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ORIGINAL ARTICLE

Capacitated disassembly scheduling with random demand and operation time

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ABSTRACT

The disassembly activity, regarding as the crucial stage in recycling operations, has attracted increasing focus owing to the significance of eco-economics and environmental issues. This paper examines the capacitated disassembly scheduling with demand and disassembly operation time uncertainty consideration, which is the problem of determining the quantity of the end-of-life (EOL) products (root item) to be disassembled while satisfying recycling market. The addressed problem is formulated as a novel stochastic programming model and a hybrid genetic-based algorithm (HGA) is proposed to derive the best solution. To deal with the uncertain demand of disassembled parts/modules (leaf item) and the disassembly operation time, the fixed sample size (FSS) sampling strategy is employed and embedded into the designed heuristic algorithm, lunched by the Monte Carlo Simulation. The numerical instances under different scales are performed, and results show that the developed HGA manifests good performance in terms of accuracy and efficiency.

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Capacitated disassembly scheduling; random demand and operation time; disassembly yield; fixed sample size (FSS) sampling strategy; HGA

1. Introduction

Driven by the green philosophy and sustainable requirement of the manufacturing industry and the society, the end-of-life product (EOL) recycling has tended to be a strategic business for industrial plants, also contributing to the sustainability achievement of the supply chain (Cai et al., 2019; D'Adamo & Rosa, 2016; Kim & Xirouchakis, 2010). This kind of recycling activities has been widely applied in various industrial sectors, such as EOL vehicle, EOL ship, EOL aircraft, steel products, and electronics (Go et al., 2011; Xiao et al., 2018; Zhou et al., 2020). The recycling business including recovery process, re-manufacturing and recycling operations, has been regarded as a promising branch of sustainable operations in production management (Jaehn, 2016; Zhou, Lim, He, & Pratap, 2019). Disassembly is a whole process that systematically separates an EOL product into several groups, modules, component items, parts, material and waste, regarding as one of the key techniques in product recovery or EOL recycling (Ullerich & Buscher, 2013; Zhou, Wang, et al., 2018; Zhou, Baldacci, et al., 2018; Zussman & Zhou, 1999). The prerequisite of the EOL product recycling is effective disassembly, and the efficiency of disassembly production plays a significant role on recycling process (Godichaud et al., 2012; Zhou, Lim, He, Lin, et al., 2019). Therefore, the disassembly scheduling problem has be focused by industrial practitioners and academic researchers, and become increasingly serious in the recycling sector (Godichaud & Amodeo, 2018). In the past decades, a vast majority of research efforts are performed on the disassembly modelling, solution algorithms, procedure optimization and industrial applications with an energy-saving and cost-effective way (Ehm, 2019; Jia et al., 2018; Kim, Lee, & Xirouchakis, 2007).

Disassembly scheduling is the problem of determining the ordering and disassembly schedule of EOL components or returned products to satisfy the further remanufacturing and recycling operations by producing individual parts or components (Lee, Xirouchakis, & Zust, 2002). The disassembly scheduling problems have been studied for several decades. Kim & Xirouchakis (2010) stated that previous disassembly scheduling studies could be classified into two branches: deterministic and non-deterministic. The variables and parameters were supposed to be known for deterministic disassembly scheduling scenarios; however, the non-deterministic disassembly scheduling considered random factors due to the uncertainty consideration in industrial plants.

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Most related researches focus on the deterministic disassembly scheduling under the assumption of the certain parameters. The deterministic disassembly scheduling is known as the reverse materials requirements planning (RMRP), since its procedure is a reversed form of the regular MRP (Gupta & Taleb, 1994), and the basic disassembly scheduling problem is defined and formulated for one single product type by Gupta. Taken into the capacity constraints of the disassembly process, Lee et al. (2002) extended a disassembly scheduling research with capacity constraints by an integer programming model. Barba-Gutiérrez, Adenso-Diaz, and Gupta (2008) extended the typical disassembly scheduling (Gupta & Taleb, 1994) by considering the lot-sizing variable in reverse MRP situation, and the period order quantity (POQ) lot-sizing technique was used to embedded in the designed algorithm to facilitate the lot-sizing consideration. Kim et al. (2009) studied the disassembly scheduling with assembly product structure, and a branch and bound algorithm incorporating the Lagrangean relaxation-based upper and lower bounds was designed to determine the quantity of EOL products. Ji et al. (2016) developed a mixed-integer programming model targeted the total cost minimization, and a two-stage Lagrangian heuristic algorithm was designed to generate good solutions in acceptable time. The disassembly economic order quantity (EOQ) model was constructed to determine the procurement quantity and specific time in disassembly plants over a planning horizon, where disassembly cost and inventory cot were the two crucial optimization segments of the objective function (Godichaud & Amodeo, 2018). The disassembly scheduling studies also can be divided into two categories based on the number of product types, that is, single and multiple product types. Gupta & Taleb (1994) designed an algorithm to deal with disassembly scheduling problem by determining the number of root items for a single well-defined product structure. Taleb & Gupta (1997) extended the disassembly scheduling problem from a single structure to complex product structures with a multiple layer, and developed an algorithm to obtain a best disassembly scheme (Taleb, Gupta, & Brennan, 1997). Kim et al. (2003) developed an integer programming model by considering multiple product types in terms of disassembly scheduling, and a heuristic algorithm with linear programming relaxation operation was designed to find the solution.

The disassembly scheduling problem had proven to be a nonlinear and NP-hard problem, and metaheuristic algorithms are developed in different industrial scenarios (Fu et al., 2019; Gao et al., 2020; Tian et al., 2019). Feng et al. (2018) proposed a novel multi-objective ant colony algorithm to derive the best disassembly sequence by formulating a multi-objective programming model. Tian et al. (2019) designed an improved artificial bee colony heuristic algorithm to deal with the dual-objective disassembly optimization problem. The disassembly time and profit also had been regarded as optimization objective in disassembly scheduling. Guo and Liu (2014) formulated a multi-objective disassembly sequence optimization programming model to minimize the total disassembly time and maximize disassembly profit by developing a modified scatter search optimization algorithm. Besides, Guo et al. (2019) studied a sequence-dependent disassembly planning problem with multi-resource constraints, and a Lexicographic multi-objective scatter search algorithm is developed to solve this programming model. To better represent the disassembly sequence, the timed disassembly Petri Nets (TDPNs) was employed to be embedded to the optimization model, and multi-objective generic evolution algorithm is designed to derive the Pareto solution set (Guo et al., 2020). Lee and Xirouchakis (2004) studied the disassembly scheduling with assembly product structure, and developed a two-stage heuristic algorithm to minimize the total disassembly cost. Prakash, Ceglarek, and Tiwari (2012) proposed a constraint-based simulated annealing (CBSA) algorithm to derive the best disassembly schedule.

However, the deterministic disassembly scheduling studies suppose the process parameters are deterministic with precise value, and fail to consider the uncertainties in industrial plants. Therefore, many scholars extended the deterministic disassembly scheduling by considering the uncertain ingredients during the manufacturing scenarios. Compared with assembly manufacturing, there exists much more uncertainties for disassembly process, such as, the discrepant condition of EOL products and the unpredictable demand in practical industries (Kim et al., 2007). Fleischmann et al. (1997) pointed out that the reliable planning of return flow became more difficult due to the increasing uncertainty which may lead to higher safety stock levels. Inderfurth and Langella (2006) developed two heuristics of different sophistication, and disassembly yield was highlighted as a stochastic variable due to the unknown state of returned products. Kim and Xirouchakis (2010) addressed the disassembly scheduling problem with resource capacity restriction for the two-level product structure, where demand of parts/modules is regarded as a stochastic variable. Liu and Zhang (2018) studied a capacitated single-item multi-period disassembly scheduling problem with random yields and demands. Tian and Zhang (2019) proposed a capacitated disassembly scheduling and pricing solution framework, where the disassembly yield of returned products depended on their acquisition prices. Not only the uncertainties are considered in disassembly scheduling, but also, these ambiguous factors are addressed at the EOL product collection stage. Kongar and Gupta (2006) developed a multi-criteria optimization model to determine the best EOL combinations from the vast majority of returned products, and the fuzzy goal programming technique was employed to deal with the uncertainties considered. Besides, the disassembly scheduling models are mostly supposed to be accomplished in a single period, and fail to address the dynamic demands in multi periods. The disassembly scheduling with multiple periods plays a significant role in manufacturing systems. Due to the fluctuation of practical demand in industrial market, the production scheduling problem within multi periods can assist to achieve lean production by determining the dynamic scheduling solution and cost reduction.

From the above-mentioned literature, we can find that the disassembly scheduling problem mainly includes deterministic and non-deterministic branches, most of which have targeted the total cost minimization as the optimization objective (Tian & Zhang, 2019). The non-deterministic highlights extend the disassembly scheduling by taking into uncertainties consideration, better reflecting the industrial practice in disassembly plants. The deterministic disassembly scheduling problem assumes that the disassembly operation time is certain and deterministic. The uncertain factors addressed in disassembly process contain disassembled demands, EOL conditions and disassembly yield parameters in most non-deterministic disassembly scheduling publications, and the disassembly operation is usually supposed to be accomplished in a single period. Both two categories fail to consider the uncertainty of disassembly operation time and the corresponding disassembly cost segment.

