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A Heuristic Hybrid Optimization Approach for Spare Parts and Maintenance Workers Under Partial Pooling

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ABSTRACT The joint planning of spare parts and maintenance workers in a multiple echelon inventory system with lateral and cross-echelon transshipment can reduce the total cost of the system. However, partial pooling is not extensively considered in the joint optimization problem of maintenance resources. In this paper, the objective is to determine the optimal inventory of spare parts and the number of maintenance workers to minimize the total cost of the system considering partial pooling. First, a greedy heuristic is used to obtain the initial inventory. Then, the cat swarm optimization algorithm is formulated to produce nearly optimal results, which can solve larger instances with a faster computation time. Furthermore, a maintenance system with 4 local warehouses, 3 central warehouses and 1 plant serving 5 machine groups is analyzed, in which each machine consists of 5 key components that can breakdown independently. The results verify the effectiveness of the proposed optimization approach. Finally, the total cost for different resource provision scenarios, failure rates and system parameters are discussed.

INDEX TERMS Spare parts, maintenance workers, partial pooling, greedy approach, cat swarm optimization.

NOMENCLATURE

SETS AND INDICES

- I Number of components
- J Number of local warehouses
- M Number of central warehouses
- P_j Number of group assigned to local warehouse j

PARAMETERS

- β_{ij} Fraction of demand for type-i spare part at local warehouse j satisfied from stock on hand.
- α_{ijk} Fraction of demand for type-i spare part at local warehouse j satisfied through lateral transshipment from local warehouse k
- γ_{ij} Fraction of demand for type-i spare part satisfied through direct delivery from the central warehouse
- θ_{ij} Fraction of demand for type-i spare part satisfied through direct delivery from the plant
- c_{hij} Unit inventory holding cost at local warehouse j for a type-i spare part per time unit
- c_{LTi} Lateral transshipment cost at local warehouse j for a type-i spare part per distance unit
- c_{ECi} Emergency replenishment cost for using direct delivery from the central warehouse for a type-i spare part
- c_{EPi} Emergency replenishment cost for using direct delivery from the plant for a type-i spare part
- c_{NL} Normal replenishment cost for local warehouses for item i
- c_{NC} Normal replenishment cost for the central warehouse for item i

VARIABLES

- T_{NC} Average normal replenishment lead time at central warehouse j for a type-i spare part
- s_{ij} Safety stock level at the local warehouse j for a type-i spare part
- u_{sij} Available type-i spare parts at local warehouse j

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m_j	Available number of maintenance workers at local warehouse j
D_{si}	Average demand for type -i spare part
D_m	Average demand for maintenance workers
λ	Average demand rate
$W_{ij}(\underline{S})$	The target mean waiting time for local warehouse j for a type-i spare part
$W_{Mij}(\underline{S})$	The maximum average waiting time applied by local warehouse j for a type-i spare part

I. INTRODUCTION

With the development of technology, the equipment used in many important economic sectors has become increasingly capital intensive. For this reason and due to safety and security considerations, the continuous operation of such equipment is essential. If unplanned downtime due to failure occurs, it is of the utmost importance to keep the downtime as short as possible [1], [2]. To do so, the failed components are often replaced by ready for use components, since the onsite repair of the failed system requires an excessive amount of time. In such cases, the availability of ready for use spare parts and maintenance workers is critical to ensure a prompt and effective repair process. To minimize any delay due to the absence of these resources, a complex integrated multi-resource optimization problem is studied in this paper.

It is well known that excess inventory incurs a substantial inventory cost, whereas a shortage in the inventory may cause a system shutdown and lead to production losses. To guarantee an effective maintenance operation, a cost-effective solution to this problem requires a tradeoff between overstocking and shortage of spare parts and maintenance workers [3]–[6].
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Reference [7] provided extensive reviews of a series of maintenance spare part management models. Reference [8] described many spare part inventory control models and reported exact and heuristic optimization methods that focus on the system oriented perspective. Reference [9] considered a repairable system with a fixed budget for maintenance workers to select the number of maintenance workers to maximize profits, which can serve a fraction of all possible failures. In other words, this problem should be solved by joint, rather than separate or sequential, optimization of the spare parts and maintenance workers.

In addition, in terms of the maintenance resource transshipment strategy, the majority of prior studies have focused on transshipping the maintenance resources by direct transshipment from the central warehouses and did not make effective use of the resources in the same echelon warehouses by lateral transshipment [10]–[14]. However, transshipment flexibility could be advantageous in minimizing the total cost while simultaneously ensuring a fast and reliable transshipment of maintenance resources. Until now, several researchers have studied the optimal inventory level of the total inventory between the center and local warehouses in multi-echelon systems. Reference [15] represented the first research study in this field, in which an approximate model for a one item system was formulated, the result showed that the combined use of lateral transshipments and direct deliveries could lead to significant cost savings. Subsequently, [16] extended the work by addressing a multi-item problem using a complete pooling strategy for the resources. The focus of this study was on developing a solution procedure to determine the nearly optimal stocking policies, and the results demonstrated that allowing transshipment flexibility could minimize the total cost of the system incurred in the transshipment of the inventory to the local warehouses. Among early studies, a model similar to that of this problem can be found in [17], in which the authors researched the integrated planning of spare parts and maintenance workers with complete pooling to determine the optimal amount of resources considering transshipment flexibility in the case of a resource shortage.

If a failure occurs, the machine should be repaired as soon as possible because the downtime cost is considerably higher than the holding and transshipment cost. Therefore, it is reasonable to retain partial maintenance resources at each local inventory warehouse. From this perspective, in this paper, a partial pooling strategy is used to share the spare parts between local warehouses, which is in contrast from the approach used in [17]; in particular, a local warehouse offers its partially available spare parts inventory when a request is made by another local warehouse with a stock out, rather than employing transshipping to meet all the demands. Such systems are more difficult to control and optimize than systems with complete pooling because there exists an additional constraint on the inventory safety, $s_i(s_i > 0)$, which must be defined. In addition, the available inventory in each local warehouse should satisfy the maintenance requirements or it should be ensured that the remaining resources after maintenance are up to s_i before the next normal replenishment time. Currently, no study has been reported focusing on the development of a multi-echelon, multi-warehouse inventory system with a partial pooling strategy due to the computational complexity.

The main methods for solving the maintenance resource joint optimization problem are as follows:

(1) Mathematical programming. This approach addresses the maintenance resource optimization as an integer programming problem [18]–[21]. The resource scheduling process of the object is used to define the decision variables, which are usually binary. However, such a method is usually based on some simplified assumptions, and the computational time to determine the optimal solution within a bounded time is very long, consequently, the scale of the problem cannot be too large.

