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Spare Parts Closed-Loop Logistics Network Optimization Problems: Model Formulation and Meta-Heuristics Solution

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ABSTRACT Logistics network optimization is an important part of the spare parts allocation problem. In recent years, reverse logistics has greatly increased the efficiency of the supply chain. However, it also increases the difficulty of mathematical modeling and solving. In order to solve the network optimization problem of spare parts, a multi-period closed-loop logistics network is established. The practical problem is described as a mixed nonlinear integer programming model with multi-objective and multi-constraint. An improved multi-objective ant lion algorithm is proposed to solve this model. In the proposed algorithm, Levy flight and the quasi-opposites-based learning strategy are used to improve the performance of the algorithm. The numerical simulation shows that the convergence and distribution of the result of the proposed algorithm are promoted. Finally, the mathematical model is solved by the proposed algorithm, and a sensitivity analysis is carried out. The results show that, first, the proposed closed-loop supply network is superior to the traditional forward logistics network. Second, the improved ant lion algorithm is more effective than a basic ant lion algorithm and other classical algorithms.

INDEX TERMS Spare parts, closed-loop logistics networks, multi-objective optimization, ant lion optimizer.

I. INTRODUCTION

Maintenance spare parts logistics network optimization is an important part of military logistics management. The availability and lead time of spare parts have a direct effect on the maintenance tasks. Thus, lots of research works pay attention to the spare parts logistics network optimization. There are some similarities in spare parts logistics network between military and enterprise, such as scenario setting and constraint conditions. However, there are some differences in their objectives. The enterprises and factories usually consider economy, environment and other factors as the objectives. However, in the field of military logistics, in order to complete the maintenance task as quickly as possible, the time factor is usually the primary factor in logistics network optimization.

At present, there are many research works on logistics network optimization. Referring to some typical articles, this study analyzes these articles from three aspects of network structure, model type and solution method. These references have basically covered all types of logistics network optimization problems. Hao and Wei (2016) took the minimization of overall system costs and carbon emission as the targets to establish a single-period multi-echelon reverse logistics network and used mathematical programming to solve the model [1]. Harris *et al.* proposed a single period forward logistics network to solve facility location–allocation problem (CFLP). In their paper, both cost and carbon emission were considered as objectives, and a SEAMO2 algorithm was used to solve the proposed multi-objective problem [2]. Amin and Zhang established a closed-loop logistics network consisted of both forward and reverse supply chains, and the stochastic programming scenario-based model was used to solve the model [3]. Lee *et al.* took lead time, cost and fill rate as the objectives in their reverse logistics, and a multi-objective hybrid genetic algorithm and fuzzy logic controller model were proposed to solve the problem [4]. Maghouli *et al.* proposed a scenario-based multi-objective model to solve multi-period transmission expansion planning problem. To overcome the difficulties in solving the

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TABLE 1. Literature survey of logistics network design and optimization.

Article	Network structure			Period		Objective Number		Method	
	Forward	Reverse	Closed loop	Single	Multiple	Single	Multiple	Meta-heuristic	Others
Hao et al.[1]		√		√			√		√
Harris et al.[2]	√			√			√	√	
Amin and Zhang [3]			√	√		√			√
J. E. Lee et al.[4]		√		√			√	√	
Maghouli et al.[5]	√				√		√	√	
M. C. Wu et al.[6]	√			√		√		√	
Jeihoonian et al.[7]			√	√		√			√
Moghaddam[8]		√		√			√		√
Chang et al.[9]	√			√			√	√	
Fattahi et al. [10]			√		√	√		√	
Wang et al.[11]	√			√		√		√	
Lee et al.[12]	√			√			√	√	
Kumar et al.[13]			√		√	√		√	
This paper			√		√		√	√	

nonconvex and mixed integer optimization problem, the genetic-based non-dominated sorting genetic algorithm (NSGA-II) was used [5]. Wu *et al.* studied on the forward supply network of spare parts with the aim at minimize the cost, and the model was solved by two meta-heuristic algorithms [6]. Jeihoonian *et al.* proposed a two-stage stochastic mixed-integer programming model for a closed-loop supply chain network design problem. They also proposed a scenario-based approach to handle the mathematical model [7]. Moghaddam considered four objectives included total profit, total defective parts, total late delivered parts and economic risk factors in the study of reverse supply chain system. Monte Carlo simulation integrated with fuzzy goal programming was developed to determine the entire set of Pareto-optimal solutions of the proposed model [8]. Chang *et al.* established a single-stage and single-objective forward logistics network. They proposed a novel greedy-search-based multi-objective genetic algorithm to solve the problem [9]. Fattahi and Govindan addressed design and planning of an integrated forward/reverse logistics network over a planning horizon with multiple tactical periods. A single objective mathematical programming model was established and simulated annealing was used to solve the problem [10]. Wang *et al.* studied on a single-stage single-target forward supply chain, which was solved by bi-level stochastic programming and developed a genetic algorithm with efficient greedy heuristics [11]. Lee *et al.* established a single-period forward supply network with the cost and fill rate factors as its objectives. The proposed multi-objective problem was solved by multi-objective evolutionary algorithm [12]. Kumar *et al.* put forward a model of multi-period and multi-echelon vehicle routing forward-reverse logistics system. Particle swarm optimization algorithm was used to solve the mathematical model [13].

The above research works were summarized in Table 1 according to the structure of the logistics network, the number of objectives and the solution method. It can be seen that, the above literatures have covered various types of logistics network optimization problems.First of all, the structures of the logistics networks are different. From the perspective of space, it mainly includes forward logistics network, reverse logistics network and closed-loop logistics network. From the perspective of time, it mainly includes static optimization and dynamic network optimization considering multiple periods. Secondly, when studying the optimization of logistics network, economic factors, date factors, environmental factors and social factors are usually considered. Some research works only considered one of these factors, and others considered multiple objectives. In the logistics network optimization problem, it is necessary to select the appropriate optimization objectives according to the actual situation. Generally, the model with single objective is easier to solve than the multi-objective optimization problem. Lots of methods have been proposed to solve these models. These algorithms can be divided into exact methods, heuristic algorithms and meta-heuristic algorithms.

Combined with real world problems, this paper considers a multi-objective closed-loop network optimization problem. Therefore, multiple objectives should be considered in the spare parts logistics network optimization, and these objectives are conflicted with each other. In order to solve the multi-objective optimization problem (MOP), the intelligent optimization method is proposed. At present, multi-objective optimization algorithms can be categorized in Pareto based methods, decomposition based methods and index based methods [14]. The Pareto-based methods select the non-dominated solutions as the optimal solutions by comparing the dominating relations between different solutions. The most common used Pareto-based methods include the non-dominated sorting genetic algorithm II (NSGA-II) [15], strength Pareto evolutionary algorithm 2 (SPEA2) [16], and Pareto envelope-based selection algorithm II (PESA-II) [17], and so on. The decomposition-based methods aggregate the objectives by using a scalarizing function such that a single