The illustrated literatures in terms of non-deterministic disassembly scheduling mostly focus on the uncertain characteristics of demand or disassembly yield variables. However, in the industrial disassembly process, the practical disassembly operation time is usually uncertain with a high stochastic characteristic (Fu et al., 2019; Tempelmeier, 2011). Different with the assembly production, the raw material of disassembly process is EOL products or returned components with high uncertainty due to the unknown utilizations and conditions. Besides, the conditions of the EOL products play a significant role on the workers' maturity of disassembly operations. The discrepancy of disassembly operation cost caused by stochastic disassembly operation time for EOL products argues that we should concentrate on the stochastic characteristic of the corresponding disassembly cost. Therefore, this study examines a capacitated disassembly scheduling problem with multiple periods, multiple product types in a two-level product structure, also targeting the disassembly operation time and demand as non-deterministic. To the best of our knowledge, this research is the first study to formulate a non-deterministic disassembly scheduling programming model involving these two uncertain ingredients simultaneously (demands and operation time) in multi periods. A non-deterministic programming model is formulated to determine the disassembly quantity solution under uncertainties consideration. The stochastic variables make the formulated model to be a non-deterministic one, a much more complex problem which is difficult to be resolved by exact algorithms. The heuristic algorithms show better performance on the non-deterministic programming model for production planning and scheduling problems (Dao et al., 2019; Hecker et al., 2014; Liu et al., 2019; Liu et al., 2020; Ojstersek, Brezocnik, & Buchmeister, 2020). As a stochastic optimization method based on biological evolution mechanism, genetic algorithm (GA) has proven to an effective heuristic algorithm to search a best solution for production scheduling management (Hecker et al., 2014; Shi, Zhao, & Meng, 2020). For its advantages on global search capability and fast convergence ability, the genetic operators are employed, and we design an integrated heuristic algorithm to deal with the novel stochastic disassembly scheduling problem. The main contributions of this study are three-fold, summarized as follows:

1. A novel stochastic disassembly scheduling problem with capacity constraints within multi periods is formulated, where demand and disassembly processing time are treated as stochastic variables simultaneously. To the state-of-the-art, this is the first study to consider these two uncertain ingredients in non-deterministic disassembly scheduling within one model.
2. The hybrid GA-based (HGA) heuristic algorithm integrating GA, SA and local search operations is developed to find the best solution of the programming model. The fixed sample size (FSS) sampling strategy by Monte Carlo simulation is employed to deal with the stochastic variables considered.
3. The numerical cases are performed to verify the effectiveness of the model and the performance of the developed algorithm. Results show that the proposed study enables to deal with uncertain variables with high efficiency, and assists to

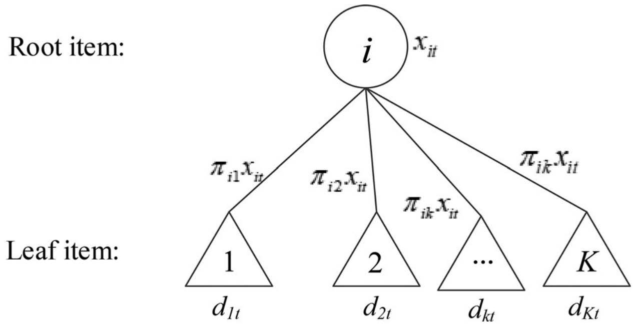

Figure 1. The two-level disassembly structure.

find an optimal disassembly scheduling solution, facilitating to promote disassembly scheduling management.

The rest of this paper is organized as follows. Section 2 describes the disassembly scheduling problem by highlighting the stochastic variables in real industrial plants. Section 3 is devoted to an analytically mathematical model of the illustrated problem. Then in Section 4, we design a hybrid genetic-based algorithm (HGA) to search an optimal disassembly scheduling solution. Some numerical experiments are carried to verify the effectiveness of our designed algorithm in Section 5. The theoretical contributions and practical implications are summarized in Section 6. Finally, we conclude the paper in Section 7.

2. Problem description

The end-of-life (EOL) products or components delivered to the dismantling plant will be processed by disassembly operations, producing the disassembled parts for the reuse, remanufacturing or recycling (Zhou & Ma, 2019). Therefore, the effective disassembly is the prerequisite of the EOL recycling (Berzi et al., 2016; Zhou et al., 2016). A two-level product structure disassembly scheduling problem is addressed, and the returned procured items (EOL product or components calling root items) are disassembled into components or parts (leaf items), aiming at satisfying the uncertain demand in each period. An example of the two-level disassembly scheduling structure is given in Figure 1, in which the number in each parenthesis represents the number of the corresponding leaf items obtained from root item i. The yield ratio of leaf items obtained from the root item is π, which is defined as the number of leaf item k successfully disassembled from root item i.

Where π_{ik} is yield of leaf item k of the root item i. Suppose $\pi \sim U[a, b]$, Notably, a and b is the minimum and maximum value respectively that can be disassembled successfully from one root item because of the degradation discrepancy. b is less than the corresponding value in the root item's BOM and $a \geq 0$ (Liu & Zhang, 2018). The yield variable π_{ik} is derived and represented by the mean value.

The demand variable regarded as uncertainty has been studied by many literatures in manufacturing activities, re-manufacturing factories and disassembly plants (Bollapragada, Kuppusamy, & Rao, 2015; Rossi, Kilic, & Tarim, 2015). Different from the assembly production, the demand of disassembly parts is treated as a stochastic variable due to the ambiguous requirement. In this study, the demand of each leaf item in each period D follows a normal distribution, which has been widely used and proven to be effective in previous literature (Disney et al., 2015; Guijarro, Cardós, & Babiloni, 2012; Liao & Shyu, 1991; Silver & Bischak, 2011; Tempelmeier, 2011; Wang & Gerchak, 2003).

Another uncertain variable is the operation time in industrial manufacturing scenarios, contributing to the ambiguity of lead time in MRP system at the procurement stage (Li et al., 2015; Song, Yano, & Lerssrisuriya, 2000; Zhou, Wang, et al., 2019; Zhou et al., 2017). Different with assembly activities, the disassembly processing time has played a great significant role on the damage degree of the end-of-life product (Zhou, Lim, He, Lin, et al., 2019). Due to the discrepant utilization and residual condition of the end-of-life product, there exists a high uncertainty for the disassembly time of the EOL products. In this research, the disassembly operation processing time in terms of each kind of leaf item are assumed to be random variables with the normal probability distribution (Bentaha Battaïa, & Dolgui, 2015).

The objective of this study is to derive the optimal decisions and the best disassembly scheduling solution by minimizing the total disassembly cost. The best disassembly scheduling strategy in multi periods is resolved by a novel stochastic programming model and a hybrid heuristic algorithm.

3. Model formulation

3.1. Notations and assumptions

The variables and their notations in this research are presented in the following Table 1. We use the

Table 1. Variable symbols and notation description.

Symbols	Description
Indices	
I	Set of root items ($i = 1, 2, \ldots, N$)
K	Set of leaf items ($k = 1, 2, \ldots, K$)
Parameters	
l_i	Disassembly operation time for root item i
$f(\bullet)$	The probability density function of disassembly operation time
$F(\bullet)$	The distribution probability function of disassembly operation time
D_{kt}	Demand for leaf k at period t
$g(\bullet)$	The probability density function of demand
$G(\bullet)$	The distribution probability function of demand
Q_{kt}	Output quantity of leaf item k at period t
I_{kt}	Inventory of leaf item k at period t
π_{ik}	The yield of leaf item k of root item i
c_o	Inventory cost for one unit of root item i
c_s	Backorder penalty cost for one unit of leaf item i
cd_i	Disassembly cost per unit root item i and unit time
pc_{it}	Procurement price of root item i at period t
CP_t	Capacity available in period t
$E[\bullet]$	Expected value of $\bullet$
Decision variable	
x_{it}	Disassembly quantity of root item i at period t

following notations to develop the proposed mathematical model.

Also, we make the following assumptions to develop the proposed model.

i. The supply of raw materials (root items) is sufficient, and the time of EOL products and components collection and delivery can be ignored.
ii. Backlogging is not allowed and the disassembly can be finished as required.
iii. The yield ratios of all leaf items disassembled from the root item are different, regarded as stochastic variable with high uncertainty.
iv. The disassembly operation time is a stochastic variable, and the disassembly operation cost is influenced by the disassembly operation time.
v. The production preparation time is not separately addressed and the disassembly operation time variable includes the production preparation.

