 
17:     Convert the constrained problem to unconstrained one
using the equation (8) for each objective function, for
each solution in  $P$ 
18:     Assign Rank (level) based on Pareto – sort
19:     Calculate the crowding distance between members on
each front
20:   end for
21:   (elitist) Select the members of the combined
population based on least dominated  $N$  solution to
make the population  $P$  of the next generation. Ties are
resolved by taking the less crowding distance.
22:   Calculate the rank of objectives values,
 $R_{f_i}, (i = 1, 2, \dots, k)$  for each solution,  $R_{f_i} \in [1 - N]$ .
23:   Calculate the rank of the sum of the constraints
violation  $R_g$  for each solution  $R_g \in [(N + 1) - (2N)]$ .
24:   Convert the constrained problem to unconstrained one
using the equation (8) for each objective function, for
each solution in  $P$ .
25:   Assign Rank (level) Based on Pareto dominance sort.
26:   Calculate the crowding distance between members on
27:    $Q =$  Create next generation from  $P \{$  .
28:   { Ranked based Roulette Wheel Selection.
29:   Recombination and Mutation.
30:   Evaluate objective values and constraints } |.
31: end for

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Fig. 1 Pseudo code of proposed NRGGA [22]

E. Stopping Criteria

The algorithm is stopped after a predetermined number of iterations.

At end, to clarify the trend of the proposed NRGGA, Pseudo code of NRGGA is represented in Fig. 1.

IV. RESULTS

To evaluate the performances of the proposed NRGGA, four standard metrics of multi-objective algorithms including diversity (D), spacing (S), and number of Pareto solution (NOS) are applied [25].

As mentioned above, the proposed multi-objective algorithm is applied to solve the multi objective facility location problems in the literature [12]. The experiments are implemented on 20 test problems. The demand rate of service requests from customer batch node i follows a uniform distribution, i.e., $\lambda_i \approx Uni[2,15]$. The service rate for server j follows a uniform distribution in [65, 95] as well, i.e., $\mu_j \approx Uni[65,95]$. The travelling time t_{ij} is calculated as a proportion of the Euclidean distance among customer batch i and potential facility j and follows a uniform distribution in the interval [65, 95]. The batch size is random variable following a geometric distribution with parameter 0.5, i.e., $S \approx Geometric(0.5)$. The fixed costs of locating and cost of adding one unit to system's capacity are related to service rate for each size of problem. Fixed cost of establishing facility j at potential node j follows a uniform distribution in the interval [100,500], i.e., $C_j \approx Uni(100,500)$. The other parameters are $\alpha = 0.5$, $\beta = 0.95$. The input parameters of the NRGGA including $P_c, P_m, nPop$, and nIt are set on 0.8, 0.2, 25, and 100, respectively.

The algorithm compare with non-dominated sorting genetic algorithm (NSGA-II) to demonstrate capability of the proposed algorithm to solve the multi-objective optimization problems. The result analysis show that in NOS metric both algorithms work same; while, in spacing and diversity metrics, the proposed NRGGA perform better performance. To clarify the results, Figs. 2-4 represent the provided results, graphically.

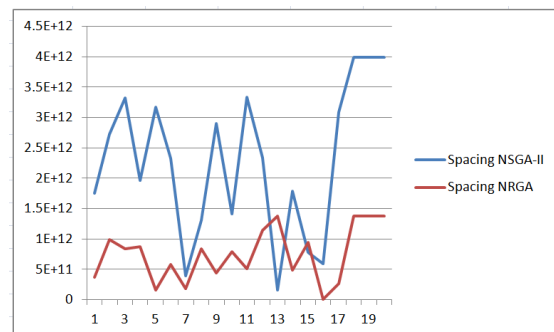


Fig. 2 Comparisons of NRGGA and NSGA-II on Spacing

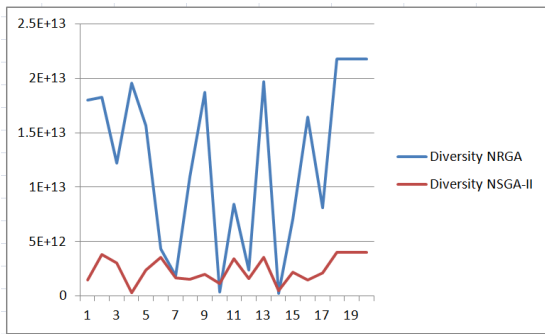


Fig. 3 Comparisons of NPGA and NSGA-II on Diversity

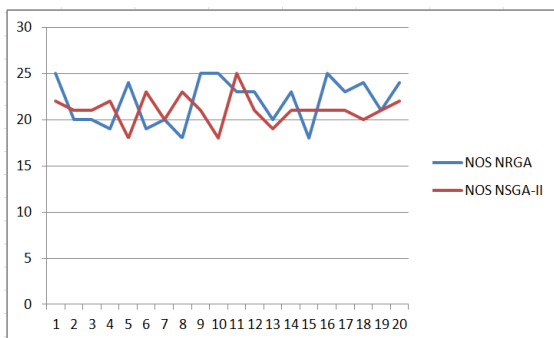


Fig. 4 Comparisons of NPGA and NSGA-II on NOS

V. CONCLUSION AND FUTURE RESEARCH

In this paper, a Pareto-based multi-objective meta-heuristic algorithm named NPGA is proposed to solve multi-facility location-allocation problem. The proposed NPGA is justified using several numerical illustrations taken from the specialized literature. The performance of our approach shows that NPGA algorithm is able to work better than NSGA-II especially in terms of diversity and spacing as two common standard metrics for comparing multi-objective optimization problems. As future research, one can develop other Pareto-based multi-objective meta-heuristic algorithm meta-heuristic and compared it with our proposed NPGA according to standard metrics.

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