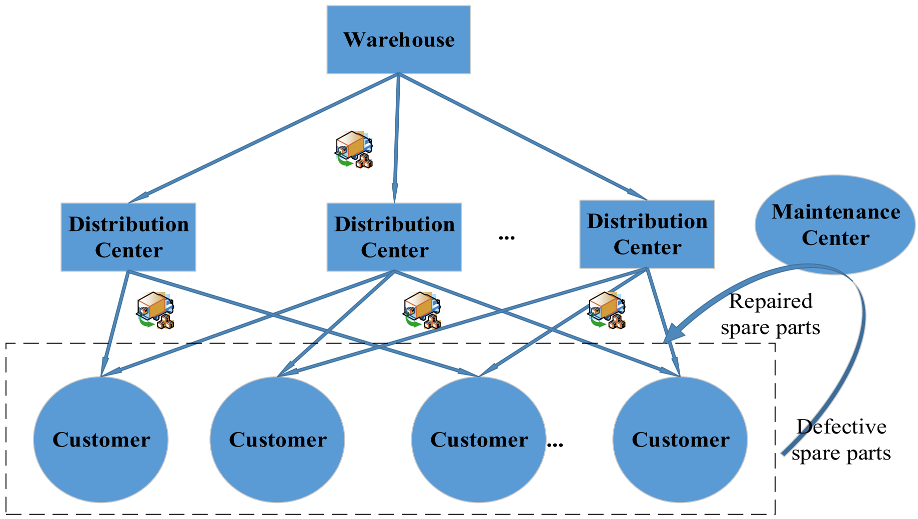


FIGURE 1. Spare parts closed-loop logistics network.

scalar value is generated. In these algorithms, the diversity of a population is maintained by specifying a set of well-distributed reference points to guide its individuals to search simultaneously towards different optima. The decomposition based multi-objective evolutionary algorithm (MOEA/D) is one of the most common used decomposition based algorithms [18]. The idea of indicator-based algorithms is to apply performance indicators to guide the search during the evolutionary process. The most common used indicators are ε indicator [19], inverted generational distance (IGD) [20], and the hypervolume (HV) indicator [21]. It can be seen from Table 1 that, these algorithms and their improved algorithms have been widely used in supply network optimization.

In this paper, a swarm intelligence algorithm named ant lion algorithm is improved and used to solve the model [22]. In order to solve the multi-objective optimization problem by using ant lion algorithm, Mirjalili proposed a multi-objective ant lion algorithm, and a large number of experiments proved that the performance of multi-objective ant lion algorithm is better than that of traditional algorithms such as MOPSO, NSGA-II, and so on [23]. Because of the superiority of the ant lion algorithm, the algorithm has been applied and popularized in lots of real world engineering problems such as parameter optimization [24] and path planning problem [25]. However, the basic ant lion algorithm converges slowly at the end of iteration when solving real world problems and is still prone to fall into local optimum. Therefore, this paper tries to improve its ability of global exploration and local exploitation in solving multi-objective problems by proposing an improved algorithm named quasi-oppositional Levy flight multi-objective ant lion optimizer algorithm (QOLMALO). After the performance of the improved algorithm has been tested, the QOLMALO algorithm has been used to solve the spare parts logistics network optimization model.

The remaining sections of this article are organized as follows. In section 2, the maintenance spare parts logistics network optimization problem is described. A multi-period closed-loop logistics network is proposed, and a non-linear integer program model with multi-objective and multi-constraint is established to formulate the MOP. Section 3 describes the improved ant lion algorithm. The performance of the proposed algorithm is tested by numerical simulation in section 4. In section 5, the improved algorithm is used to solve the proposed mathematical model. The sensitivity analysis and control experiment are carried out in order to show the flexibility and efficiency of the proposed model. We summarize the paper with suggestions for future improvement in section 6.

II. MODELING THE SPARE PARTS CLOSED-LOOP LOGISTICS NETWORK

A. PROBLEM DESCRIPTION

The three-echelon spare parts logistics network consists of warehouses, distribution centers and the end-users which are often called customers. A maintenance center is set up in the closed-loop spare parts logistics network, which is used to realize the reverse flow. The structure of the logistics network is shown in Figure 1. When the requirement occurs at the first period, spare parts are delivered from warehouses to distribution centers, and then transported from distribution centers to customers. The defective parts in customers are sent to maintenance center for repair. In the maintenance center, the repaired spare parts are sent to distribution centers as inventory to support the next period of spare parts supply.

When spare parts demand of the next period is needed, spare parts are still transported from warehouses to distribution centers and then send to customers. At this point, since there is already inventory in distribution centers, the amount of spare parts shipped from warehouses to distribution center is reduced. Generally, the distance between the warehouses and distribution center is longer than that between maintenance centers and distribution center. Therefore, the total lead time will be greatly reduced.

The following assumptions are made in the model:

1) Only one kind of spare parts is considered and the spare part is repairable;
2) The location of each node is known. The unit deliver time from warehouse to distribution centers, distribution centers to customers, customers to maintenance center and maintenance center to distribution centers are known and fixed;
3) The storage capacity of each warehouse is unlimited, and the spare parts reserve in warehouses is sufficient;
4) The maximum capacity of each distribution center is known and fixedč"
5) The customers are equally important, and the requirements in each period are known. The threshold of the maximum fill rate of the customers is knownč"
6) The maintenance capacity of the maintenance center is known and fixed. Unit maintenance time is knownč"
7) Due to the particularity of military tasks, priority is given to ensuring that spare parts requirements are met in the shortest time. The costs of storage and transportation are not taken into account.

B. DECISION VARIBLES AND PARAMETERS

The notations of the model are defined as following:

Indices

L : index of warehouses, $l = 1, 2, \cdots, L$

I : index of distribution centers, $i = 1, 2, \cdots, I$

J : index of customers, $j = 1, 2, \cdots, J$

K : index of the periods of spare parts supply, $k = 1, 2, \cdots, K$

Parameters

D_j^k : spare parts demand of the customer j at the period k

T_{li} : unit delivery time of spare parts from warehouse l to distribution center i

T_{ij} : unit delivery time of spare parts from distribution center i to customer j

T_{jq} : unit delivery time of spare parts from customer j to maintenance center

T_{qi} : unit delivery time of repaired spare parts from maintenance center to distribution center i

T_q : unit maintenance time of maintenance center

σ_j : maximum fill rate of the customer j

C_i : maximum capacity of the distribution center i

ω : repair capacity at maintenance center

The decision variables are denoted as follows:

x_{li}^k : the amount of spare parts from warehouse l to distribution center i at the stage k

y_{ij}^k : the amount of spare parts from distribution center i to customer j at the period k

z_i^k: the amount of spare parts from maintenance center to distribution center i at the period k.

C. MATHEMATICAL MODELING

In the model, the shortest lead time and the maximum fill rate are considered simultaneously as the two conflictive objective functions. The following constraints should also be considered. At first, the number of spare parts enters each distribution center should not exceed the maximum capacity of the distribution center. Secondly, the flow of each node (distribution centers or maintenance centers) should be balanced, that is, the output should not exceed the sum of input and inventory. Thirdly, the spare parts fill rate of each customer should be greater than 1 and below the prescribed threshold.

At the first period, the total time of spare parts supply includes the deliver time from warehouses to distribution centers, transportation time from distribution centers to customers, transportation time from customers to maintenance center, transportation time from maintenance center to distribution centers and maintenance time in maintenance center. The formula is as follows:

$$T^1 = \sum_l \sum_i (x_{li}^1 \times T_{li}) + \sum_i \sum_j (y_{ij}^1 \times T_{ij}) + \sum_j (D_j^1 \times T_{jq}) + \sum_i (z_i^1 \times T_{qi}) + \sum_l (D_j^1 \times T_q) \quad (1)$$