3.2. Mathematical model

Similar to the assembly manufacturing process, the disassembly production on end-of-life products is the inverse manufacturing focusing on dismantling operations. The cost segments for disassembly scheduling are similar to the optimization business in the assembly manufacturing process (Karmarkar, 1987; Zhou et al., 2017). The total cost minimization is targeted as the objective of the programming model, including procurement cost, disassembly operation cost and inventory cost segments, illustrated in the following Equation (1). The constraints of the model are formulated by the Equations (2)–(5).

$$\text{Min } TC = \sum_{i=1}^{N}\sum_{t=1}^{T} pc_{it}x_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} cd_i E[L_i]x_{it} + \sum_{k=1}^{K}\sum_{t=1}^{T}\left(c_o \cdot E\left[I_{kt}^{+}\right] + c_s \cdot E\left[I_{kt}^{-}\right]\right) \tag{1}$$

s.t.

$$Q_{kt} = \sum_{i=1}^{N} \pi_{ik} \sum_{j=1}^{t} x_{ij}\left[F(t-j+1) - F(t-j)\right] \tag{2}$$

$$I_{kt} = I_{kt-1} + Q_{kt} - D_{kt} \tag{3}$$

$$x_{it} \geq 0 \tag{4}$$

$$\sum_{i=1}^{N} x_{it} \leq CP_t \tag{5}$$

Specifically, the output quantity of leaf item k at period t is derived by the following Equation (6).

$$\begin{aligned} Q_{kt} &= \pi_{1k}\begin{pmatrix} x_{11}P\{t-1 \leq l<t\} + x_{12}P\{t-2 \leq l<t-1\} \\ + \cdots + x_{1t-1}P\{1 \leq l<2\} \end{pmatrix} \\ &+ \pi_{2k}\begin{pmatrix} x_{21}P\{t-1 \leq l<t\} + x_{22}P\{t-2 \leq l<t-1\} \\ + \cdots + x_{2t-1}P\{1 \leq l<2\} \end{pmatrix} \\ &+ \cdots + \pi_{Nk}\begin{pmatrix} x_{N1}P\{t-1 \leq l<t\} + x_{N2}P\{t-2 \leq l<t-1\} \\ + \cdots + x_{Nt-1}P\{1 \leq l<2\} \end{pmatrix} \\ &= \sum_{i=1}^{N}\pi_{ik}\sum_{j=1}^{t} x_{ij}\left[F(t-j+1) - F(t-j)\right] \end{aligned} \tag{6}$$

where π_{ik} in Eq. (2) is established by the mean value of $\pi_{ik} \sim U[a_{ik}, b_{ik}]$. The operation time variable l and the demand variable are regarded as stochastic variables, and which are supposed to follow the normal distributions. The Eq. (1) is the objective function by minimizing the total cost including procurement cost, disassembly operation cost, stock-out cost and inventory cost. Eq. (2) is the output quantity formulation of leaf item k at period t. Eq. (3) is the inventory formulation of leaf item k at period t. Eq. (4) is the range of disassembly quantity of root item i at period t. Eq. (5) is the disassembly capacity constraint at period t.

The inventory cost of leaf item k during period t is calculated in the following Eq. (7).

$$\begin{aligned} & c_o \cdot E\left[I_{kt}^{+}\right] + c_s \cdot E\left[I_{kt}^{-}\right] \\ &= c_o \int_0^{I_{kt-1}+Q_{kt}} (I_{kt-1} + Q_{kt} - y)g(y)dy \\ &+ c_s \int_{I_{kt-1}+Q_{kt}}^{\infty} (y - I_{kt-1} - Q_{kt})g(y)dy \\ &= c_o(I_{kt-1} + Q_{kt} - E[D_{kt}]) \\ &+ (c_o + c_s)\int_{I_{kt-1}+Q_{kt}}^{\infty} (y - I_{kt-1} - Q_{kt})g(y)dy \end{aligned} \tag{7}$$

where $I_{kt}^{+} = \max(I_{kt-1} + Q_{kt} - y, 0)$, $I_{kt}^{-} = \max(y -$

$I_{kt-1} - Q_{kt}, 0)$, y is a stochastic variable, which denotes demand, and $g(y)$ is the probability density function of demand.

Then, the original objective function of the total cost minimization in Eq. (1) becomes the following Eq. (8).

$$\sum_{i=1}^{N}\sum_{t=1}^{T} pc_{it}x_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} cd_i E[L_i]x_{it} + \sum_{t=1}^{T}\sum_{k=1}^{k}\Big\{c_o(I_{kt-1} + Q_{kt} - E[D_{kt}]) + (c_o + c_s)\int_{I_{kt-1}+Q_{kt}}^{\infty}(y - I_{kt-1} - Q_{kt})g(y)dy\Big\} \tag{8}$$

4. Solution algorithm

The disassembly scheduling problem has proven to be NP-complete (Ji et al., 2016), and a hybrid GA-based algorithm (HGA) is developed in this part due to its advantages of global search performance. The GA steps are employed to search the best disassembly scheduling solutions. Besides, the local search strategy is adopted to improve the local search ability by generating new populations. The fixed sample size sampling strategy using Monte Carlo simulation is employed to deal with the random variables in the stochastic programming model. To avoid falling into local optimum and improve the global search capability, the self-adaptive simulated annealing (SA) operations are embedded into the GA steps. The hybrid heuristic-based evolutionary algorithm is presented in the following Figure 2.

4.1. GA-based steps

4.1.1. Chromosome coding

Genetic algorithm is a heuristic-based evolutionary algorithm, which has been widely used in production scheduling models and management applications (Kadri & Boctor, 2018; Zhou, Baldacci, et al., 2018). The chromosome coded with a numerical solution scheme, maps to a practical disassembly scheduling solution. In this formulated disassembly scheduling model, the real-number coding technique is adopted to represent the practical solution based on the characteristic of the decision variable. The chromosome code of the disassembly scheduling solution with multi periods is presented in the following Figure 3. There are N root items in each period, and the element "2" means the disassembly quantity of root item 1 at the first period is 2. The other genes have the similar meaning with real number, and a chromosome represents a disassembly solution.

4.1.2. Fitness function formulation

The fitness function reflects the performance of the iterated solution, which is used for solution assessment during the evolutionary search process. Based on the objective function in Eq. (1), we designed the fitness function presented in the following Eq. (9).

$$\begin{aligned} fitness(x_{it}) &= 1/TC \\ &= 1/\Big\{\sum_{i=1}^{N}\sum_{t=1}^{T} pc_{it}x_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} cd_i E[L_i]x_{it} \\ &\quad + \sum_{k=1}^{K}\sum_{t=1}^{T}(c_o \cdot E[I_{kt}^{+}] + c_s \cdot E[I_{kt}^{-}])\Big\} \end{aligned} \tag{9}$$

4.1.3. Adaptive genetic operators

The new solutions are generated and filtered by genetic operators, keeping diversity of the disassembly solutions. The following sub-section presents the selection operator, crossover operator and mutation operator.

1. Selection operator

In this study, the roulette wheel selection strategy is adopted to create a new generation, and the adaptive replication probability is calculated by the following Eq. (10). Those individual solutions with better performance measured by fitness function will be copied to the next generation with probability $p(S_i)$.

$$p(S_j) = f_j(S_j) / \sum_{j=1}^{G_n} f_j(S_j) \tag{10}$$

where S_j is the individual disassembly solution; $p(S_j)$ is the selection probability which will be copied to the next generation; and $f_j(S_j)$ is the fitness value of individual solution S_j.

1. Two-point crossover operator

The selection operator tries to find a better individual solution, while the crossover operator could assist to expand the solution domain. The two-point crossover operator is employed to generate the new individual solutions by crossover operation, illustrated in Figure 4. The crossover probability is of great significance on the performance of the heuristic algorithm. The high probability contributes to the search efficiency improvement of the designed algorithm, but may lead to the loss of good genes. Therefore, the adaptive crossover operator is adopted to perform the crossover operation, which is adjusted based on the fitness performance of the updated individual solution, found in Eq. (11). The new offspring will be obtained from two parent individual solutions with certain probability.