(2) Heuristic algorithm. This approach can solve a relatively large scale planning problem in combination with other methods [22], [23]. Due to its easy computation, high efficiency and satisfactory real time performance, this approach has been widely used in optimization research. Reference [1] described multiple inventory models and presented the exact and heuristic optimization methods. Reference [24] described an efficient heuristic to manage systems with more than two locations. The heuristic is based on a greedy initialization method combined with a local search improvement method. The results show that the heuristic method performs satisfactorily. Some authors used an exact method and a heuristic procedure for the evaluation of an optimized problem with more than five types of spare parts, and the results demonstrated that the use of approximate evaluations is faster than using exact evaluations as the system becomes more complex. However, some special heuristic rules could be studied for a given problem [25], [26].

(3) Intelligent search algorithm. Intelligent search algorithms have been broadly used in the optimization field due to their random global search and fast computation, and they can also easily be combined with other excellent algorithms [7], [27]–[29]. Reference [30] proposed a multi-objective dynamic optimal dispatch model to coordinate multiple different scheduling objectives, and a heuristic optimization algorithm was used to identify a well-distributed set of Pareto optimal solutions of the problem; the best compromise solutions (BCSs) were identified from all the solutions with the use of a decision analysis by integrating fuzzy C-means clustering and gray relation projection. Reference [31] considered a continuously monitored multi-component system and used a genetic algorithm to determine the optimal maintenance resource level to optimize the cost objectives. Reference [32] proposed a hybrid algorithm that combined particle swarm optimization and an iterative local search for solving the hybrid resource optimization problem. The authors presented a detailed comparison of the present efficient algorithms, including the *iterated local search, particle swarm optimization* and *information gain*, and verified the effectiveness of the proposed algorithm.

In this paper, the joint optimization of a spare parts inventory and maintenance workers under partial pooling is studied. The objective is to minimize the total system cost that consists of the holding cost and the transshipment cost under the average waiting time constraint. The main contribution of this paper can be summarized as follows. A comprehensive maintenance resource joint optimization system considering partial pooling is analyzed, which includes multiple echelons and multiple types of maintenance resources. Because there exists an additional constraint for the inventory level, $s_i(s_i > 0)$, which should be defined when using a partial pooling strategy, this system is more difficult to control and optimize than systems with complete pooling. To date, very few papers have considered managing this complex inventory system with this approach. The greedy heuristic and the cat swarm optimization algorithm are used to obtain the optimal inventory S, which can flexibly support the joint planning of the spare parts and maintenance workers with the scheduling strategies of lateral transshipment and emergency direct transshipment.

The remainder of this paper is organized as follows. Section 2 presents the description and modeling for the maintenance resource provision scenario model. Section 3 presents a solution framework, including the generation of an initial maintenance resource inventory scheme using a greedy approach and an improvement approach for optimizing a maintenance resource inventory with a cat swarm optimization algorithm. Subsequently, a case study is presented based on the proposed model that consists of 1 plant, 3 central warehouses, 4 local warehouses and 5 groups including 20 machines; furthermore, the analysis and discussion is presented in Section 4. Finally, the conclusions and future research directions are provided in Section 5.

II. PROBLEM DESCRIPTION AND MODELING

A. CHARACTERISTICS OF THE INVENTORY SYSTEM

The system treated in this paper is composed of P groups of similar machines. Each group of machines is assigned to exactly one local warehouse. Let P_j denote the group of machines that is assigned to local warehouse j. A local warehouse can serve one or more groups or zero groups. Each machine consists of I components that can breakdown independently. The failure rates (demand rates) for each type-i component in different types of equipment are assumed to follow a Poisson process with a constant rate of λ_i. A repair request consists of a simultaneous demand for two resources, namely, the spare parts and maintenance workers. In general, the repair of highly complex machines may require a team of professionals and a set of spare parts. However, because on-site repair is time-consuming, the replacement of the failed components on-site by one generic maintenance worker is considered exclusively in this paper. If the maintenance resources are requested by group $p \in P_j$, they are provided immediately by local warehouse j if this local warehouse has stock on hand; otherwise, it will be provided by other warehouses, for example, other local warehouses through a lateral transshipment, central warehouses or another plant by direct transshipment. In this paper, it is assumed that J local warehouses, M central warehouses and the plant have an infinite supply capacity. The detailed maintenance resource provision relationship is shown in FIGURE 1. The waiting

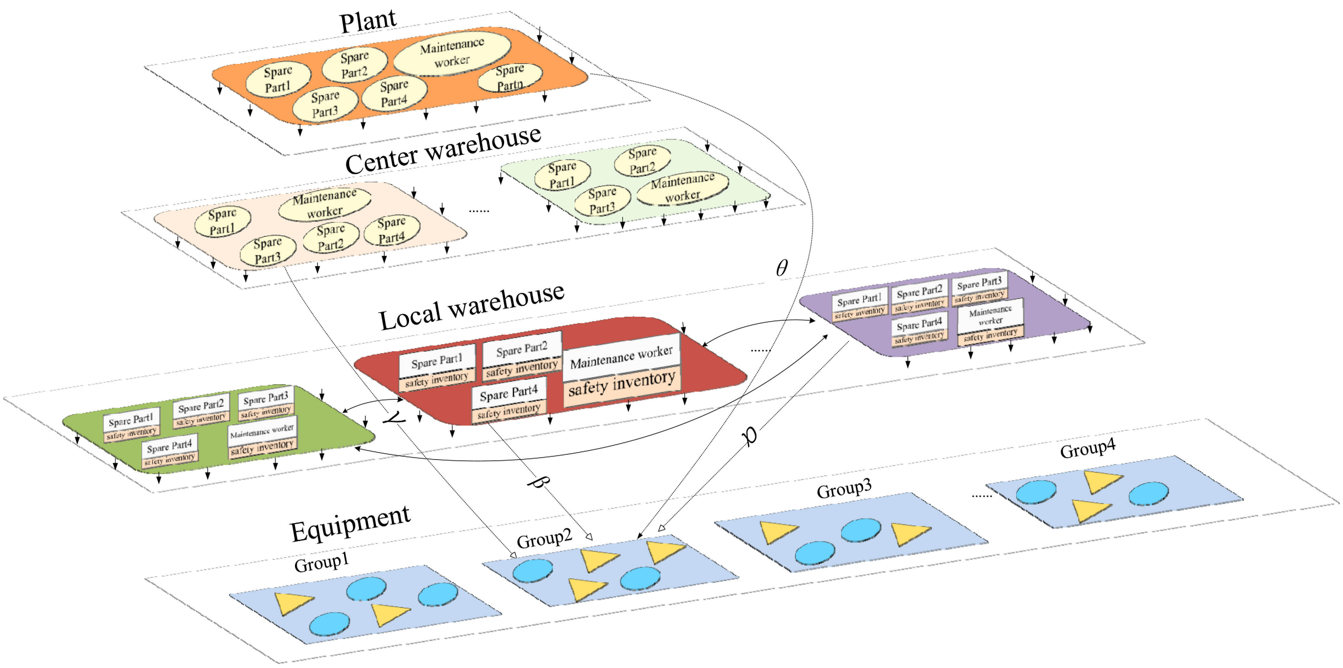

FIGURE 1. The maintenance resource supply relationship.

time is denoted by $W_{ij}(\underline{S})$, and the maximum expected waiting time for a maintenance request is denoted by $W_{Mij}(\underline{S})$. The expected total system cost includes the holding, normal transshipment and emergency transshipment cost. The goal is to determine an optimal inventory level $\underline{S}$ to minimize the expected total system cost under the waiting time constraints.