The overall fill rate of the customers region is the ratio of the quantity supplied to demand. The formula of the fill rate at the first period is as follows:

$$S^1 = \frac{\sum_i \sum_j y_{ij}^1}{\sum_j D_j^1} \quad (2)$$

The total fill rate should be between 1 and the maximum threshold, which is formulated as follows:

$$1 \le \frac{\sum_i \sum_j y_{ij}^1}{\sum_j D_j^1} < \sigma_j \quad (3)$$

When the spare parts reach the distribution centers from the warehouses, the capacity of each distribution centers is limited, which is formulated as follows:

$$\sum_l x_{li}^1 < C_i \quad (4)$$

When the repaired spare parts reach the distribution centers, the capacity of each distribution center is limited, which is formulated as follows:

$$\sum_l x_{li}^1 - \sum_j y_{ij}^1 + z_i^1 < C_i \quad (5)$$

The output of spare parts at each distribution center should not be greater than the input:

$$\sum_j y_{ij}^1 < \sum_l x_{li}^1 \quad (6)$$

In the maintenance center, the number of repaired spare parts is equal to the number of defective spare parts multiplied by the maintenance capacity:

$$\sum_i z_i^1 = \omega \sum_j D_j^1 \quad (7)$$

At the next $k-1$ periods, the calculation of the total spare parts supply time is the same as that in the first period, with the following formula:

$$T^k = \sum_l \sum_i (x_{li}^k \times T_{li}) + \sum_i \sum_j (y_{ij}^k \times T_{ij}) + \sum_j (D_j^k \times T_{jq}) + \sum_i (z_i^k \times T_{qi}) + \sum_l (D_j^k \times T_q), \quad k \in 2, 3, \cdots K \tag{8}$$

The total fill rate of the customers at period k is calculated in the same way as the first period:

$$S^k = \frac{\sum_i \sum_j y_{ij}^k}{\sum_j D_j^k}, \quad k \in 2, 3, \cdots K \tag{9}$$

Total fill rate constraint of customers at period k is given as follow:

$$1 \le \frac{\sum_i \sum_j y_{ij}^k}{\sum_j D_j^k} < \sigma_j, \quad k \in 2, 3, \cdots K \tag{10}$$

As the supply at first period lets the distribution centers to have inventory, when the next batch of spare parts arrive at the distribution centers from the warehouse, the supply flow and the existing stock should not exceed the capacity limitation of the distribution centers. The formula is as follows:

$$\sum_l x_{li}^{k-1} - \sum_j y_{ij}^{k-1} + z_i^{k-1} + \sum_l x_{li}^k < C_i, \quad k \in 2, 3, \cdots K \tag{11}$$

Similarly, the capacity constraint when repaired spare parts reach the distribution centers at period k is as follows:

$$\sum_l x_{li}^{k-1} - \sum_j y_{ij}^{k-1} + z_i^{k-1} + \sum_l x_{li}^k - \sum_j y_{ij}^k + z_i^k < C_i, \quad k \in 2, 3, \cdots K \tag{12}$$

The output of spare parts at each distribution center should not be greater than input:

$$\sum_j y_{ij}^k < \sum_l x_{li}^k, \quad k \in 2, 3, \cdots K \tag{13}$$

In the maintenance center, the amount of repaired spare parts is equal to the number of defective spare parts multiplied by the maintenance capacity:

$$\sum_i z_i^k = \omega \sum_j D_j^k, \quad k \in 2, 3, \cdots K \tag{14}$$

Above all, the following constrained multi-objective nonlinear integer programming model is established:

$$\min F_1 = \sum_k T^k, \quad k = 1, 2, 3, \cdots, K$$

$$\max F_2 = \sum_k S^k, \quad k = 1, 2, 3, \cdots, K$$

$$s.t. \begin{cases} 1 \le \dfrac{\sum_i \sum_j y_{ij}^k}{\sum_j D_j^k} < \sigma_j, \ k = 1, 2, 3, \cdots, K \\ \sum_l x_{li}^1 < C_i \\ \sum_l x_{li}^1 - \sum_j y_{ij}^1 + z_i^1 < C_i \\ \sum_l x_{li}^{k-1} - \sum_j y_{ij}^{k-1} + z_i^{k-1} + \sum_l x_{li}^k \\ \quad < C_i, \ k = 2, 3, \cdots, K \\ \sum_l x_{li}^{k-1} - \sum_j y_{ij}^{k-1} + z_i^{k-1} + \sum_l x_{li}^k - \sum_j y_{ij}^k \\ \quad + z_i^k < C_i, \ k = 2, 3, \cdots, K \\ \sum_j y_{ij}^k < \sum_l x_{li}^k, \ k = 1, 2, 3, \cdots, K \\ \sum_i z_i^k = \omega \sum_j D_j^k, \ k = 1, 2, 3, \cdots, K \\ x_{li}^k, y_{ij}^k, z_i^k \in N^+, \ k = 1, 2, 3, \cdots, K \end{cases}$$

III. THE PROPOSED QOLMALO ALGORITHM

A. DESCRIPTION OF BASIC ANT LION OPTIMIZER

The way that ant lion optimizer find the optimal solutions is simulating the process of ant lions build trap and prey ants in nature. So there are two populations in the ant lion algorithm, that is, the ant lions and the ants. The hunting process consists of five basic steps: random walk of ants, ants fall into traps, ants slid towards ant lions, ant lions catch ants and ant lions reconstruct traps. The basic steps of the ant lion optimizer simulate the above process, and the mathematical description is as follows:

(1) The random walk of ants is formulated as follows:

$$x(t) = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \ldots, cumsum(2r(t_n) - 1)] \tag{15}$$

where *cumsum* calculates the cumulative sum, t is the number of iterations, and n is the maximum number of iterations. $r(t) = \begin{cases} 1 & if\ rand > 0.5 \\ 0 & if\ rand \le 0.5 \end{cases}$ is a random function related to t, and *rand* satisfies the uniform distribution of $[0 \sim 1]$.

In order to ensure that ants move randomly in search space and prevent them from crossing the boundary, it is necessary to normalize the position of ants:

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i^t - c_i^t)}{b_i - a_i} + c_i^t \tag{16}$$

where c_i^t and d_i^t indicate the minimum value and the maximum value of the variable i of one ant at the $t-th$ iteration respectively; a_i and b_i indicate the minimum value and the maximum value of the variable i of the ant respectively.

(2) By simulating the process of random walking around the ant lion and falling into a trap, the formula is as follows:

$$c_i^t = Antlion_j^t + c^t d_i^t = Antlion_j^t + d^t \tag{17}$$

where c^t and d^t are the minimum and maximum values of all variables in the $t-th$ iteration; $Antlion_j^t$ is the position of ant lion j at the $t-th$ iteration.

(3) By adaptively reducing the random walk range of the ants, the process of the ants to slide into the ant lion is simulated as follows:

$$c^t = \frac{c^t}{I}, \quad d^t = \frac{d^t}{I} \tag{18}$$

where $I = 1 + 10^{\omega \frac{t}{T}}$ is gradually increased as the number of iterations increases. t is the number of iterations, T is the maximum number of iterations, $t = 1, 2, \cdots, T$, ω is dynamically adjusted with the number of iterations.

(4) The simulation of capture process is as follows:

$$Antlion_j^t = Ant_i^t \ if\ f(Ant_i^t) < f(Antlion_j^t) \tag{19}$$

where $Antlion_j^t$ is the position of ant lion j at the $t-th$ iteration, Ant_i^t is the position of ant i at the $t-th$ iteration.

Select the ant lion with optimal fitness as elite individual which decides the position of ants in the next iteration. Ants move randomly towards both a randomly selected ant lion and the elite ant lion, with the following formulas:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{20}$$

where R_A^t is a random movement around an ant lion selected by roulette wheel selection mechanisms. R_E^t is a random movement around the elite ant lion.

(5) Reconstruction the trap. Use an external archive to store the non-dominant solution set. The niche technique is used to measure the distribution of solutions in archives. The distribution of the solution is measured by the number of other solutions in the neighborhood of each solution. The more the solution in the neighborhood, the denser the individual is.

B. QUASI-OPPOSITION BASED LEARNING STRATEGY

Traditional meta-heuristic algorithms usually begin with a set of random initial solutions, but the randomly generated initial solutions may be far from the optimal solutions. So it takes a long time for the algorithm to converge to the optimal solutions. Therefore, in this paper, the quasi-opposition based learning (QOBL) strategy is used to optimize the initial population [26]. In this way, the convergence rate of the algorithm can be improved, as well as, the diversity of the population can be increased.