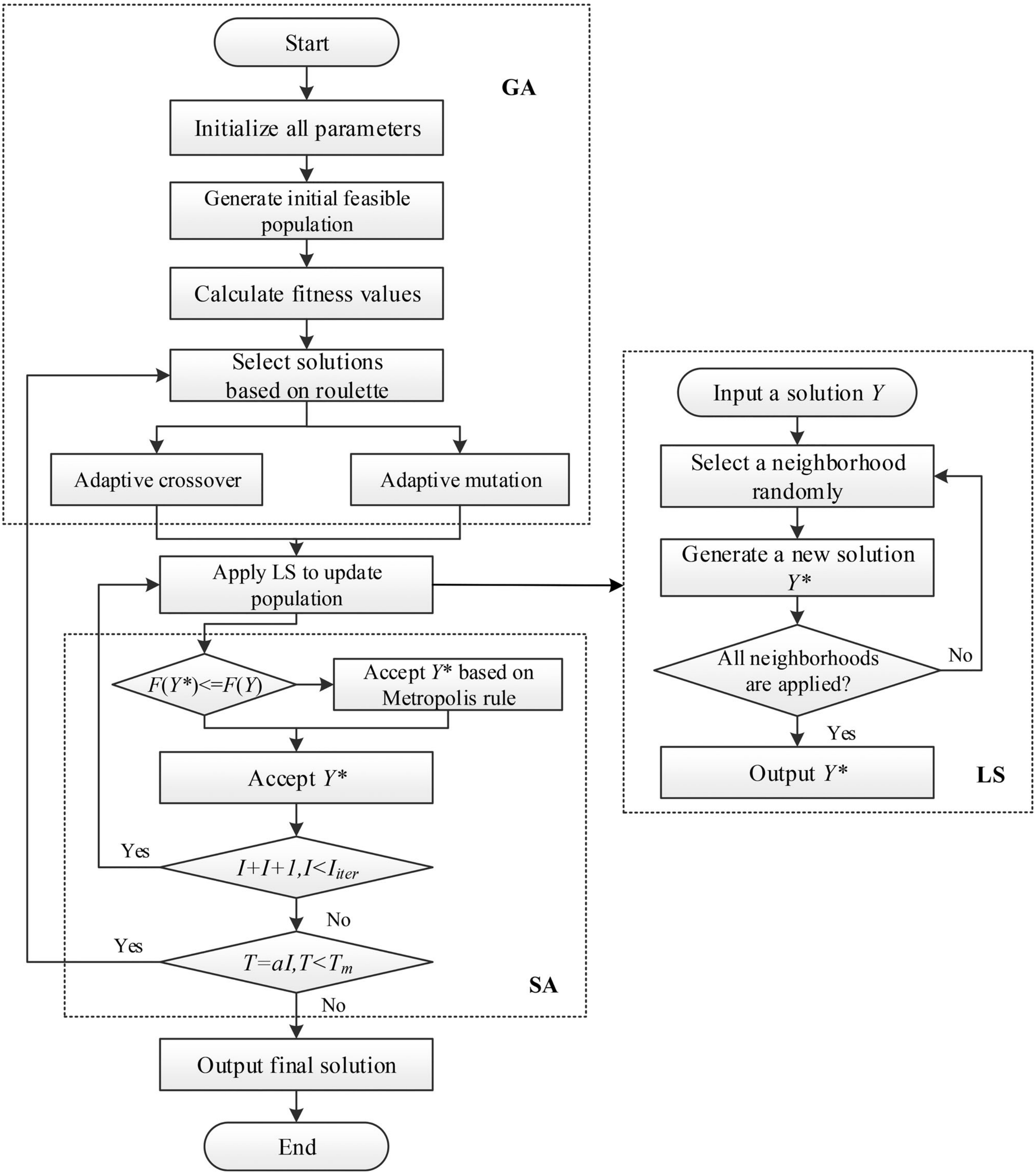

Figure 2. The implementation steps of the designed HGA.

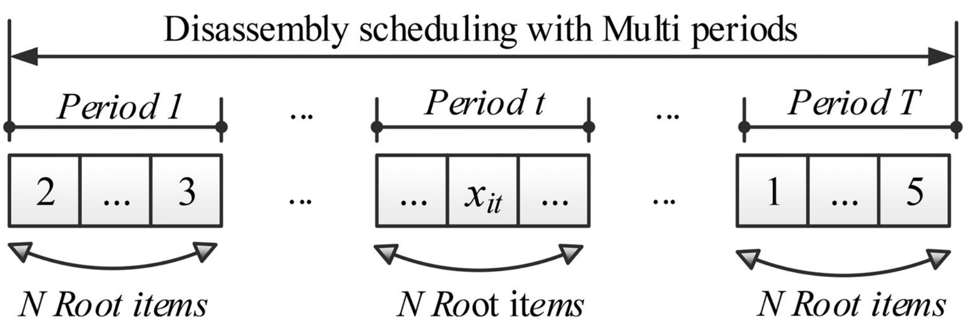

Figure 3. Chromosome code chart with real-number coding technique.

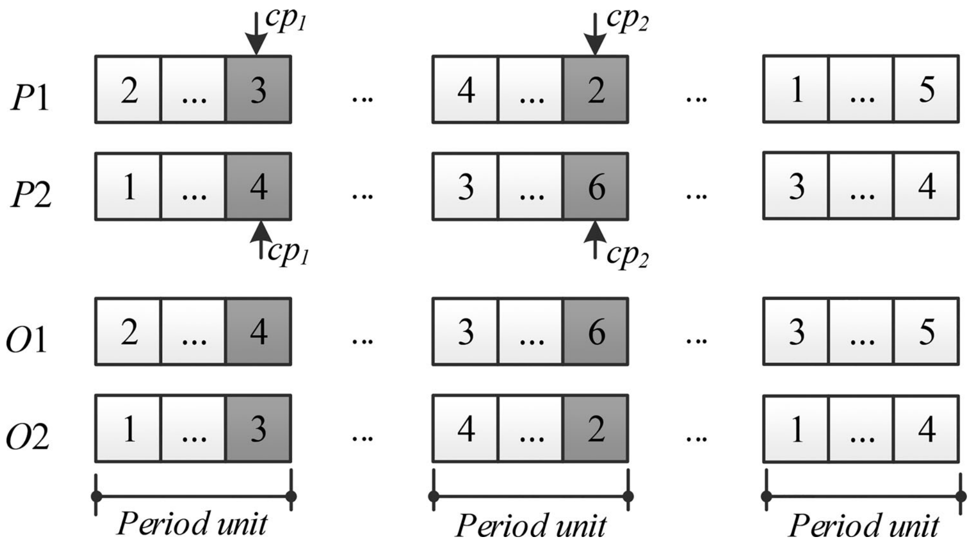

Figure 4. Two-point crossover operator.

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c1})(f' - f_{avg})}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ P_{c1}, & f' < f_{avg} \end{cases} \tag{11}$$

Where f_{avg} is the average fitness of the population, and $f_{\max}$ is the maximum fitness. Generally speaking, P_{c1}=0.9, P_{c2}=0.6 (Zhou, Baldacci, et al., 2018).

1. Multi-point mutation operator

Another genetic operator is the mutation operation by selecting the mutation chromosome with a certain probability. In terms of the characteristics of the disassembly scheduling problem, the multi-point mutation operator is adopted, which is found in Figure 5. Besides, the adaptive mutation operation is performed to generate the new solution, whose mutation probability is calculated in Equation (12).

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f_{\max} - f')}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ P_{m1}, & f' < f_{avg} \end{cases} \tag{12}$$

where P_m is the mutation probability, and generally speaking P_{m1}=0.1, P_{m2}=0.001 (Zhou, Wang, et al., 2019).

4.2. Local search strategy

To improve the search efficiency and speed up the evolutionary process of the proposed algorithm, the local search (LS) strategy is adopted to find local optimum by different regions exploration in terms of search space. The performance of LS strategy depends on the structure of neighbourhood search and the initial solution (Zhou, Lin, et al., 2019). Based on characteristics of the formulated model on disassembly scheduling, the neighbourhood exchanging-based search structure is developed to perform the local search strategy. The gene is chosen randomly, and the nearest solutions are selected to test whether the performance is better or not. The individual solution with better fitness performance will be identified and chosen (Zhou, Wang, et al., 2019). Based on the formulated model, the following two local search strategies are proposed to improve the search efficiency based on the backorder penalty cost and inventory cost: ① if the stock-out cost item of the individual solution is large enough, we need to increase the purchasing volume in certain period; ② if the inventory cost item of the selected solution is large enough, the determinations should be reduced in this period. According to these two optimization strategies, the LS operation is performed to elevate the search efficiency.

4.3. SA technique

To improve the global search ability, the simulated annealing technique is employed to avoid local optimum (Vahdani et al., 2017). There is an initial temperature in SA, and the new solution Y is generated from initial state X randomly, which will be accepted by Metropolis rule in Equation (13).

$$p = \begin{cases} 1, & f(Y^*) \geq f(Y) \\ \exp\left[\left(-f(Y) - f(Y^*)\right)/KT\right], & f(Y^*) < f(Y) \end{cases} \tag{13}$$

The detail SA procedure is found in the Figure 2. Where I_{iter} is the number of iterations under specific temperature; T_m is the terminal temperature; α is the cooling coefficient, and K is the Boltzmann constant.

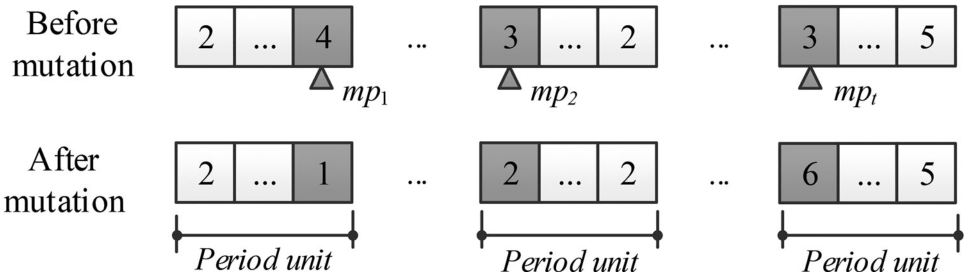

Figure 5. Multi-point mutation operator.

4.4. Fixed sample size (FSS) sampling strategy

To deal with the random variables in this study, the fixed sample size (FSS) sampling strategy is employed to simulate the random factors, which has been proven to be an effective tool for stochastic programming (Li et al., 2016; Taş et al., 2019). The fixed sample with a size of N is used in FSS strategy, and the designed algorithm is performed to generate the best solution of N samples, which is performed by Monte Carlo simulation (Ferrenberg, Xu, & Landau, 2018). Then, a large sample N' is used to evaluate the generated solution through the objective value. To improve the accuracy of the solution, the larger the sample size, the better performance the algorithm will have. However, the increasing sample size will lead to the efficiency reduction of the designed algorithm. Therefore, we need to focus on the trade-off between the accuracy and the efficiency of the stochastic programming process.

5. Illustrative examples

To verify the formulated programming model and the proposed hybrid heuristic algorithm, the numerical experiments are performed to derive the optimal disassembly solution. The experimental study is conducted on a laptop with an Inter Core i7 processor @ 3.3 GHz on Windows 8. The designed hybrid heuristic algorithm is coded and conducted using commercial solver software IntelliJ IDEA. The experimental instances are texted under different problem scales, also providing some computation results and comparison analysis.

5.1. Parameter establishment

The numerical instances are generated to verify the formulated model and the proposed algorithm is preformed to optimize the disassembly solution. We perform test cases with different scales in three levels of root kinds (5, 10, and 20), and three cycle scales (10, 20 and 30). Parameters in the formulated programming model are established and set as follows based on previous studies (Kim & Xirouchakis, 2010; Liu & Zhang, 2018).