Note that for a given inventory, the total fraction of the emergency demand for type i maintenance resources at each local warehouse $j \in J$ is such that

$$\alpha_{ijk} + \beta_{ij+}\gamma_{ij+}\theta_{ij} = 1 \tag{1}$$

The fraction of the demand met by the emergency transshipment from the central warehouses or from plants is the same; more specifically, for all the local warehouses, the supplementation takes place when the resources on hand fall below the safety inventory, and for all the central warehouses, the resource requests occur when no resources are available.

$$\gamma_{1j=\ldots=}\gamma_{ij=}\gamma_i \tag{2}$$

$$\theta_{1j=\ldots=}\theta_{ij=}\theta_i \tag{3}$$

The joint optimization model for the maintenance resources employs the following notation.

B. OPTIMIZATION FORMULATION

The objective of this paper is to determine the optimal maintenance resource inventory for each type of maintenance resource at each local warehouse to minimize the expected total system cost under the expected waiting time constraint.

$$\begin{aligned} minC_c(\underline{S}) &= \sum_{i=1}^{I}\sum_{j=1}^{J} C_{Hij} + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{Tij} \\ &= \sum_{i=1}^{I}\sum_{j=1}^{J} c_{hij}S_{ij} + \sum_{i=1}^{I}\sum_{j=1}^{J} \\ &\quad \times (c_{NL}T_{NL} + c_{NC}T_{NC} + c_{LTi}\alpha_{ij}T_{LTi} \\ &\quad + c_{ECi}\gamma_{ij}T_{ECi} + c_{EPi}\theta_{ij}T_{EPi}) \end{aligned} \tag{4}$$

$$\text{subject to} \quad \alpha_{ijk} + \beta_{ij+}\gamma_{ij+}\theta_{ij} = 1 \tag{5}$$

$$\begin{aligned} W_{ij}(\underline{S}) = \sum_{i=1}^{I}&[\alpha_{ijk}(T_{LTi} + \Delta WL_{ij}) + \gamma_{ij}(T_{ECi} + \Delta WD_{ij}) \\ &+ \theta_{ij}T_{EPi}] \le W_{Mij}(\underline{S}) \end{aligned} \tag{6}$$

TABLE 1. Spare part related parameters.

Requirement satisfaction method	Inventory state (beginning)	Required amount	Order amount	Inventory state (end)
β_{sij}	$D_{si}+s_{ij}\le u_{sij}$	D_{si}	0	u_{sij}-D_{si}
α_{sijk}	$D_{si} \le u_{sij} < D_{si}+ s_{ij}$ && $D_{si}+ s_{ij}\le u_{sik}(k\ne j)$	D_{si}	s_{ij}-(u_{sij}-D_{si})	s_{ij}
γ_{sij}	$0<u_{sij}\le D_{si}$ && $s_{ij+}D_{si}$-$u_{sij}\le u_{sin}(n=1,2,\ldots,N)$	D_{si}	(D_{si}-u_{sij})+s_{ij}	s_{ij}
θ_{sij}	$0<u_{sij}\le D_{si}$ && $s_{ij+}D_{si}$-$u_{sij}>u_{sin}(n=1,2,\ldots,N)$ && $s_{ij+}D_{si}$-$u_{sij}\le u_{sip}$	D_{si}	(D_{si}-u_{sij})+s_{ij}	s_{ij}

Due to the use of partial pooling in this paper, the available inventory in all the local warehouses should be reserved for the safety inventory. Therefore, each local warehouse $j(j = 1, 2, \ldots, J)$, employs an order up to policy (s, S); in other words, an order is placed when the spare parts inventory cannot satisfy the maintenance requirements or the resources remaining after maintenance are below the safety inventory level. The quantity ordered is set to ensure that the spare parts inventory level of the next normal replenishment time is up to s_{ij}.

TABLE 2. Maintenance worker related parameters.

Spare part requirement satisfaction method	Maintenance worker requirement satisfaction method	Inventory state (beginning)	Employed amount
β_{sij}	β_{wij}	$D_{wi} \leq u_{wij}$	0
	α_{wijk}	$0<u_{wij}<D_{wi}$ && $D_{wi}-u_{wij} \leq u_{wik}(k \neq j)$	$D_{wi} - u_{wij}$
	γ_{wij}	$0<u_{wij}<D_{wi}$ && $D_{wi} - u_{wij} \leq u_{win}(n=1,2,\ldots,N)$	$D_{wi} - u_{wij}$
	θ_{wij}	$0<u_{wij} \leq D_{wi}$ && $u_{win}<D_{wi}-u_{wij}(n=1,2,\ldots,N)$ && $D_{wi} - u_{wij} \leq u_{ip}$	$D_{wi} - u_{wij}$
α_{sijk}	α_{wijk}	$0<u_{wij}<D_{wi}$ && $D_{wi}-u_{wij} \leq u_{wik}(k \neq j)$	$D_{wi} - u_{wij}$
γ_{sij}	γ_{wij}	$0<u_{wij}<D_{wi}$ && $D_{wi} - u_{wij} \leq u_{win}(n=1,2,\ldots,N)$	$D_{wi} - u_{wij}$
θ_{sij}	θ_{wij}	$0<u_{wij} \leq D_{wi}$ && $u_{win}<D_{wi}-u_{wij}(n=1,2,\ldots,N)$ && $D_{wi} - u_{wij} \leq u_{ip}$	$D_{wi} - u_{wij}$

After defining the spare part related parameters, the probability of the status of maintenance workers is studied. Note that the approach for satisfying the requirement of the maintenance workers depends on the available spare parts inventory on hand. When the available spare parts inventory is empty, the maintenance worker demand is satisfied by the emergency direct transshipment together with the spare parts. To ensure that the available spare parts inventory is sufficient, a separate classification analysis is used for the maintenance operations, such as for the status probability of the spare parts. As analyzed above, assuming that there exists only one kind of maintenance worker who can repair all types of failure, the demands for the maintenance workers follow the Poisson processes, which are similar to the failure distributions.

In contrast to the spare parts inventory strategy, a complete pooling strategy is applied to manage the maintenance workers; in particular, a local warehouse shares all the maintenance workers with the same echelon warehouses when a demand for maintenance workers is raised. This assumption is reasonable because after finishing one maintenance task, the maintenance workers return to their warehouse to wait for the next task, and it can be considered that the maintenance workers are employed continuously.