For a real number x with search interval $[a, b]$, its opposite number ox is defined as follows:

$$ox = a + b - x \tag{21}$$

Its quasi-opposites number is defined as follows:

$$qox = rand((\frac{a+b}{2}), ox) \tag{22}$$

Then, for a D dimensional individual $X = [X_1, X_2, \ldots, X_D]$, its quasi-opposites individual is $QOX = [qox_1, qox_2, \ldots, qox_D]$. The value of $i-th$ variable in QOX is $qox_i = rand((\frac{a_i+b_i}{2}), ox_i)$.

After the quasi-opposite population is obtained, it is mixed with the individual of the original population as the new population.

C. LEVY FLIGHT

Levy flight is a style of movement in nature, and its step length obeys a heavy-tail probability distribution. The definition of a Levy flight stems from the mathematics related to chaos theory and is useful in stochastic measurement and simulations for random or pseudo-random natural phenomena [27]. This stochastic technique has been used in a lot of metaheuristic optimization algorithms such as particle swarm optimization [28], grey wolf optimizer [29], cuckoo search algorithm [30], and so on. Some scholars have also improved the theory and proposed the normalized truncated Levy walks [31]. Its trajectory is shown in Figure 2. It can be seen from the figure that the particle moves in the form of Brownian motion with an occasional long-distance flight. Therefore, using this mechanism in ant lion algorithm can make the population have good ability of both local exploitation and global exploration.

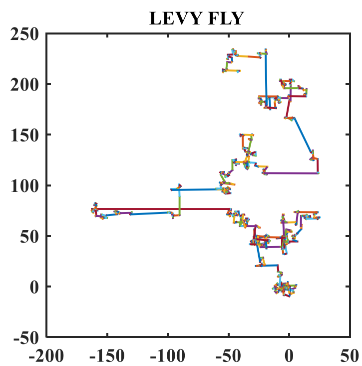


FIGURE 2. Trajectory of Levy flight.

The position updated formula of Levy flight is as follows:

$$x_{t+1} = x_t + s \tag{23}$$

where x_t is the position at the $t-th$ iteration, x_{t+1} is the position at the $(t+1)-th$ iteration, s is step length which obeys Levy distribution.

Levy distribution is a distribution of the sum of N random variables distributing identically and independently. In general, Levy distribution should be defined in terms of Fourier transform: $F_N(k) = \exp(-N|k|^\beta), 0 < \beta \leq 2$ where, N is a scale parameter, and β is an index parameter. However, it is difficult to get the actual distribution $L(s)$, because there is no analytical forms of the integral $L(s) = \frac{1}{\pi}\int_0^\infty \cos(ks)\exp(-N|k|^\beta)dk, 0 < \beta \leq 2$, except for a few special case such as $\beta = 1$ and $\beta = 2$. The generation of steps obeys Levy distribution is quite tricky, and there are a few ways of achieving this currently. The step length s is often simulated by Mantegna algorithm, and the formulas are as follows [32]:

$$s = \frac{\mu}{|\upsilon|^{1/\beta}} \tag{24}$$

where μ and υ are normal distributed with an expectation of zero. Their variances are shown as follows:

$$\sigma_{\mu} = \left\{ \frac{\Gamma 1 + \beta \sin \frac{\pi\beta}{2}}{\Gamma \frac{1+\beta}{2} \beta^{2} \frac{\beta-1}{2}} \right\}^{\frac{1}{\beta}}, \quad \sigma_{v} = 1 \tag{25}$$

β usually equal to 1.5.

Therefore, the random walk mechanism in the basic ant lion algorithm, shown as Eqs. (15), is replaced as follow:

$$x(t) = [0, cumsum(L(t_1)), cumsum(L(t_2)), \ldots, cumsum(L(t_n))] \tag{26}$$

where $L(t)$ is the Levy fly in $t - th$ iteration.

D. COMPLETE ALGORITHM

In the improved algorithm, Levy flight is used to replace the random walk mechanism in the basic algorithm to increase the ability of local exploitation and global exploration of the algorithm. Firstly, the elite ant lion and random ant lion are selected from the external archive based on non-dominance relationships and crowding distance. Secondly, we make these two individuals to perform Levy flight. The process is actually to make every dimension variable on each individual to perform Levy flight process. Quasi-opposites learning strategy is adopted after the population is updated using Eq. (20). In this way, it's possible to increase diversity of the population and improve the convergence speed. The detail of the proposed QOLMALO algorithm is presented in Algorithm 1.

Algorithm 1 QOLMALO

```
Define the fitness function, F = [F_1, F_2, ..., F_M] ∈ Ω^M
Set the individual dimensions, population size, scale
  of external archival, value range of variable,
  maximum iteration number
Initialize the population and the external
  archive.(step1)
While (t < iter_max)
  for i = 1 : n
    Calculate the fitness value and find the elite ant
      lion(step2)
    Update and maintain external archives(step3)
    Select the random ant lion and elite ant
      lion(step4). Levy flight is adopted based on
      Eqs. (26), and the individual position of
      population is updating according to Eqs. (20)
  end for
  for i = 1 : n
    for j = 1 : d
      Calculate the opposite and quasi-opposite
        values of each decision variable by
        Eqs. (21) and Eqs.(22)
      M_{i,j} = (a_i + b_i)/2
      If (X_{i,j} < M_{i,j})
        QOX_{i,j} = M_{i,j} + (OX_{i,j} − M_{i,j}) × rand
      else
        QOX_{i,j} = OX_{i,j} + (M_{i,j} − OX_{i,j}) × rand
      end if else
    end for
  end for
  The quasi opposite population is mixed with the
    original population, and the fitness of the new
    population is calculated. According to the
    dominance relation and the crowding degree, the
    new population is selected to form the mixed
    population.
end while
The individuals in external archive are optimal
  solution set
```

IV. PERFORMANCE TEST

A. METRIC AND BENCHMARKS

For multi-objective optimization algorithms, the performance of the algorithms is mainly reflected in convergence and distribution of the results [33]. Convergence describes the degree of approximation distance between the results obtained by the algorithm and the true Pareto front (TF). The stronger the convergence of the algorithm, the closer the solution set is to the true optimal solution, and the more accurate the result is. The distribution describes the distribution characteristics of the obtained results in the objective space. On the one hand, the results should be distributed as much as possible on the whole PF, and on the other hand, the results should be distributed as evenly as possible. The stronger the distribution of the algorithm represents a better global exploration ability of the algorithm. An example is shown in Figure3:

It can be see that, the result of Figure (A) has good distribution and convergence, the result of Figure (B) has a week convergence, and the results of Figure (C) and Figure (D) have week distribution.

To measure the performance of the algorithm, among the many metrics, inverted generation distance (IGD) and hyper volume (HV) were selected because they can reflect the convergence and distribution of the algorithm at the same time.

IGD describes the average distance from the result to the reference point. The smaller the value, the closer the solution set to the real PF, and the better distribution is. The formula is as follows:

$$IGD = \sum_{z \in P^*} d(z, P) / \left|P^*\right| \tag{27}$$

TABLE 2. Benchmarks of ZDT.