Cycle 20

Root item $N = 5$

Leaf item $K = 5$

Disassembly processing time l_i : Normally generated from

$$N(\mu_i, \sigma_i^2)|\{N(1.5, 0.5); N(1.7, 0.5); N(1.9, 0.5); N(2.0, 0.5); N(1.6, 0.5)\}$$

Procurement price $pc_{i.}$ equals (1.0, 1.2, 1.4, 1.5, and 1.1)

Demand D : Normally generated from $N(70, 5)$

Disassembly yield π : Uniformly generated from [2, 4]

Capacity CP: 35

Initial inventory level IV_{k0} is generated randomly by the formula $IV_{k0} = \beta D_{k0}$ ($\beta \in [0.8, 1.2]$)

5.2. Sample size of FSS strategy

The FSS sampling strategy is employed to deal with the formulated stochastic programming model, and the appropriate sample size is of great significance on the accuracy and efficiency of the heuristic algorithm. To determine the sample size of the strategic sampling, the experimental test that the influence study of sample size on performance of the proposed algorithm is conducted to determine a suitable sample size. Therefore, we test performance and efficiency of the HGA in different experiment scenarios in terms of different sample size scales (sample size = 10, 20, 50, 100, 200).

We set six experiment instances based on the number of the root items (5, 10 and 20) and disassembled leaf items (5 and 10) in 20 production cycles. The Figure 6 demonstrates the CPU running time of the algorithm for settled experimental instances under different sample size.

From the Figure 6, the CPU running time of the HGA increases with the sample size of FSS strategy raises for experimental instances. And specifically, the efficiency of the algorithm begins to dramatically decrease when sample size increases more than 100. To testify the efficiency of the HGA, the minimum

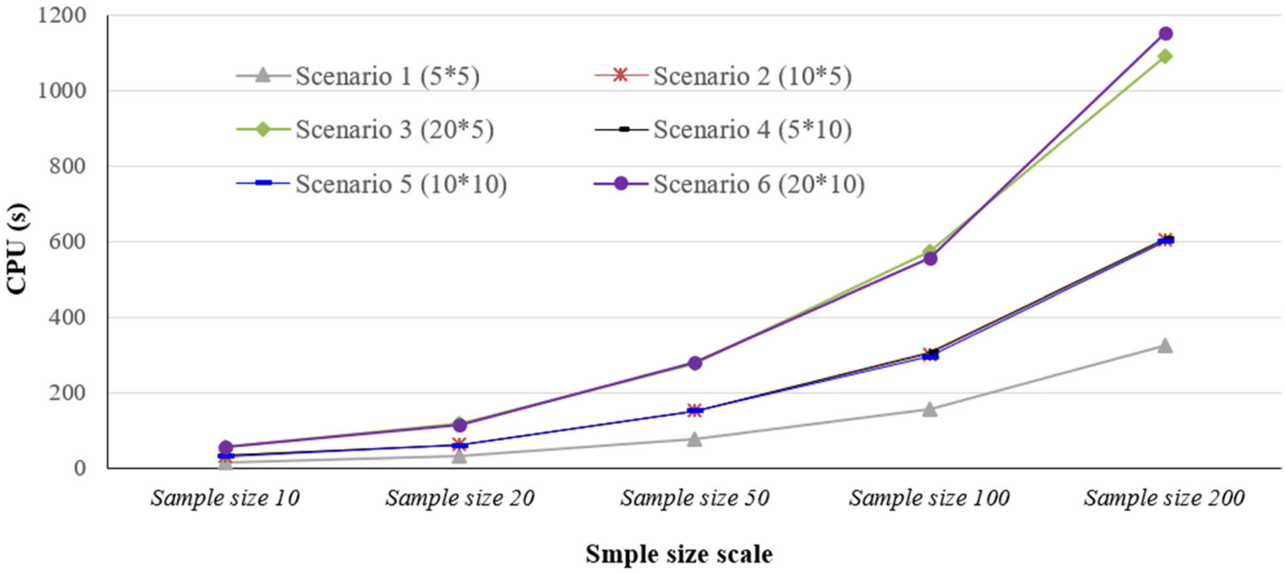

Figure 6. CPU running time under different sample size.

total disassembly cost of the best solution and CPU time are recorded in terms of different sample size, found in Table 2.

For the experimental tests in scenario 3 and scenario 6, the best objective value appears when samples size is 50, while for other four experimental instances, it occurs at 100. From the Table 2, we can find that the best objective function value keeps a decreasing tendency and shows a better performance with the increasing of sample size. However, the quality of the computed solutions displays no further improvement when the sample size is larger than 100. It is worth noting that the CPU time soars very fast when sample size exceeds 100. Therefore, this sample size (100) is selected to perform the FSS strategy in this study.

5.3. Results and comparison analysis

The proposed algorithm is lunched to conduct experimental test for Scenario 1 case (Sample size = 100) as the designed logic steps, and the best disassembly scheduling solution is generated by minimizing the objective function. To verify the effectiveness of the proposed HGA, the computation analysis is performed by comparing with traditional GA procedures and TS algorithm in terms of optimal objective values and CPU running time (Cesaret, Oğuz, & Salman, 2012; Ojstersek et al., 2020; Senécal & Dimitrakopoulos, 2020). The convergence procedure of the objective function with iterations among different algorithms is presented in Figure 7.

From the convergence map in Figure 7, the proposed HGA shows a better performance than traditional GA and TS in terms of the solution quality, which has the minimum objective function value. The designed HGA shows a fewer iterations to a convergence on achieving the best solution with minimum total cost (11088.90), comparing with 1850 iterations for GA and after 2000 iterations for TS. For the computation efficiency, the CPU running time of three algorithms (GA, HGA, and TS) for the experimental case is 91 s, 157 s and 118 s respectively. Both GA and TS show better computation efficiency than the proposed HGA, however, the solution quality is not as good as the HGA. The computation time of all three algorithms can be accepted and tolerated in industrial applications. For disassembly scheduling problem, industrial managers would like to seek a best solution to spend the minimum cost in tolerated time. The experimental test verifies the effectiveness and advantage of the designed HGA on disassembly scheduling problem.

5.4. Model comparison test

According to the above-mentioned experimental analysis, this study extends the disassembly scheduling problem by addressing the two random factors simultaneously, which is more suitable for industrial plants due to the uncertainty consideration. These uncertain considerations are common in industrial factories, which play significant role on the disassembly procedures. The uncertain variables considered in this study make the formulated programming model more in line with the industrial disassembly plants. To verify the significance of the uncertainty considerations in disassembly scheduling problems, we conduct the comparison analysis between deterministic and non-deterministic scheduling model in terms of CPU time and best objective value. Based on the number of root items and leaf items, we generate four instances (5*5, 5*10, 10*5, and 10*10). Besides, the three cycles (10, 20 and 30) for disassembly scheduling problem is also

Table 2. Algorithm performance in terms of FSS.

Instance / Sample size	Scenario 1 (5*5*20)		Scenario 2 (10*5*20)		Scenario 3 (20*5*20)	
	CPU (s)	Best value	CPU (s)	Best value	CPU (s)	Best value
Sample size 10	15	11019.55	33	9447.88	58	8636.45
Sample size 20	33	10883.53	63	9146.44	118	8354.18
Sample size 50	77	11023.37	153	9172.41	279	8079.58
Sample size 100	157	10705.56	303	8769.02	573	8105.99
Sample size 200	325	11044.09	604	9218.65	1089	8216.41
	Scenario 4 (5*10*20)		Scenario 5 (10*10*20)		Scenario 6 (20*10*20)	
	CPU (s)	Best value	CPU (s)	Best value	CPU (s)	Best value
Sample size 10	34	25230.30	32	23125.25	58	19114.51
Sample size 20	62	25160.20	61	22677.91	117	18770.06
Sample size 50	152	25170.08	152	22610.55	280	18705.39
Sample size 100	307	25052.04	296	22576.06	556	18784.74
Sample size 200	607	24883.82	600	22609.10	1152	18750.30

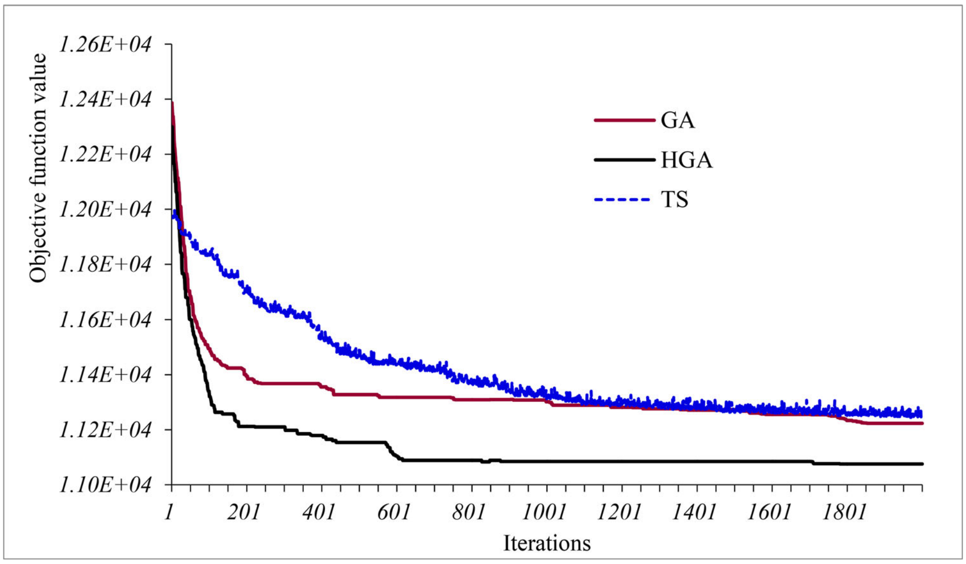

Figure 7. Convergence iteration of objective function value for different algorithms.

combined in this experiment, leading to the total 12 instances, and the comparison results are presented in Table 3.