In accordance with the characteristics of the inventory system and maintenance resource provision strategies described above, the detailed definitions for the holding cost, normal replenishment cost and emergency transportation cost are as follows:

(1) Holding cost

During a given period, all the spare parts in the inventory warehouse generate the holding cost, which is computed for each type i spare part according to a uniform distribution U [4], [12], denoted by c_{hij}. The differences in the holding cost for each type i spare part among all the local warehouses, central warehouses and plants are negligible.

$$C_{Hij} = \sum_{i=1}^{I} \sum_{j=1}^{J} c_{hij} S_{ij} \tag{7}$$

(2) Transportation cost

The transportation cost includes the normal replenishment cost and emergency transshipment cost. The normal replenishment transshipment times from a plant to the local warehouses and central warehouses are denoted by T_{NL} and T_{NC}, respectively; in addition, the transshipment times for a type i spare part from the local warehouses by lateral transshipment, or from the central warehouses and plant by emergency transshipment, are denoted as T_{LTi}, T_{ECi} and T_{Epi}, respectively, all of which are exponentially distributed [15]. Reference [25] proved that in a multiple echelon inventory system, the lateral transshipment is preferred over the emergency delivery transshipment, and considering the actual transshipment scenarios, it is assumed that $T_{LTi} < T_{ECi} < T_{EPi} < T_{NC} < T_{NL}$ for all i, j and k. The expected total transportation cost incurred per unit time equals:

$$C_{Tij} = c_{NL} T_{NL} + c_{NC} T_{NC} + c_{LTi} \alpha_{ij} T_{LTi} + c_{ECi} \gamma_{ij} T_{ECi} + c_{EPi} \theta_{ij} T_{EPi} \tag{8}$$

where $c_{NL} = c_{NC} < c_{LTi} < c_{ECi} = c_{EPi}$

In Eq. (1), $C_c(\underline{S})$ is defined as the expected total system cost for one type of inventory $\underline{S}$. The set of constraints implies that the mean waiting time for each local warehouse must not exceed its maximum expected waiting time. It can be seen from Eqs. (4) and (6) that the values of $\beta_{ij}(\underline{S})$, $i \in I, j \in J$; $\alpha_{ijk}(\underline{S})$, $i \in I, j \in J$; $k \in J$, $k \neq j$; $\gamma_{ij}(\underline{S})$, $i \in I, j \in J$; and $\theta_{ij}(\underline{S})$, $i \in I, j \in J$ are the key issues for determining the $C_c(\underline{S})$ and $W_{ij}(\underline{S})$. Since the probability values of α_{ijk}, β_{ij}, γ_{ij} and θ_{ij} are determined by the available inventory in each inventory warehouse, the exact probability values are difficult to evaluate. In this paper, these values are determined according to the actual application scenarios.

III. OPTIMIZATION ALGORITHM DESIGN

In this paper, the aim is to determine an optimal inventory level $\underline{S}$ that minimizes the expected total cost in a multiple echelon multiple equipment inventory system under waiting time constraints. The maintenance resources in the same echelon can be mutually scheduled to avoid shortages. In addition, the safety inventory level $s_i(s_i > 0)$ should be determined to satisfy the maintenance requirements or ensure that the remaining resources after maintenance are up to s_i before the next normal replenishment time, which makes the problem NP hard. Hence, the solution procedure for this problem consists of two steps. In the first step, a greedy approach is applied to generate an initial feasible solution. In the second step, the initial solution is improved by applying a cat swarm algorithm.

The cat swarm algorithm mixes two subgroups of global search and local search, and hence, it can simultaneously perform a global and local search when dealing with optimization problems. This unique algorithm structure guarantees the convergence speed of the algorithm, which considerably alleviates the local optimization problem and long computation time. Currently, the algorithm has been well applied in continuous function optimization [33]–[35] and image processing [36], [37], which proves that it has an excellent convergence speed and the ability to overcome the local search ability of the genetic algorithm and the local optimal problem of the particle swarm optimization algorithm when solving discrete problems.

In addition, cats are extremely alert, and they always remain alert even if they are resting. One can simply note that resting cats lying anywhere are always observing the environment; once a target is identified, the cat quickly captures the target and expends a considerably amount of energy. Similar to the optimization problem proposed in this paper, when there is no maintenance resource requirement, the inventory resources of each inventory warehouse are at a standstill (except for the monthly normal replenishment). Once there is a request for maintenance resources, according to the preset rules, the optimal inventory warehouse is found that minimizes the total cost; at the same time, all the inventory warehouses with the remaining inventory are ready for the scheduled requirement. In addition, the cat swarm algorithm simultaneously performs a global and local search in the optimization process; the search has a strong convergence, and the convergence speed is very high. In the discrete problem, the cat swarm algorithm exhibits excellent performance compared to those of traditional optimization algorithms, such as the genetic or particle swarm algorithms.

A. GENERATION OF THE INITIAL MAINTENANCE RESOURCE INVENTORY

A greedy approach is applied to generate the initial feasible solution. The basic idea of this approach is to add one unit of resource at a time for the local warehouses such that the largest decrease in the distance to the set of feasible solutions per extra unit of total cost can be gained. The procedure is terminated when a feasible solution is obtained.

Since it is assumed that the plants can provide infinite resources, the initial inventory in the plants is infinite, while the center and local warehouses have zero stock for all the resources.

For each solution $\underline{S}$, the distance to the set of feasible solutions is defined as

$$max(0, \sum_{j=1}^{J} (W_{ij}(\underline{S}) - W_{Mij}(\underline{S}))) \tag{9}$$

For each combination of $i \in [0,1,\ldots, I]$ and $j \in [1,\ldots, J]$, the ratio is calculated as

$$r_{ij} = \Delta W_{ij}(\underline{S})/\Delta C_c(\underline{S}) \tag{10}$$

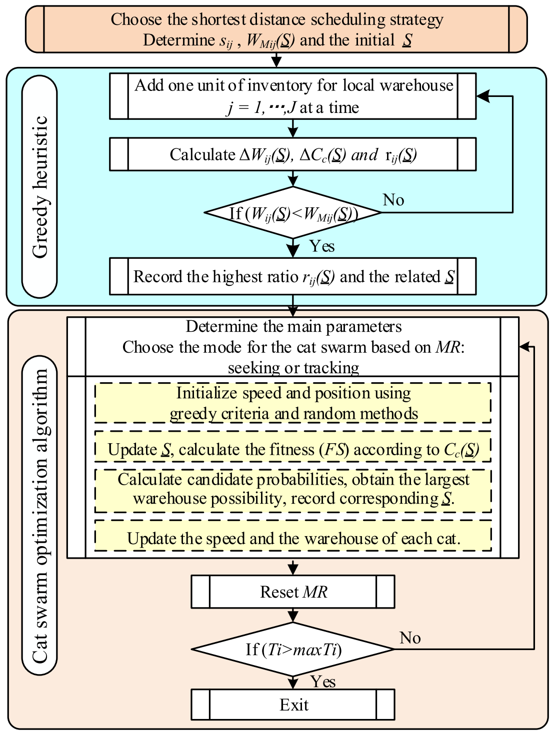

FIGURE 2. Solution framework.