Benchmark	Description	Domain	True PF
ZDT1	$f_1 = y_1$ $g = 1 + 9\sum_{i=1}^{k} z_i / k$ $h = 1 - \sqrt{f_1 / g}$ $f_2(y,z) = g(z)h(f_1(y)g(z))$	[0,1]	Convex, continuous
ZDT2	$f_1 = y_1$ $g = 1 + 9\sum_{i=1}^{k} z_i / k$ $h = 1 - (f_1 / g)^2$ $f_2(y,z) = g(z)h(f_1(y)g(z))$	[0,1]	Concave, continuous
ZDT3	$f_1 = y_1$ $g = 1 + 9\sum_{i=1}^{k} z_i / k$ $h = 1 - \sqrt{f_1 / g} - (f_1 / g)\sin(10\pi f_1)$ $f_2(y,z) = g(z)h(f_1(y)g(z))$	[0,1]	Convex, discontinuous
ZDT4	$f_1 = y_1$ $g = 1 + 10\mathrm{k} + \sum_{i=1}^{k} (\mathrm{z}_i^{\,2} - 10\cos(4\pi f_1))$ $h = 1 - (f_1 / g)^{1/2}$ $f_2(y,z) = g(z)h(f_1(y)g(z))$	$y_1 \in [0,1]$ $z_{1,2,\ldots,k} \in [-5,5]$	Convex, continuous
ZDT6	$f_1 = 1 - \exp(-4y_1)\sin^6(6\pi y_1)$ $g = 1 + 9(\sum_{i=1}^{k} z_i / k)^{1/4}$ $h = 1 - (f_1 / g)^2$ $f_2(y,z) = g(z)h(f_1(y)g(z))$	[0,1]	Concave, continuous

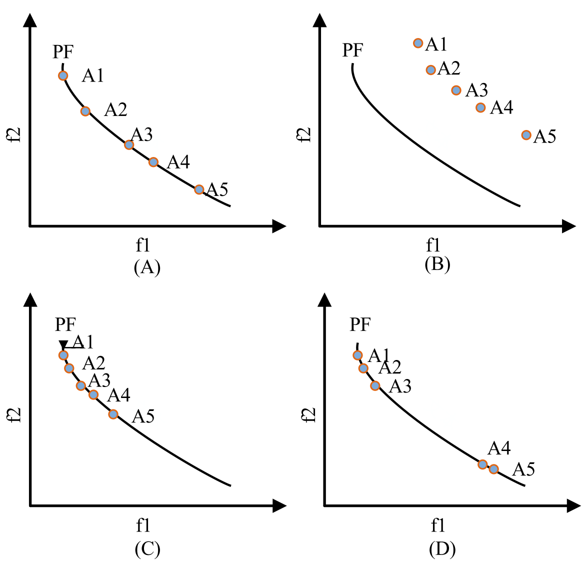


FIGURE 3. Illustration of distribution and convergence.

where P^* indicates reference point, which is selected from the true PF. P is the front line of the solution obtained by the algorithm, $d(z, P)$ is the minimum Euclidean distance from the P^* to the P, and $|P^*|$ is the size of P^*.

HV indicates the hyper volume of the points and reference points obtained by the algorithm in the target space. The larger value represents better convergence and distribution of the algorithm. The formula is as follows:

$$HV = \Lambda(\left\{\bigcup h_i | p_i \in P\right\}) = \Lambda(\bigcup_{p_i \in P} \{x | p_i < x < x_{ref}\}) \quad (28)$$

where Λ is Lebesgue measure, P is the solution obtained by the algorithm, x_{ref} indicates reference point.

In order to study the performance of the improved algorithm, five representative benchmark functions ZDT1, ZDT2, ZDT3, ZDT4 and ZDT6 are selected from ZDT series benchmarks [34]. Among them, ZDT1 and ZDT4 have convex TF, ZDT2 and ZDT6 have concave TF, and ZDT3 has a discontinuous TF. The exact description is shown in Table 2.

B. EXPERIMENTS AND ANALYSIS

In this paper, the improvement of the QOLMALO algorithm compared with the original MALO algorithm, MOPSO algorithm and the NSGA-II algorithm is verified by experiments. The simulation studies were carried out in a MATLAB 2014b platform on an ASUS laptop with 5-6300HQ 2.3GBz CPU, 4GB RAM in Windows 7.0(64-bit) environment. In order to

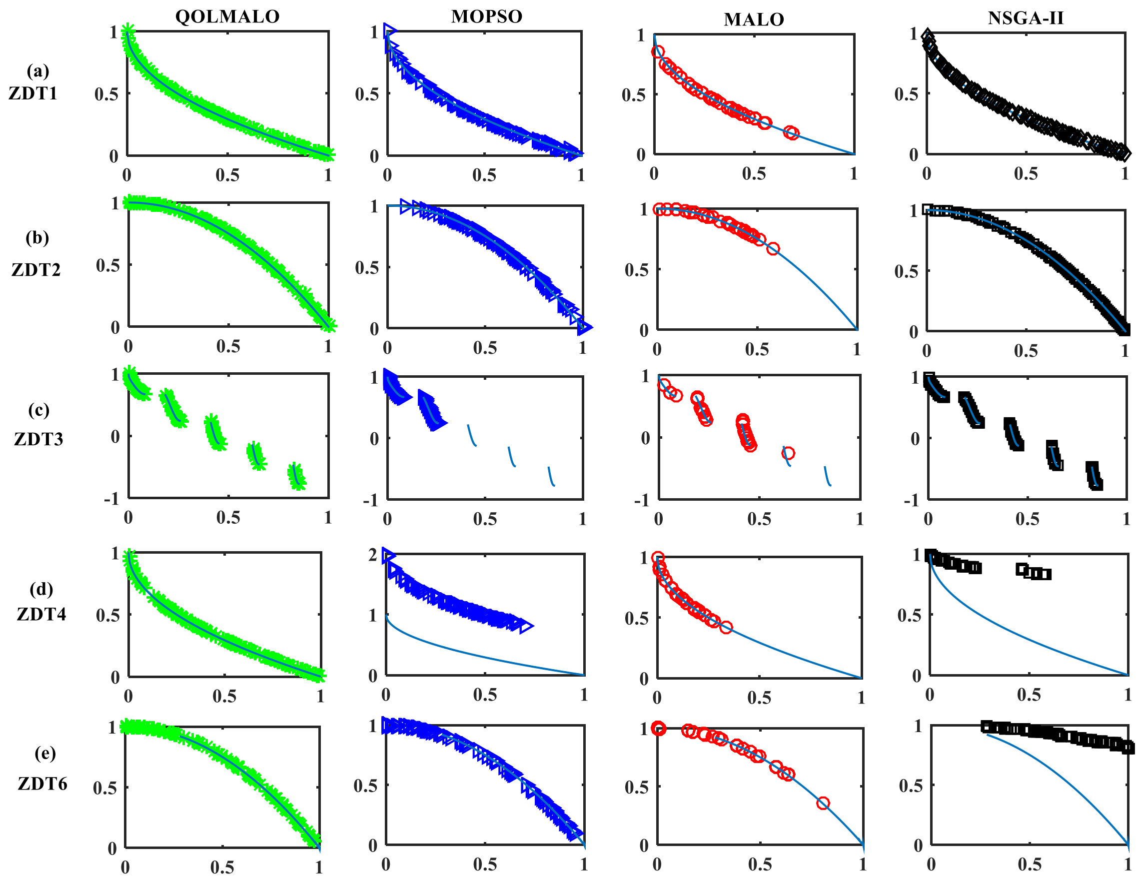


FIGURE 4. Distribution of optimal solution in each algorithm.

ensure fairness, the population size of all experiments was 100, and the number of iterations was 100.

The above four algorithms are used to solve the five benchmark functions, and the distribution of the optimal solutions in the objective space are shown in Figure 4.