The Table 3 presents the comparison analysis between deterministic and non-deterministic DSP under different 12 experimental instances. As we can see from the Table 3, the ignorance of these uncertain factors will lead to the total cost increasing, and the non-deterministic model helps to achieve a better performance with less total disassembly cost in each experimental instance. With the increasing of disassembly process cycle, the algorithm scale increases reflected from CPU and total cost indicators. It will take less time for deterministic DSP compared with non-deterministic DSP models. Even though it takes more CPU time to derive the best solution for non-deterministic instances, all of them show a better performance than deterministic alternatives with better objective value for all instances. This comparison result verifies that the proposed non-deterministic disassembly scheduling model performs a better performance and practical significance for industrial disassembly plants within an acceptable CPU time.

5.5. Sensitivity analysis

There are two uncertain factors (demand and disassembly operation time) addressed in the formulated

Table 3. Comparison analysis between deterministic and non-deterministic problem.

Problem type / Instances	Deterministic DSP		Non-deterministic DSP	
	CPU (s)	Best value	CPU (s)	Best value
Scenario 1-1 (5*5*10)	5	5454.51	42	5156.07
Scenario 1-2(5*5*20)	5	10930.57	87	10628.48
Scenario 1-3 (5*5*30)	9	17010.69	129	16269.5
Scenario 2-1 (5*10*10)	5	12377.34	44	12016.7
Scenario 2-2 (5*10*20)	6	25177.81	87	24628.88
Scenario 2-3 (5*10*30)	7	37752.6	133	37048.91
Scenario 3-1 (10*5*10)	4	4792.99	71	4273.89
Scenario 3-2 (10*5*20)	7	9934.57	153	9172.41
Scenario 3-3 (10*5*30)	10	14639.76	230	13744.38
Scenario 4-1 (10*10*10)	6	11798.3	70	11027.17
Scenario 4-2 (10*10*20)	8	23538.65	145	22669.08
Scenario 4-3 (10*10*30)	9	35134.88	228	34003.63

Note DSP is short for disassembly scheduling problem.

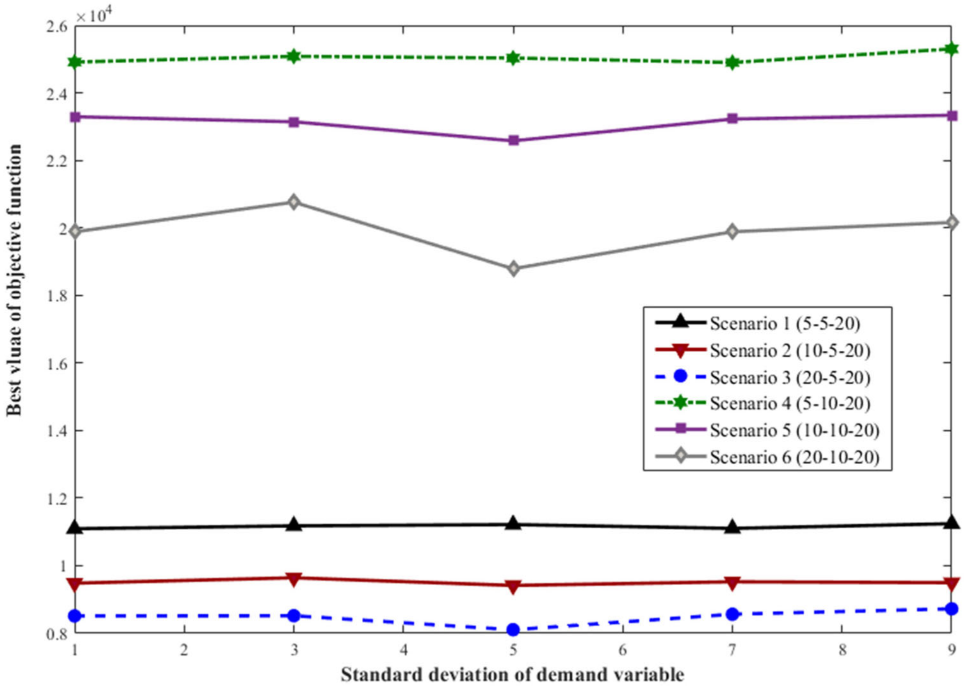

Figure 8. Sensitivity analysis of demand variable for six experimental instances.

non-deterministic disassembly scheduling model. To evaluate the influence of considered uncertainties on the best solution of the formulated model, the experimental tests of sensitivity analysis on these two uncertain variables are performed to illustrate the heuristic steps. The six experimental instances (Scenario 1–Scenario 6) as settled in previous subsection are used to test the experimental sensitivity analysis within 20 production cycles. To perform the sensitivity analysis, we conduct the experimental test by setting different standard deviation ($\sigma_d = 1, 3, 5, 7, 9$) of demand variable and disassembly operation time variable ($\sigma_l = 0.1, 0.3, 0.5, 0.7, 0.9$). The objective function value variation of six instances in the settled five experimental conditions is derived and sensitivity analysis on two uncertain variables is found in the following Figures 8 and 9 respectively.

As we can see from Figs. 8 and 9, the best objective function value fluctuates with the variation of uncertain variables. From the sensitivity analysis on the demand variable in Fig. 8, there is a slight fluctuation of the best objective function value in five experimental instances, except the Scenario 6. When the uncertainty of disassembly operation time varies, the variation of the best objective function values shows a relatively steady tendency for all six experiment instances in Fig. 9. The experimental test of the sensitivity analysis on these two uncertain factors demonstrates that the impact of these two uncertain factors on disassembly scheduling is not as serious as supposed even there are some impacts on the total disassembly cost.

6. Theoretical implications and managerial insights

This study severs both scientific and practical contributions by providing some theoretical implications and managerial insights on the disassembly management. In this section, we address the theoretical implications to disassembly scheduling problem and provide managerial implications for industrial application.

6.1. Implications to theoretical knowledge

This research contributes to the theoretical knowledge by proposing a non-deterministic disassembly scheduling solution framework considering the uncertainty of demand and disassembly operation time simultaneously. These two uncertain factors are regarded as stochastic variables based on the disassembly scheduling practice in industrial plants. A novel non-deterministic disassembly scheduling programming model with capacity constraints is developed to derive the best solution. Besides, to improve the local search capability, a novel HGA heuristic algorithm is designed where the SA and LS strategy is coupled with genetic operations. The fixed sample size (FSS) sampling strategy by Monte Carlo operation is simulated to solve the considered stochastic variables.

This paper extends the capacitated disassembly scheduling problem by considering uncertain demand and disassembly operation time factors within multiple periods. The formulated non-

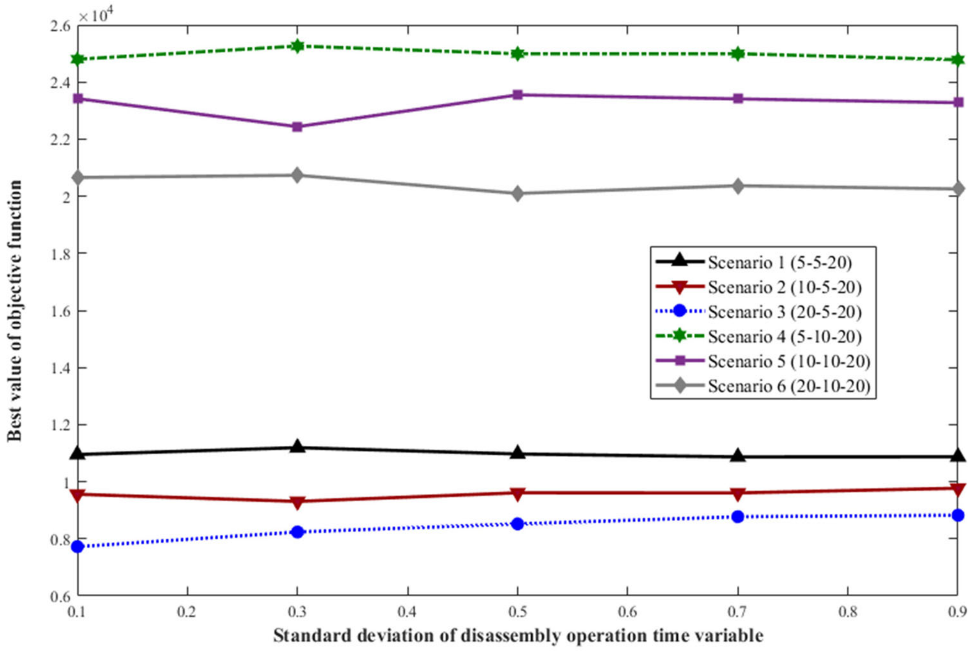

Figure 9. Sensitivity analysis of operation time for six experimental instances.

deterministic programming model is much closer to the disassembly production practice by taking into these two uncertain factors, which provides an effective solution for the addressed capacitated disassembly scheduling management.