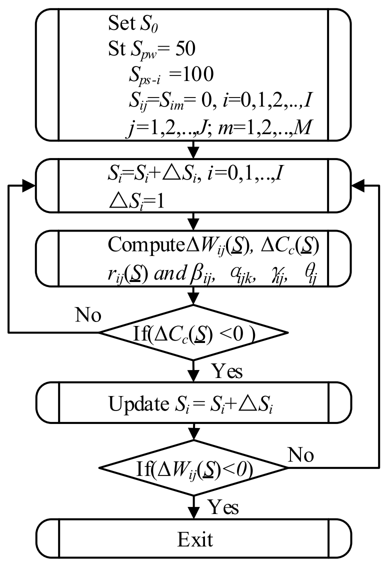

FIGURE 3. The flow of the greedy algorithm.

where

$$\Delta W_{ij} = max(0, \sum_{j=1}^{J} (W_{ij}(\underline{S}) - W_{Mij}(\underline{S}))) - max(0, \sum_{j=1}^{J} (W_{ij}(\underline{S} + \Delta S) - W_{Mij}(\underline{S}))) \tag{11}$$

$$\Delta C_c(\underline{S}) = C(\underline{S} + \Delta S) - C(\underline{S}) \tag{12}$$

One unit of resource is then added for the combination with the largest ratio. A formal statement of this initialization procedure is as follows:

Step 1. Set the initial solution and calculate $W_{ij}(\underline{S})$ for all the local warehouses $j = 1, \ldots, J$;

Step 2. For all $i \in [0, 1, \ldots, I]$ and j $\in [1, \ldots, J]$, set $\underline{S} = \underline{S} + \Delta\underline{S}$ and calculate $\Delta W_{ij}(\underline{S})$, $\Delta C_c(\underline{S})$ and r_{ij}.

Step 3. Record the highest ratio of r_{ij}. If $W_{ij}(\underline{S}) \leq W_{Mij}(\underline{S})$ for j $\in [1, \ldots, J]$, go to END; otherwise, go to Step 2.

END

The total cost associated with the initial solution, $\underline{S} = 0$, in all the local and central warehouses can be quite high due to the exceedingly high cost of emergency direct transshipment from the plant. In this case, increasing the inventory level may lead to a reduction in the total cost. Hence, the optimal $\underline{S}$ can be determined. If there exists more than one combination with the same lowest cost, the one which can provide the largest decrease in the ratio is chosen.

B. IMPROVEMENT APPROACH FOR OPTIMIZING THE MAINTENANCE RESOURCE INVENTORY

The objective of this procedure is to a determine a better maintenance resource inventory for the current solution $\underline{S}$. In this section, the cat swarm algorithm is chosen to optimize the current solution $\underline{S}$. The real number encoding scheme is used in this approach to address the joint scheduling problem of maintenance resources. For example, the similar machines groups are represented by 0, 1, 2, 3; the local inventory warehouses are represented by 4, 5, 6, 7; the central inventory warehouses are represented by 8, 9, 10; and the factory is represented by 11. Among these values, 0: (1,1), 1: (5,8), 2: (11,2), 3: (20,7), 4: (9,14), 5: (13,6), 6: (7,4), 7: (15,12), 8: (18,10), 9: (4,19), 10: (21,3), and 11: (17,23). The real sequence 11-9-6-1 indicates the maintenance resources scheduled from plant 11 to central inventory warehouse 9 to local inventory warehouse 6, and subsequently, to the maintenance base of the failed machine group.

At present, the cat swarm algorithm generally adopts a fixed ratio to select the cat behavior in the seeking mode or tracking mode; consequently, the global cats and local cats cannot be effectively allocated according to the optimization degree. According to [38], if the number of cats in the tracking mode is larger in the early stage of the algorithm, the global search ability of the algorithm can be increased. If the proportion of cats is larger in the seeking mode at the later state, the accuracy and convergence of the solution can be improved. Therefore, to reasonably allocate the proportion of local and global search, the mixed ratio (*MR*) is used in this research to generate different car proportions in different iteration stages.

Since the failures among components do not affect each other, it is rational to optimize each kind of resource at one time. Accordingly, each individual cat represents the inventory amount of one resource at an individual inventory $\underline{S}_{ij}$, that needs to be optimized in this paper. The cat swarm represents the resource configuration at all the inventory warehouses according to the maintenance requirements and the actual available remaining inventory in each warehouse scheduling maintenance resource.

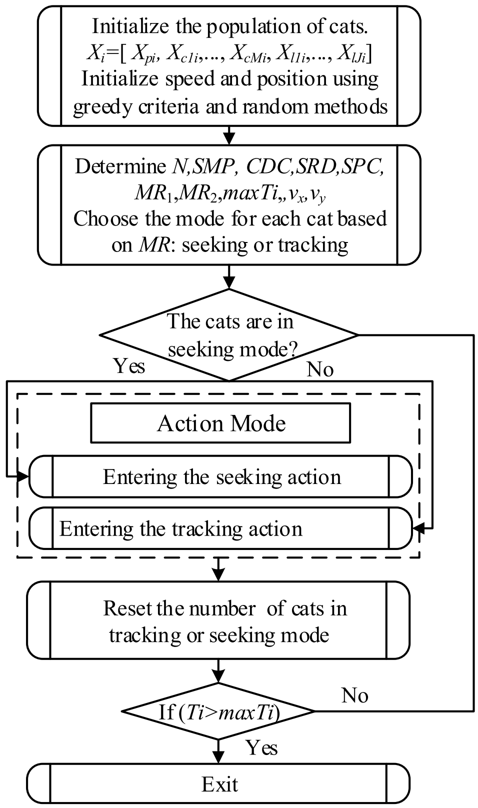

FIGURE 4. **The cat swarm optimization algorithm flow.**

In this paper, the total system cost function is used as the fitness function, and the fitness value is used as the guiding result for the maintenance resource inventory. By constantly resetting *MR*, the above operation is repeated. After multiple iterations and feedback cycles, the output $\underline{S}_{ij,}$ minimizes the total system cost.

The main steps of the cat swarm optimization algorithm can be described as follows:

Step 1: Initialize the cat swarm

The initial cat swarm is generated through roulette; however, the result generated by this approach has a lower fitness, and the convergence speed is restricted to some extent. Therefore, in this paper, the combination of the greedy criteria [39] and roulette is applied to initialize the cat swarm, which can increase both the convergence rate and the diversity of the initial solution.