The solid line indicates the True PF (TF) of the benchmark functions, and the scatter represents the optimal solutions obtained by different algorithms. The figures represent the results of each algorithm for solving the ZDT1, ZDT2, ZDT3, ZDT4 and ZDT6. In Figure 4, the x-axis and y-axis labels corresponding to the fitness function f_1 and fitness function f_2 respectively. From left to right correspond to the results of QOLMALO, MOPSO, MALO, and NSGA-II respectively. The performance of the algorithm can be observed intuitively from the graph. Compare the four graphs in Figure (a), it can be found that the solutions of all algorithms can land on the solid line when solving the ZDT1 problem, which shows that the four algorithms have good convergence for solving the ZDT1 problem. However, it is obvious that the solution of MALO is not well distributed on the whole TF, while the other three algorithms are widely distributed and uniform. It is showed that the distribution of QOLMALO, MOPSO and NSGA-II are better than that of MALO as solving ZDT1 problem. In the same way, we can find that the four algorithms have good convergence in solving ZDT2, but the distribution of QOLMALO, MOPASO and NSGA-II is better than that of MALO. Comparing the results in Figure (c), we can find that the convergence and distribution of QOLMALO and NSGA-II are very good when solving the ZDT3 problem. At the same time, the convergence of MOPSO is very good, but the distribution is not satisfied. Meanwhile, the convergence and distribution of MALO algorithm are both poor. Figure (d) and Figure (e) show that the convergence and distribution of QOLMALO are of good performance, however, the performances of MOPSO, MALO and NSGA-II when solving the ZDT4and ZDT6 are poor.

In summary, it can be seen from the distribution of the optimal solutions that the proposed QOLMALO algorithm has better convergence and distribution in solving all kinds of benchmark functions. This shows that the proposed improved algorithm greatly improves the performance of the original MALO algorithm and has good adaptability and robustness in solving multi-objective problems.

In order to get accurate results from the data, each benchmark was tested 30 times using each algorithm. The IGD and HV of each trial were counted. By analyzing the values of IGD and HV in Table 3, the performance of the four algorithms can be judged accurately.

TABLE 3. Mean and standard deviation of each metric for the three algorithms to solve the benchmarks.

		QOLMALO		MALO		MOPSO		NSGA-II	
		mean	std	mean	std	mean	std	mean	std
ZDT1	IGD	**0.0071**	**7.3560e-04**	0.0787	0.0469	0.0251	0.0158	0.0185	0.0097
	HV	0.8669	**0.0011**	**0.9204**	0.0607	0.8490	0.0119	0.8396	0.0232
ZDT2	IGD	**0.0068**	**4.3522e-04**	0.1076	0.0689	0.0088	0.0014	0.0092	0.0163
	HV	0.5330	**0.0016**	0.4008	0.0696	**0.5394**	0.0573	0.5324	0.0497
ZDT3	IGD	**0.0084**	**8.5258 e-04**	0.0743	0.0317	0.1882	0.0841	0.0123	0.0059
	HV	**1.0206**	**6.6502 e-04**	0.9298	0.0430	0.7957	0.1056	0.9907	0.0075
ZDT4	IGD	**0.0066**	**5.0210 e-04**	0.1019	0.0690	0.5363	0.0921	0.7026	0.1121
	HV	**0.8615**	**9.3659 e-04**	0.7841	0.0458	0.2301	0.0890	0.1980	0.1007
ZDT6	IGD	**0.0327**	**0.0041**	0.0449	0.0349	0.1647	0.1551	0.2196	0.1782
	HV	**0.4316**	**0.0013**	0.4272	0.0477	0.4003	0.0416	0.4237	0.0154

For the mean value, the best algorithm corresponds to the minimum value of IGD and the maximum value of HV. It can be seen from the bold numbers that the value of IGD with QOLMALO algorithm is the smallest among all the benchmark functions, that is, the convergence and distribution of the QOLMALO are the best. Although the HV of the QOLMALO algorithm can only reach the maximum value just in the ZGT3 problem, the value of HV (0.5330) is not far from that of the MOPSO algorithm (0.5394).

For the standard deviation, the smaller value corresponds to a better stability of the algorithm. The bold numbers show that, the minimum of all standard deviations corresponds to the QOLMALO algorithm. This shows that the QOLMALO algorithm has good stability in solving all benchmarks.

TABLE 4. Spare parts deliver time between pairwise nodes (*h*).

	Wh	Cus 1	Cus 2	Cus 3	Mc
Dc 1	72	6	8	5	4
Dc 2	60	5	6	9	6
Dc 3	96	3	7	5	2
Cus 1	INF	0	INF	INF	1
Cus 2	INF	INF	0	INF	3
Cus 3	INF	INF	INF	0	2

TABLE 5. Maximum capacity of each distribution center.

Dc 1	Dc 2	Dc 3
30	60	50

TABLE 6. Demand for spare parts in each period of customer.

	Cus1	Cus 2	Cus 3
Period 1	30	15	25
Period 2	25	20	20

V. QOLMALO FOR SPARE PARTS CLOSED-LOOP LOGISTICS NETWORK OPTIMIZATION

A. SIMULATION EXPERIMENTS

A two periods three-echelon spare parts logistics network is considered. The unit deliver time, maximum capacity of each distribution center, and spare parts requirements at each period of the customers are shown in Table 4, 5 and 6. The maximum fill rate of the customers is 1.2, the repair capacity of maintenance center is 0.6, and the unit spare parts maintenance time is $5h$.

There are 30 decision variables, 2 objectives and 24 constraints in this multi-objective optimization model. In this paper, the penalty function method is used to transform the constrainted problem into an unconstrained problem [35]. Therefore, the final fitness functions of the model are as follows:

$$\begin{aligned} \Phi_1(X) &= F_1(X) + M \times (\sum G(X) + \sum H(X)) \\ \Phi_2(X) &= 1/F_2(X) + M \times (\sum G(X) + \sum H(X)) \end{aligned} \tag{29}$$

where $F_1(X)$, $F_2(X)$ are two objective functions in the model, $G(X)$ and $H(X)$ indicate the corresponding violation function of inequality constraints and equality constraints in the model, respectively, $G(X) = \max[0, g(x)]$, $H(X) = \max[0, |h(x) - \xi|]$. $g(x)$ indicates inequality constraints, $h(x)$ indicates equality constraints. The penalty factor M is 100000 in this paper.

B. COMPARISION OF DIFFERENT ALGORITHMS

In order to test the effectiveness of the QOLMALO algorithm, three classical algorithms, NSGA-II, MOPSO, SPEA2 and the original MALO algorithm are selected to solve the model. The results of different algorithms are compared to analyze the advantages and disadvantages of each algorithm. In order to ensure the fairness of the experiment, the population size of all the algorithms is 100 and the maximum iteration number is 1000. Each algorithm runs 10 times independently, and the results of 10 times are compared according to the dominating relation. The non-dominant solutions are chosen as the final supply project of each algorithm.

In Figure 5, the x-axis and y-axis labels corresponding to the fitness function Φ_1 and fitness function Φ_2 respectively, which are formulated in Eqs. (29). Figure 5 shows that the results of other algorithms are dominated by the results of the QOLMALO algorithm. That is, the total supply time occupied by the result of QOLMALO algorithm is less than the supply time obtained by the other algorithms. At the same time, the overall spare parts fill rate of the customers is also larger than the results of other algorithms. It is obvious that the proposed algorithm has a great improvement compared

TABLE 7. Statistical result of each algorithm.

Methods	Number of optimal solutions	Mean		Maximum		Minimum		Standard deviation	
		F_1	F_2	F_1	F_2	F_1	F_2	F_1	F_2
NSGA-II	24	10134	2.1826	11040	**2.4000**	9425	2.0111	**408.1228**	**0.0563**
MOPSO	30	10338	2.1678	11264	**2.4000**	9611	2.0167	421.2615	0.0626
SPEA2	34	10664	2.1851	11595	**2.4000**	10067	2.0095	428.2773	0.0719
MALO	37	10247	2.1876	11254	**2.4000**	9437	1.9683	489.8065	0.0702
QOLMALO	32	**9592**	**2.1992**	**10547**	**2.4000**	**8770**	**2.0342**	521.5321	0.0786

TABLE 8. Statistical result for different maintenance capacity.