6.2. Implications to industrial practice and managerial insights

This study also carries a few practical implications and managerial insights which will assist recycling industrial sector to improve lean operation by the formulated stochastic programming model. The disassembly scheduling model provides technical and methodological support on disassembly operation management for recycling enterprises, assisting to achieve cost reduction, efficiency improvement and reputation promotion.

From a managerial point of view, the non-deterministic disassembly scheduling model enables industrial managers to determine the best disassembly solution considering the addressed uncertain factors. Numerical instances validate that the designed HGA heuristic algorithm outperforms than the compared benchmarking heuristics. The experimental test on the numerical instances indicates that the non-deterministic model showing a much better performance on solution determination than the deterministic one. The sensitivity analysis of experimental tests demonstrates that these two uncertain variables show a limited influence on the best objective function value. The impact of these two uncertain factors on disassembly scheduling is not as obvious as imaged in industrial plants, even if there is some influence. The demand and disassembly operation time parameters can be treated as certain variables if there are limited resources in practical scenarios. These interesting findings will assist industrial managers better understand the non-deterministic disassembly scheduling decision-making and perform the dismantling management practice.

7. Concluding remarks

In this research, the capacitated disassembly scheduling with random demand and operation time was addressed by formulating a novel stochastic programming model. The total disassembly scheduling cost optimization is regarded as the objective function, including procurement cost, disassembly operation cost, stock-out cost and inventory cost item. This study extends a disassembly scheduling problem with multi-periods in terms of a two-level disassembly product structure, which aims at determining the quantity of EOL disassembling products for satisfying separated parts. In particular, the stochastic demand and disassembly operation time are highlighted and treated as non-deterministic due to uncertainties occurred in disassembly plants.

To cope with the novel disassembly scheduling problem, a hybrid heuristic evolutional algorithm (HGA) is designed to derive the best solution. Besides, the fixed sample size (FSS) sampling strategy is employed to deal with the stochastic variables using Monte Carlo Simulation during the heuristic-based steps. Illustrative examples validate the effectiveness of the formulated model and the designed HGA algorithm. Computational results show that the proposed hybrid heuristic algorithm outperforms most of the previously applied methods. To our surprise, the sensitivity analysis on these two uncertain variables indicates that the influence of these two variables on the best objective function value is not as significant as imaged in practical disassembly operation. These two parameters can be regarded as precise variables if there are not enough endeavours for industrial plants.

There are some limitations due to the assumptions we made in this paper. Firstly, the more perplex capacitated disassembly scheduling problem with multi-level structure can be studied to portray a more realistic industrial application. Secondly, other random factors or detail uncertainties are also of great significance for further study, such as the lead time, defective parts or uncertain arrivals of EOL products. Thirdly, other accurate algorithms can be designed based on the characteristics of the novel disassembly scenarios, as well as the intelligence-based algorithms.

Disclosure statement

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References

Barba-Gutiérrez, Y., Adenso-Diaz, B., & Gupta, S. M. (2008). Lot sizing in reverse MRP for scheduling disassembly. *International Journal of Production Economics*, *111*(2), 741–751. https://doi.org/10.1016/j.ijpe.2007.03.017

Bentaha, M. L., Battaïa, O., & Dolgui, A. (2015). An exact solution approach for disassembly line balancing problem under uncertainty of the task processing times. *International Journal of Production Research*, *53*(6), 1807–1818. https://doi.org/10.1080/00207543.2014.961212

Berzi, L., Delogu, M., Pierini, M., & Romoli, F. (2016). Evaluation of the end-of-life performance of a hybrid scooter with the application of recyclability and recoverability assessment methods. *Resources, Conservation and Recycling*, *108*, 140–155. https://doi.org/10.1016/j.resconrec.2016.01.013

Bollapragada, R., Kuppusamy, S., & Rao, U. S. (2015). Component procurement and end product assembly in an uncertain supply and demand environment. *International Journal of Production Research*, *53*(3), 969–982. https://doi.org/10.1080/00207543.2014.951522

Cai, W., Lai, K-h., Liu, C., Wei, F., Ma, M., Jia, S., Jiang, Z., & Lv, L. (2019). Promoting sustainability of manufacturing industry through the lean energy-saving and emission-reduction strategy. *Science of the Total Environment*, *665*, 23–32. https://doi.org/10.1016/j.scitotenv.2019.02.069

Cesaret, B., Oğuz, C., & Salman, F. S. (2012). A tabu search algorithm for order acceptance and scheduling. *Computers & Operations Research*, *39*(6), 1197–1205. https://doi.org/10.1016/j.cor.2010.09.018

D'Adamo, I., & Rosa, P. (2016). Remanufacturing in industry: Advices from the field. *International Journal of Advanced Manufacturing Technology*, *86*, 2575–2584. https://doi.org/10.1007/s00170-016-8346-5.

Dao, S. D., Abhary, K., Marian, R., & Goh, M. (2019). Optimisation of production scheduling for multi-product orders in VCIM systems using. *Soft Computing*, *23*(20), 10199–10224. https://doi.org/10.1007/s00500-018-3578-y

Disney, S. M., Gaalman, G. J. C., Hedenstierna, C. P. T., & Hosoda, T. (2015). Fill rate in a periodic review order-up-to policy under auto-correlated normally distributed, possibly negative, demand. *International Journal of Production Economics*, *170*, 501–512. https://doi.org/10.1016/j.ijpe.2015.07.019

Ehm, F. (2019). A data-driven modeling approach for integrated disassembly planning and scheduling. *Journal of Remanufacturing*, *9*(2), 89–107. https://doi.org/10.1007/s13243-018-0058-6

Feng, Y., Zhou, M., Tian, G., Li, Z., Zhang, Z., Zhang, Q., & Tan, J. (2019). Target disassembly sequencing and scheme evaluation for CNC machine tools using improved multiobjective ant colony algorithm and fuzzy integral. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *49*(12), 2438–2451. https://doi.org/10.1109/TSMC.2018.2847448

Ferrenberg, A. M., Xu, J., & Landau, D. P. (2018). Pushing the limits of Monte Carlo simulations for the three-dimensional Ising model. *Physical Review. E*, *97*(4-1), 043301. https://doi.org/10.1103/PhysRevE.97.043301

Fleischmann, M., Bloemhof-Ruwaard, J. M., Dekker, R., van der Laan, E., van Nunen, J. A. E. E., & Van Wassenhove, L. N. (1997). Quantitative models for reverse logistics: A review. *European Journal of Operational Research*, *103*(1), 1–17. https://doi.org/10.1016/S0377-2217(97)00230-0

Fu, Y., Zhou, M. C., Guo, X., & Qi, L. (2019). Scheduling dual-objective stochastic hybrid flow shop with deteriorating jobs via bi-population evolutionary algorithm. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *50*(12), 5037–5048. https://doi.org/10.1109/TSMC.2019.2907575

Gao, K. Z., He, Z. M., Huang, Y., Duan, P. Y., & Suganthan, P. N. (2020). A survey on meta-heuristics for solving disassembly line balancing, planning and scheduling problems in remanufacturing. *Swarm and Evolutionary Computation*, *57*, 100719. https://doi.org/10.1016/j.swevo.2020.100719

Go, T. F., Wahab, D. A., Rahman, M. N. A., Ramli, R., & Azhari, C. H. (2011). Disassemblability of end-of-life vehicle: A critical review of evaluation methods. *Journal of Cleaner Production*, *19*(13), 1536–1546. https://doi.org/10.1016/j.jclepro.2011.05.003

Godichaud, M., & Amodeo, L. (2018). Economic order quantity for multistage disassembly systems. *International Journal of Production Economics*, *199*, 16–25. https://doi.org/10.1016/j.ijpe.2018.02.008

Godichaud, M., Tchangani, A., Pérès, F., & Iung, B. (2012). Sustainable management of end-of-life systems. *Production Planning & Control*, *23*(2-3), 216–236. https://doi.org/10.1080/09537287.2011.591656

Guijarro, E., Cardós, M., & Babiloni, E. (2012). On the exact calculation of the fill rate in a periodic review inventory policy under discrete demand patterns. *European Journal of Operational Research*, *218*(2), 442–447. https://doi.org/10.1016/j.ejor.2011.11.025

Guo, X., & Liu, S. (2014). A scatter search approach for multiobjective selective disassembly sequence problem. *Discrete Dynamics in Nature and Society*, *2014*, 1–9. https://doi.org/10.1155/2014/756891

Guo, X., Zhou, M., Liu, S., & Qi, L. (2020). Lexicographic multiobjective scatter search for the optimization of sequence-dependent selective disassembly subject to multiresource constraints. *IEEE Transactions on Cybernetics*, *50*(7), 3307–3317. https://doi.org/10.1109/TCYB.2019.2901834

Guo, X., Zhou, M. C., Liu, S., & Qi, L. (2021). Multiresource-constrained selective disassembly with maximal profit and minimal energy consumption. *IEEE Transactions on Automation Science and Engineering*, *18*(2), 804–816. https://doi.org/10.1109/TASE.2020.2992220

Gupta, S., & Taleb, K. (1994). Scheduling disassembly. *International Journal of Production Research*, *32*(8), 1857–1866. https://doi.org/10.1080/00207549408957046