First, the inventory warehouse i is selected randomly and added to $\Gamma i = \{\pi_1, \pi_2, \ldots, \pi_{1+J+M}\}$. This value is used as the inventory warehouse of the current scheduling resource. Next, according to the maintenance resource scheduling strategy, the next inventory warehouse is searched and added into the remaining inventory warehouses until all the inventory warehouses are processed in the order set $\Gamma i = \{\pi_1, \pi_2, \ldots, \pi_{1+J+M}\}$; $\underline{S}_{ij}$ is assigned to π_i. Finally, the initial solution sequence is transformed into the position vectors within a certain interval by using the following formula:

$$x_{k,d} = x_{k,min} + \frac{x_{k,max} - x_{k,min}}{n} \cdot \left(s_{k,d} - 1 + \omega\right) \quad (13)$$

where $x_{k,d}$ represents cat k, which is currently in warehouse d; $s_{k,d}$ represents the cat k in the d inventory warehouse in the current position vectors; $x_{k,min}$ and $x_{k,max}$ represent cat k in the near-term position vector in continuous space; and $\omega \in [0, 1]$.

The initial position and speed are generated as follows:

$$X_i = X_{min} + (X_{\max} - X_{min})\omega_1 \quad (14)$$
$$V_i = V_{min} + (V_{\max} - V_{min})\omega_2 \quad (15)$$

where X_i is the continuous change in intervals X_{max} and X_{max}; and V_i is the continuous change in intervals V_{max} and V_{max}.

Step 2: Determine MR

In the algorithm execution process, to adjust the proportion of the global search to the local search, the *MR* selection method is used. Initially, a larger MR_1 is used to improve the global search ability and subsequently changed to MR_2 to accelerate the convergence of the algorithm until the termination condition is satisfied. The total linear *MR* calculation formula is as shown in Eq. (11):

$$MR = MR_1 + (MR_2 - MR_1) \cdot Ti/maxTi \quad (16)$$

where *Ti* represents the current number of iterations; and *maxTi* represents the maximum number of iterations.

Step 3: Determine the candidate probability of each inventory warehouse

When there is no maintenance resource demand, all the cats are in the resting state. Once a request is received, the cats adjust their state according to the following rules:

1. Define the number of copies (P) of the current inventory $\underline{S}_{ij}$, $SMP = P$.

2. Update $\underline{S}_{ij}$: according to the *CDC*, perform the following actions:

i. Randomly add or subtract the *SRD* values from the current $\underline{S}_{ij}$.

ii. Replace the old $\underline{S}_{ij}$ for all the copies.

3. Compute the fitness (*FS*) for all the copies according to $C_c(\underline{S}_{ij})$.

4. Judge the *FS*: if all the *FS* values are different, calculate the candidate probability of each inventory warehouse according to $(FS_i\text{-}FS_{max})/(FS_{max}\text{-}FS_{min})$; otherwise, set all the candidate possibilities to 1.

5. Obtain the largest candidate probability of the inventory warehouses and record the corresponding $\underline{S}_{ij}$.

Step 4: Update the inventory change speed

This step corresponds to the global search in the optimization problem; the process actually determines the speed of the inventory change in the selected *CDC* inventory warehouse. This process is implemented by adding a random disturbance mechanism. The specific steps are as follows:

1. Determine the disturbance speed:

$$v_{k,d}(t+1) = v_{k,d}(t) + r \cdot c \cdot (X_{b,d}(t) - x_{k,d}(t)), \quad d = 1, 2, \ldots, (1 + M + J) \quad (17)$$
$$if v_{k,d}(t) > V_{max\ d}(t) : v_{k,d}(t+1) = V_{max\ d}(t) \quad (18)$$
$$if v_{k,d}(t) < V_{min\ d}(t) : v_{k,d}(t+1) = V_{min\ d}(t) \quad (19)$$

where $v_{k,d}(t+1)$ represents the rate value of cat k in warehouse d after the latest update;

$X_{b,d}(t)$ represents the location of the cat that has the best fitness value; $x_{k,d}(t)$ represents cat k, which is currently in warehouse d; and $r, c \in [0, 1]$.

2. Update the speed of each cat to determine whether the dimension speed is within the maximum and minimum speed range, and if it is outside the range, force it to the boundary value.

3. Update the warehouse of each cat.

$$x_{k,d}(t+1) = x_{k,d}(t) + v_{k,d}(t+1), \quad d = 1, 2, \ldots, (1 + M + J) \quad (20)$$

where $x_{k,d}(t+1)$ represents the inventory warehouse of cat k after the latest update.

Step 5: Reset MR

Reset the number of cats in the tracing and seeking modes according to the MR, and perform constant iteration until the termination condition is reached.

IV. CASE STUDY

A. INPUT DATA

A system with 4 local warehouses, 3 central warehouses and 1 plant is analyzed, and in total, 5 groups of machines are considered. Each of the 4 local warehouses serves one or two groups, and each group has 4 machines each consisting of 5 key components that can break down independently.

TABLE 3. The cost of each type of resource.

i	λ_i	*MTTR* (hour)	Holding cost for each type of spare part (€)	Labor cost for each maintenance worker (€)
1	0.035	8	3	10
2	0.058	7	4	12
3	0.031	8	3	11
4	0.086	5	6	18
5	0.071	6	5	15

The failure rates (demand rates) per time unit for each type i component are assumed to follow the Poisson processes with a constant rate of λ_i. The replacement time (*MTTR*) of the failed components is correlated with its accessibility, and the λ_i and *MTTR* values for all the types of components are presented in TABLE 3. $W_{Mij} = 0.8$ is set for all j. The remaining system parameters are fixed as follows: $c_{NL} = c_{NC} = 4$; $c_{LTi} = 5$; $c_{ECi} = c_{EPi} = 8 f$ or all i. According to the above definition, the transshipment time obtained by sampling from an exponential distribution is as follows: $T_{LTi} = 0.8$, $T_{ECi} = 2$, $T_{EPi} = 4$, $T_{NC} = 5$, $T_{NL} = 7$ for all i, j and k, and $\Delta WL_{ij} = \Delta WD_{ij} = 1$.

From the pre-experiment, even for the maximum demand rates, a low safety inventory is sufficient to guarantee high fill rates. For this reason, the instances are limited to 2 spare parts for each type of spare part, and the number of maintenance workers is limited to 1 in each local warehouse. In addition, it is assumed that 1 spare part and 1 maintenance worker are consumed for each maintenance activity; however, it is easy to extend the model to other strategies. The shortest distance scheduling strategy is applied to formulate the optimization problem; hence, the exact probability values of β_{ij} are higher than those of α_{ijk}, γ_{ij} and θ_{ij}. In this paper, the respective values are 0.5, 0.3, 0.15, 0,05.

TABLE 4. The parameters of the cat swarm optimization algorithm.

N	SMP	P	MR_1	MR_2
200	5	5	0.6	0.4
SRD	CDC	$maxTi$	v_x	v_y
0.15	4	200	50	30

The cost of each type of resource is presented in TABLE 3. Meanwhile, the parameters of the cat swarm optimization algorithm are presented in TABLE 4.

B. RESULTS AND ANALYSIS

Because the failures among the components do not affect each other, for each type of component, the optimal inventory is computed by the greedy approach and the cat swarm optimization algorithm. Subsequently, the percentage gaps of the total cost, waiting time and computation time between the two $\underline{S}$ values are calculated (GAP_c = (total cost from the greedy approach – total cost from the cat swarm optimization)/total cost from the greedy approach $\cdot$ 100; GAP_w = (waiting time from the greedy approach–waiting time from the cat swarm optimization)/waiting time from the greedy approach $\cdot$ 100; GAP_r = (computation time from the greedy approach – computation time from the cat swarm optimization)/ computation time from the greedy approach $\cdot$ 100).