Maintenance capacity	Number of optimal solutions	Mean		Maximum		Minimum		Standard deviation	
		F_1	F_2	F_1	F_2	F_1	F_2	F_1	F_2
ω=0	33	12793	1.7789	13789	**2.4000**	11956	1.6452	480.2610	0.0699
ω=0.2	42	12340	1.9138	13874	**2.4000**	11499	1.8601	545.8160	0.0816
ω=0.4	35	11308	2.0055	13389	**2.4000**	10395	1.9753	612.9091	0.0778
ω=0.6	33	10665	2.1839	11536	**2.4000**	10007	2.0191	387.9822	**0.0505**
ω=0.8	24	76267	2.1758	9894	**2.4000**	9865	2.1067	**349.9535**	0.0766
ω=1	37	**76252**	**2.1770**	**9691**	**2.4000**	**7829**	**2.1096**	451.7355	0.0689

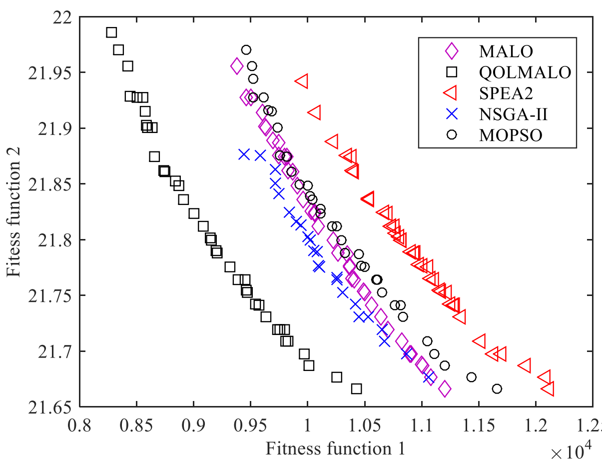


FIGURE 5. Result of each algorithm.

with the original MALO algorithm. The QOLMALO algorithm is superior to other traditional methods in solving the spare parts supply network model as well.

Table 7 gives the number of non-dominant solutions, the average, maximum, minimum and standard deviation of the two objectives corresponding to each algorithm. It should be emphasized that F_1 and F_2 is the value of objective functions of the model rather than the fitness functions. F_1 indicates the total time of supply, and the smaller the value will get the better the result. F_2 indicates the overall fill rate of the spare parts, and the greater the value corresponds to the better the result. The bold numbers correspond to the minimum of F_1 and the maximum of F_2. It can be seen that, compared with the other algorithms, the mean, maximum and minimum values of the F_1 with QOLMALO are minimal, and the average and maximum value of F_2 are the maximal. This means that the supply scheme obtained by QOLMALO algorithm is better than the results of other methods.

C. COMPARISION OF DIFFERENT MAINTENANCE CAPACITY

In order to study the effect of maintenance center on the whole logistics network, the maintenance capacity ω of the maintenance center is set as 0, 0.2, 0.4, 0.6, 0.8 and 1 respectively. The structure of the network is different from other situations while $\omega = 0$. In this case, there is no maintenance center in the logistics network, so it is a traditional forward supply network. The demands of the customers must be met within single period. The situation with $\omega = 1$ indicates that the maintenance center can repair all defective spare parts as new.

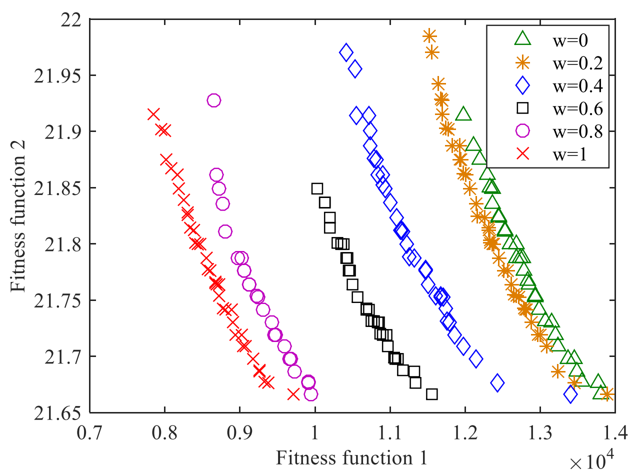


FIGURE 6. Result of each maintenance capacity.

Figure 6 shows that the results obtained while $\omega = 1$ dominate the results in other cases. That is, when the maintenance center can repair all the defective spare parts, the total time consumed by the logistics network will be the shortest. In the case of without maintenance center, the logistics network is a traditional forward network, which takes the longest time and the minimum spare parts fill rate. Therefore, compared with the traditional forward logistics network, the proposed multiple periods closed-loop logistics network with maintenance center has reduced the supply time and obtain greater fill rate of spare parts at the same time.

The number of non-dominant solutions, mean value, maximum, minimum and standard deviation of the two objectives corresponding to each case are in Table 8. The mean, maximum and minimum values of F_1 are minimal, as well as, the minimum and the maximum of F_2 are maximal in the case of $\omega = 1$. This shows that the results in the case of $\omega = 1$ are better than the results of other situations. Therefore, decision-makers can improve the efficiency of the closed-loop network by improving the maintenance capacity of maintenance center.

VI. CONCLUSION

In order to improve the efficiency and effectiveness of the spare parts supply, the characteristics of closed-loop logistics network have been analyzed firstly. A multi-period closed-loop logistics network has been designed with the aim at obtaining the shortest deliver time and the maximum fill rate under the constraints of other practical situations. A nonlinear integer programming model with multi-objective and multi-constraint has been established which transforms the spare parts supply problem into constrained multi-objective optimization problem.

To solve this multi-objective optimization problem, an improved multi-objective ant lion optimization algorithm is proposed. Based on the traditional ant lion algorithm, the following improvements are made in QOLMALO. Firstly, the quasi-opposites learning strategy is used to optimize the population, which can increase the diversity of the population and improve the convergence speed of the algorithm. Secondly, Levy flight is used to replace the random walk mechanism in the original algorithm. On the one hand, the Brownian motion of the individual is used to complete the local exploration of the algorithm. On the other hand, the occasional long distance flight is used to improve the global exploration of the algorithm to overcome the problem of premature convergence. In order to test the performance of the proposed algorithm, five standard benchmark functions with typical characteristics are selected. The proposed QOLMALO is compared with the original multi-objective ant lion algorithm and other classical multi-objective optimization algorithm. The simulation results show that the improved algorithm has better convergence and distribution than other algorithms in solving all the benchmark functions.

Through the contrast experiment, it is verified that the proposed QOLMALO algorithm has good adaptability and robustness in solving spare parts logistics network optimization problems. On the other hand, the advantages of closed-loop logistics network over traditional forward network in spare parts supply are verified. The next step of this paper will continue to improve the algorithm to solve many-objective optimization problem. At the same time, a new constraint treatment method is explored to solve practical engineering problems.

REFERENCES

[1] H. Yu and D. S. Wei, "A general reverse logistics network design model for product reuse and recycling with environmental considerations," *Int. J. Adv. Manuf. Technol.*, vol. 87, nos. 9–12, pp. 2693–2711. Dec. 2016.

[2] I. Harris, C. L. Mumford, and M. M. Naim, "A hybrid multi-objective approach to capacitated facility location with flexible store allocation for green logistics modeling," *Transp. Res. E, Logistics Transp. Rev.*, vol. 66, no. 1, pp. 1–22, Jun. 2014.