During the simulation process, each cat searches for the inventory configuration $\underline{S}$ that can iteratively reduce the total system cost. The total system cost changes with the number of iterations, as shown in FIGURE 5.

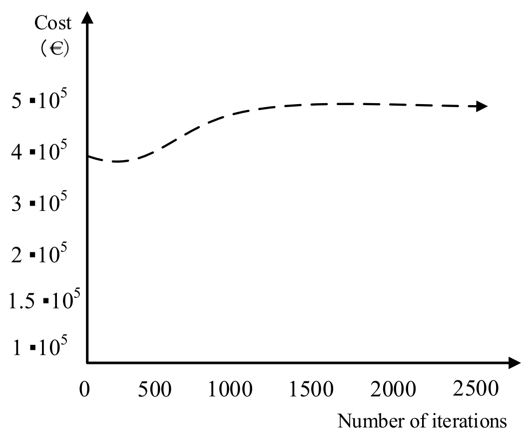

FIGURE 5. The convergence graph.

It can be seen from FIGURE 5 that the data tend to be stable when the simulation runs 1000 times, which is sufficient to prove that the cat swarm algorithm can maintain satisfactory convergence and stability for the system inventory optimization process.

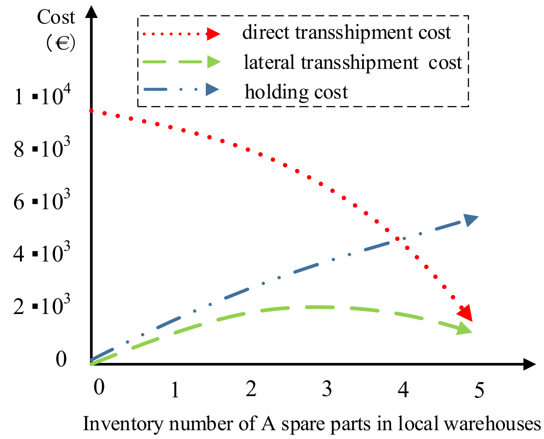

FIGURE 6. The changes in cost based on the spare parts inventory.

For each type of spare part, increasing the aggregate inventory level decreases the emergency direct transshipment cost. In contrast, the expected holding cost increases. The expected total lateral transshipment cost first increases with the aggregate inventory level but later decreases if the inventory level is sufficiently high, thereby reducing the need for lateral transshipment.

The optimal maintenance resource inventory configuration obtained by the greedy algorithm and the cat swarm algorithm are shown in FIGURE 7. It can be seen from the figure that the optimal inventory of each maintenance resource exhibits little difference. Furthermore, the comparison of these two optimization results on the total cost, waiting time and running time are shown.

Based on the comparison of the results, several conclusions can be drawn as follows:

(1) The results of the greedy heuristic and cat swarm optimization algorithm are almost the same in terms of the total cost, suggesting that the cat swarm optimization can determine the optimal solution in the cases.

(2) A slight difference exists in terms of the waiting time because the optimal solutions are almost the same; however, the cat swarm optimization algorithm performs well in terms of the computation time, which remains within a few minutes for the executed cases.

The presented total cost, waiting time and computation time are indicative and might differ for other test cases. In the Discussion section, the impact of the problem size on these parameters is analyzed.

C. DISCUSSION

1) THE RESEARCH ON THE SCALABILITY OF THE PROPOSED METHOD

The simulation results show that the number of components (I) and number of local warehouses (J) are two dominant

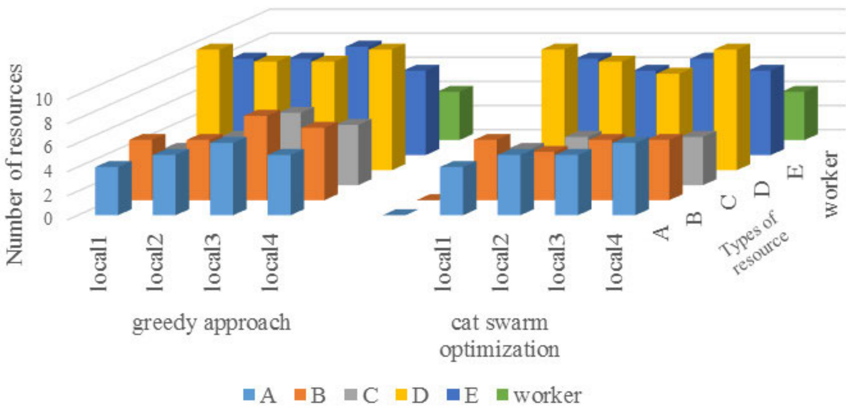

FIGURE 7. Maintenance resource inventory.

TABLE 5. The computation time.

I	J = 4	5	6	7	8
5	9.32	73.14	469.83	1686.34	6210.27
8	28.68	187.38	917.36	3678.39	16829.12
15	67.23	328.21	1563.81	7839.33	24829.37

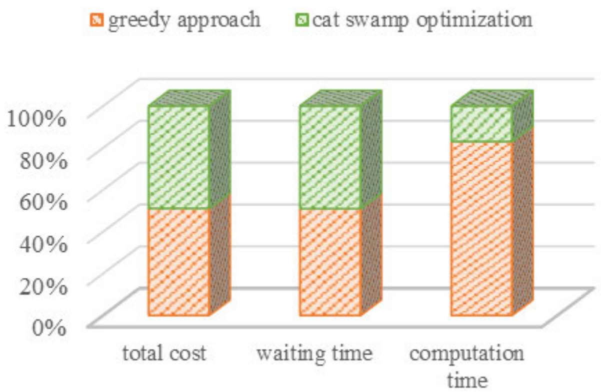

FIGURE 8. Comparison of results.

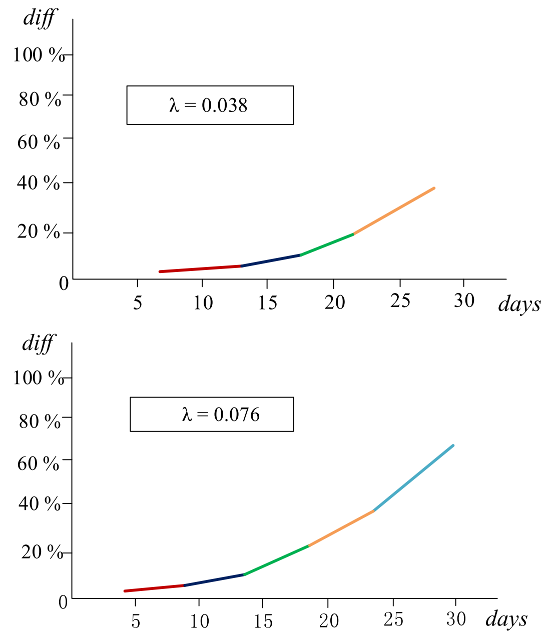

FIGURE 9. Difference between joint and separate optimization techniques.

factors affecting the computation time. FIGURE 8. indicates that the cat swarm optimization algorithm performs better in terms of the computation time. Subsequently, additional test cases were added to test the algorithm when addressing larger problems, consisting of four to eight local warehouses with the same parameter settings as those used in the previous experiment. TABLE 5 indicates that although the computation time (measurement unit: min) increases almost linearly with the number of components, it increases considerably faster with the number of local warehouses.