[3] S. H. Amin and G. Zhang, "A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return," *Appl. Math. Model.*, vol. 37, no. 6, pp. 4165–4176, Mar. 2013.

[4] J.-E. Lee, K.-Y. Chung, K.-D. Lee, and M.-Gen, "A multi-objective hybrid genetic algorithm to minimize the total cost and delivery tardiness in a reverse logistics," *Multimedia Tools Appl.*, vol. 74, no. 20, pp. 9067–9085, Oct. 2015.

[5] P. Maghouli, S. H. Hosseini, M. O. Buygi, and M. Shahidehpour, "A scenario-based multi-objective model for multi-stage transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 26, no. 1 pp. 470–478, Feb. 2011.

[6] M.-C. Wu, Y.-K. Hsu, and L.-C. Huang, "An integrated approach to the design and operation for spare parts logistic systems," *Expert Syst. Appl.* vol. 38, no. 4, pp. 2990–2997, Apr. 2011.

[7] M. Jeihoonian, M. K. Zanjani, and M. Gendreau, "Closed-loop supply chain network design under uncertain quality status: Case of durable products," *Int. J. Prod. Econ.*, vol. 183, pp. 470–486, Jan. 2017.

[8] K. S. Moghaddam, "Fuzzy multi-objective model for Supplier selection and order allocation in reverse logistics systems under supply and demand uncertainty," *Expert Syst. Appl.*, vol. 42, nos. 15–16, pp. 6237–6254, Sep. 2015.

[9] F.-S. Chang, J.-S. Wu, C.-N. Lee, and H.-C. Shen, "Greedy-search-based multi-objective genetic algorithm for emergency logistics scheduling," *Expert Syst. Appl.*, vol. 41, no. 6, pp. 2947–2956, May 2014.

[10] M. Fattahi and K. Govindan, "Integrated forward/reverse logistics network design under uncertainty with pricing for collection of used products," *Ann. Oper. Res.*, vol. 253, no. 1, pp. 193–225, Jun. 2017.

[11] K.-J. Wang, B. Makond, and S.-Y. Liu, "Location and allocation decisions in a two-echelon supply chain with stochastic demand—A genetic-algorithm based solution," *Expert Syst. Appl.*, vol. 38, no. 5, pp. 6125–6131, May 2011.

[12] L. H. Lee, E. P. Chew, S. Teng, and Y. Chen, "Multi-objective simulation-based evolutionary algorithm for an aircraft spare parts allocation problem," *Eur. J. Oper. Res.*, vol. 189, no. 2, pp. 476–491, Sep. 2008.

[13] V. S. N. A. Kumar, V. Kumar, M. Brady, J. A. Garza-Reyes, and M. Simpson, "Resolving forward-reverse logistics multi-period model using evolutionary algorithms," *Int. J. Prod. Econ.*, vol. 183, pp. 458–469, Jan. 2017.

[14] L. Miqing, "Evolutionary many-objective optimization pushing the boundaries," Ph.D. dissertation, Dept. Comput. Sci., Brunel Univ. London, England, U.K., 2015.

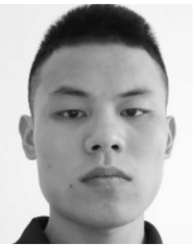
[15] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.

[16] E. Zitzler and L. Thiele, "Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach," *IEEE Trans. Evol. Comput.*, vol. 3, no. 4, pp. 257–271, Nov. 1999.

[17] D. W. Corne, N. R. Jerram, J. D. Knowles, and M. J. Oates, "PESA-II: Region-based selection in evolutionary multiobjective optimization," in *Proc. 3rd Annu. Conf. Genetic Evol. Comput. (GECCO)*, Jul. 2001, pp. 283–290.

[18] H. Li and Q. Zhang, "Multiobjective optimization problems with complicated pareto sets, MOEA/D and NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 13, no. 2, pp. 284–302, Apr. 2009.

[19] M. Laumanns, L. Thiele, K. Deb, and E. Zitzler, "Combining convergence and diversity in evolutionary multiobjective optimization," *Evol. Comput.* vol. 10, no. 3, pp. 263–282, Sep. 2002.
[20] C. A. Coello and M. R. Sierra, "A study of the parallelization of a coevolutionary multi-objective evolutionary algorithm," in*Proc. Mex. Int. Conf. Artif. Intell. (MICAI)*, Apr. 2004, pp. 688–697.
[21] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the strength Pareto evolutionary algorithm for multiobjective optimization," in *Proc. Evol. Methods Design Optim. Control Appl. Ind. Problems*, 2001, pp. 95–100.
[22] S. Mirjalili, "The ant lion optimizer," *Adv. Eng. Softw.*, vol. 83, pp. 80–98, May 2015.
[23] S. Mirjalili, P. Jangir, and S. Saremi, "Multi-objective ant lion optimizer: A multi-objective optimization algorithm for solving engineering problems," *Appl. Intell.*, vol. 46, no. 1, pp. 79–95, Jan. 2017.
[24] S. Zhao, L. Gao, D. Yu, and J. Tu, "Ant lion optimizer with chaotic investigation mechanism for optimizing SVM parameters," *J. Frontiers Comput. Sci. Technol.* vol. 10, no. 5, pp. 722–731, 2016.
[25] P. Yao and H. Wang, "Dynamic adaptive ant lion optimizer applied to route planning for unmanned aerial vehicle," *Soft Comput.*, vol. 21, no. 18, pp. 5475–5488, Sep. 2017.
[26] P. K. Roy and D. Mandal, "Quasi-oppositional biogeography-based optimization for multi-objective optimal power flow," *Elect. Power Compon. Syst.* vol. 40, no. 2, pp. 236–256, Dec. 2011.
[27] A. F. Kamaruzaman, A. M. Zain, S. M. Yusuf, and A. Udin, "Levy flight algorithm for optimization problems—A literature review," *Appl. Mech. Mater.*, vol. 421, pp. 496–501, Sep. 2013.
[28] R. Jensi and G. W. Jiji, "An enhanced particle swarm optimization with levy flight for global optimization," *Appl. Soft Comput.*, vol. 43, pp. 248–261, Jun. 2016.
[29] A. A. Heidari and P. Pahlavani, "An efficient modified grey wolf optimizer with Lévy flight for optimization tasks," *Appl. Soft Comput.*, vol. 60, pp. 115–134, Nov. 2017.
[30] X.-S. Yang, T. O. Ting, and M. Karamanoglu, "Random walks, lévy flights, Markov chains and metaheuristic optimization," in *Proc. Future Inf. Commun. Technol. Appl.*, 2013, pp. 1055–1064.
[31] M. C. Mariani and Y. Liu, "Normalized truncated Levy walks applied to the study of financial indices," *Phys. A, Stat. Mech. Appl.* vol. 377, no. 2, pp. 590–598, Apr. 2007.
[32] X. S. Yang, *Nature-Inspired Metaheuristic Algorithms*, 2nd ed. New York, NY, USA: Luniver Press, 2010.
[33] R. Fabregat, Y. Donoso, B. Baran, F. Solano, and J. L. Marzo, "Multi-objective optimization scheme for multicast flows: A survey, a model and a MOEA solution," in *Proc. Int. IFIP/ACM Latin Amer. Conf. Netw.*, Oct. 2015, pp. 73–86.
[34] S. Huband, P. Hingston, L. Barone, and L. While, "A review of multiobjective test problems and a scalable test problem toolkit," *IEEE Trans. Evol. Comput.*, vol. 10, no. 5, pp. 477–506, Oct. 2006.
[35] L. Wang, Q. He, and Y. H. Jin, "Summary of intelligent constraint handling techniques," *Control Instrum. Chem. Ind.*, vol. 35, no. 1, pp. 1–7, 2008.



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