To demonstrate the value of the integration, the results of the joint optimization of the spare parts and maintenance workers were compared with the optimization results when the number of maintenance workers and the spare parts inventory are optimized separately. The latter could be achieved by simply defining $X_0 = [x_{01}, x_{02} \ldots, x_{0J}], X_i = [x_{i1}, x_{i2} \ldots , x_{iJ}], i \in [1, 2, \ldots, I]$.

That is, the spare parts and maintenance workers are isolated from each other and analyzed separately. FIGURE 9 shows the relative cost difference between the joint and individual optimization. The relative cost difference is defined as

$$diff = (C_s - C_j)/C_s \tag{21}$$

where C_s is the total expected cost obtained using the separate optimization approach, and C_j is the total expected cost obtained using the joint optimization approach.

The figures are provided for different values of λ (the failure rate). It is clear from the figure that the joint optimization is important in reducing the total cost. The individual optimization for each resource does not take into account some maintenance resource requests due to the lack of other resources. Therefore, in such cases, the proposed joint optimization and the presented cat swarm optimization algorithm are highly effective.

TABLE 6. **The heuristic hybrid optimization approach used in complete pooling system.**

			A	B	C	D	E	workers	total cost (€)	waiting time (h)	computation time (min)
cat swarm optimization	$\underline{S}$	local1	2	3	1	6	5	3	28960.29	5.83	5.28
		local2	2	4	2	7	6	2			
		local3	1	3	2	5	7	3			

TABLE 7. **Comparison with some previous works.**

Stduy	System: No. of components	System: No. of warehouses	System: No. of echelons	Transshipment: Type	Transshipment: Pooling	Approach	Computation Time (min)
Andrei Sleptchenko (2018) [42]	2	1	1	Direct	Complete	Heuristic	4.89
S. Rahimi-Ghahroodi(2017)[17]	2	N	2	Lateral	Complete	Heuristic	5.36
A.A. Kranenburg(2009)[26]	N	N	1	Lateral	Complete	Approximate evaluation	5.98
Hartanto Wong (2007)[16]	N	N	2	Lateral and Direct	Complete	Heuristic	6.33
This paper	N	N	3	Lateral and Direct	Partial	Heuristic hybrid	9.32

2) SENSITIVITY OF THE APPROACH

This section describes the analysis of how the total cost changes with an increasing λ (failure rate). In these experiments, λ is obtained by multiplying a factor, $K_\lambda \in [0.5; 10]$, by the initial failure rate. FIGURE 10 shows the total cost per month obtained using the presented optimization algorithm, and the total cost can be noted to be a monotonically increasing function of K_λ. The part cost increases smoothly and constitutes the largest component of the total cost.

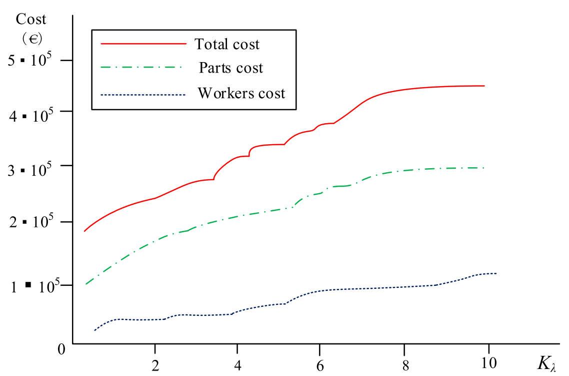

FIGURE 10. **The change in cost with the increase in the failure rates.**

Subsequently, it is studied whether the optimization algorithm can be used to perform the complete pooling. A small system with 1 plant, 2 central warehouses and 3 local warehouses that serve 4 machine groups are chosen to verify the algorithm. The results are presented in TABLE 6.

TABLE 6 shows that the optimization algorithm is also suitable for complete transshipment, which indicates that the algorithm is generic and can be used to solve most transshipment problems.

3) COMPARISON WITH OTHER STUDIES

Because the maintenance resources scheduling system is an NP-hard problem, the constraints play a critical role in the optimization of the inventory. Previous studies solved some aspects of the complex problem, however, none of them could cover all the characteristics, such as the joint optimization of multiple maintenance resources, multiple warehouses and multiple echelons, considering the partial pooling strategy. In this phase, the proposed approach was compared with previous studied in some aspects, and the results are summarized in TABLE 7.

On the basis of the experiment results and the additional test cases addressing larger problems, this approach can be used for any system with a known type of component. Furthermore, the algorithm can be used directly for optimizing each kind of resource in different inventory warehouses. Moreover, the analysis of the joint optimization of the spare parts and maintenance workers compared to the optimization separately indicates that only the joint optimization can yield a global optimal for a multiple component system.

V. CONCLUSION

In this paper, a heuristic hybrid optimization approach is proposed to optimize the maintenance resources. First, a greedy heuristic is used to obtain the initial inventory. Then, an improved cat swarm optimization algorithm is applied to optimize the current $\underline{S}$. The modifications are incorporated into the individual cat swarm mode, which make the cat swarm algorithm more efficient, reliable and robust. The main contributions of this paper are as follows:

1) A partial pooling strategy is used to share the maintenance resources between the same-echelon inventory warehouses, and the results show that the partial pooling strategy performs well in multiple echelon and resource inventory systems.

2) The greedy heuristic and cat swarm optimization algorithm are used to obtain the optimal resource inventory $\underline{S}$, which can flexibly support the combination of the spare parts

and maintenance workers with the scheduling strategies of lateral transshipment and emergency direct transshipment. The results show that the cat swarm optimization algorithm is time efficient.

3) The combination of the greedy criterion and roulette is used to initialize the cat swarm, which can accelerate the convergence rate.

4) The mixed ratio is used in the cat swarm optimization algorithm to reasonably allocate the proportion of local and global search in different iteration stages, which can increase the global search ability of the algorithm and the accuracy of the solution.

The results obtained are encouraging. In the future research, some extensions can be performed in several directions. One possible extension is to consider more types of resources (e.g., including tools), not equally skilled service engineers and possibilities to backorder the failure requests due to the lack of the resources. Another extension is to group several local inventory warehouses into a pooling group served by a central inventory warehouse. The analysis becomes more complex with these additional decisions; therefore, the analysis must be performed jointly with the inventory decisions.

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