Hecker, F. T., Stanke, M., Becker, T., & Hitzmann, B. (2014). Application of a modified GA, ACO and a random search procedure to solve the production scheduling of a case study bakery. *Expert Systems with Applications*, *41*(13), 5882–5891. https://doi.org/10.1016/j.eswa.2014.03.047

Inderfurth, K., & Langella, I. M. (2006). Heuristics for solving disassemble-to-order problems with stochastic yields. *OR Spectrum*, *28*(1), 73–99. https://doi.org/10.1007/s00291-005-0007-2

Jaehn, F. (2016). Sustainable Operations. *European Journal of Operational Research*, *253*(2), 243–264. https://doi.org/10.1016/j.ejor.2016.02.046

Ji, X., Zhang, Z., Huang, S., & Li, L. (2016). Capacitated disassembly scheduling with parts commonality and start-up cost and its industrial application. *International Journal of Production Research*, *54*(4), 1225–1243. https://doi.org/10.1080/00207543.2015.1058536

Jia, S., Yuan, Q., Cai, W., Li, M., & Li, Z. (2018). Energy modeling method of machine-operator system for sustainable machining. *Energy Conversion and Management*, *172*, 265–276. https://doi.org/10.1016/j.enconman.2018.07.030

Kadri, R. L., & Boctor, F. F. (2018). An efficient genetic algorithm to solve the resource-constrained project scheduling problem with transfer times: The single mode case. *European Journal of Operational Research*, *265*(2), 454–462. https://doi.org/10.1016/j.ejor.2017.07.027

Karmarkar, U. S. (1987). Lot sizes, lead times and in-process inventories. *Management Science*, *33*(3), 409–418. https://doi.org/10.1287/mnsc.33.3.409

Kim, H.-J., Lee, D.-H., & Xirouchakis, P. (2007). Disassembly scheduling: Literature review and future research directions. *International Journal of Production Research*, *45*(18-19), 4465–4484. https://doi.org/10.1080/00207540701440097

Kim, H.-J., & Xirouchakis, P. (2010). Capacitated disassembly scheduling with random demand. *International Journal of Production Research*, *48*(23), 7177–7194. https://doi.org/10.1080/00207540903469035

Kim, H.-J., Lee, D.-H., Xirouchakis, P., & Kwon, O. K. (2009). A branch and bound algorithm for disassembly scheduling with assembly product structure. *Journal of the Operational Research Society*, *60*(3), 419–430. https://doi.org/10.1057/palgrave.jors.2602568

Kim, H. J., Lee, D. H., Xirouchakis, P., & Züst, R. (2003). Disassembly scheduling with multiple product types. *CIRP Annals*, *52*(1), 403–406. https://doi.org/10.1016/S0007-8506(07)60611-8

Kongar, E., & Gupta, S. M. (2006). Disassembly to order system under uncertainty. *Omega*, *34*(6), 550–561. https://doi.org/10.1016/j.omega.2005.01.006

Lee, D.-H., & Xirouchakis, P. (2004). A two-stage heuristic for disassembly scheduling with assembly product structure. *Journal of the Operational Research Society*, *55*(3), 287–297. https://doi.org/10.1057/palgrave.jors.2601690

Lee, D. H., Xirouchakis, P., & Zust, R. (2002). Disassembly scheduling with capacity constraints. *CIRP Annals*, *51*(1), 387–390. https://doi.org/10.1016/S0007-8506(07)61543-1

Li, B., Krushinsky, D., Van Woensel, T., & Reijers, H. A. (2016). The Share-a-Ride problem with stochastic travel times and stochastic delivery locations. *Transportation Research Part C: Emerging Technologies*, *67*, 95–108. https://doi.org/10.1016/j.trc.2016.01.014

Li, M., Yao, L., Yang, J., & Wang, Z. (2015). Due date assignment and dynamic scheduling of one-of-a-kind assembly production with uncertain processing time. *International Journal of Computer Integrated Manufacturing*, *28*(6), 616–627. https://doi.org/10.1080/0951192X.2014.900859

Liao, C. J., & Shyu, C. H. (1991). An analytical determination of lead time with normal demand. *International Journal of Operations & Production Management*, *11*(9), 72–78. https://doi.org/10.1108/EUM0000000001287

Liu, J., Xu, W., Zhou, Z., & Pham, D. T. (2020). Scheduling of robotic disassembly in remanufacturing using Bees algorithms. In A. H. Gandomi, A. Emrouznejad, M. M. Jamshidi, K. Deb, & I. Rahimi (eds.), *Evolutionary Computation in Scheduling* (pp. 257–298). John Wiley & Sons, Inc. https://doi.org/10.1002/9781119574293.ch9.

Liu, K., & Zhang, Z. H. (2018). Capacitated disassembly scheduling under stochastic yield and demand. *European Journal of Operational Research*, *269*(1), 244–257. https://doi.org/10.1016/j.ejor.2017.08.032

Liu, Q., Dong, M., Chen, F., Lv, W., & Ye, C. (2019). Single-machine-based joint optimization of predictive maintenance planning and production scheduling.

Robotics and Computer-Integrated Manufacturing, *55*, 173–182. https://doi.org/10.1016/j.rcim.2018.09.007

Ojstersek, R., Brezocnik, M., & Buchmeister, B. (2020). Multi-objective optimization of production scheduling with evolutionary computation: A review. *International Journal of Industrial Engineering Computations*, *11*(3), 359–376. https://doi.org/10.5267/j.ijiec.2020.1.003

Prakash, P., Ceglarek, D., & Tiwari, M. K. (2012). Constraint-based simulated annealing (CBSA) approach to solve the disassembly scheduling problem. *The International Journal of Advanced Manufacturing Technology*, *60*(9-12), 1125–1137. https://doi.org/10.1007/s00170-011-3670-2

Rossi, R., Kilic, O. A., & Tarim, S. A. (2015). Piecewise linear approximations for the static–dynamic uncertainty strategy in stochastic lot-sizing. *Omega*, *50*, 126–140. https://doi.org/10.1016/j.omega.2014.08.003

Senécal, R., & Dimitrakopoulos, R. (2020). Long-term mine production scheduling with multiple processing destinations under mineral supply uncertainty, based on multi-neighbourhood Tabu search. *International Journal of Mining, Reclamation and Environment*, *34*(7), 459–475. https://doi.org/10.1080/17480930.2019.1595902

Shi, F., Zhao, S., & Meng, Y. (2020). Hybrid algorithm based on improved extended shifting bottleneck procedure and GA for assembly job shop scheduling problem. *International Journal of Production Research*, *58*(9), 2604–2625. https://doi.org/10.1080/00207543.2019.1622052

Silver, E. A., & Bischak, D. P. (2011). The exact fill rate in a periodic review base stock system under normally distributed demand. *Omega*, *39*(3), 346–349. https://doi.org/10.1016/j.omega.2010.08.003

Song, J.-S., Yano, C. A., & Lerssrisuriya, P. (2000). Contract assembly: Dealing with combined supply lead time and demand quantity uncertainty. *Manufacturing & Service Operations Management*, *2*(3), 287–296. https://doi.org/10.1287/msom.2.3.287.12346

Taleb, K. N., & Gupta, S. M. (1997). Disassembly of multiple product structures. *Computers & Industrial Engineering*, *32*(4), 949–961. https://doi.org/10.1016/S0360-8352(97)00023-5

Taleb, K. N., Gupta, S. M., & Brennan, L. (1997). Disassembly of complex product structures with parts and materials commonality. *Production Planning & Control*, *8*(3), 255–269. https://doi.org/10.1080/095372897235316

Taş, D., Gendreau, M., Jabali, O., & Jans, R. (2019). A capacitated lot sizing problem with stochastic setup times and overtime. *European Journal of Operational Research*, *273*(1), 146–159. https://doi.org/10.1016/j.ejor.2018.07.032

Tempelmeier, H. (2011). A column generation heuristic for dynamic capacitated lot sizing with random demand under a fill rate constraint. *Omega*, *39*(6), 627–633. https://doi.org/10.1016/j.omega.2011.01.003

Tian, G., Ren, Y., Feng, Y., Zhou, M. C., Zhang, H., & Tan, J. (2019). Modeling and planning for dual-objective selective disassembly using and/or graph and discrete artificial Bee colony. *IEEE Transactions on Industrial Informatics*, *15*(4), 2456–2468. https://doi.org/10.1109/TII.2018.2884845

Tian, X., & Zhang, Z.-H. (2019). Capacitated disassembly scheduling and pricing of returned products with price-dependent yield. *Omega*, *84*, 160–174. https://doi.org/10.1016/j.omega.2018.04.010

Ullerich, C., & Buscher, U. (2013). Flexible disassembly planning considering product conditions. *International Journal of Production Research*, *51*(20), 6209–6228. https://doi.org/10.1080/00207543.2013.825406

Vahdani, B., Soltani, M., Yazdani, M., & Mousavi, S. M. (2017). A three level joint location-inventory problem with correlated demand, shortages and periodic review system: Robust meta-heuristics. *Computers & Industrial Engineering*, *109*, 113–129. https://doi.org/10.1016/j.cie.2017.04.041

Wang, Y., & Gerchak, Y. (2003). Capacity games in assembly systems with uncertain demand. *Manufacturing & Service Operations Management*, *5*(3), 252–267. https://doi.org/10.1287/msom.5.3.252.16030

Xiao, S., Dong, H., Geng, Y., & Brander, M. (2018). An overview of China's recyclable waste recycling and recommendations for integrated solutions. *Resources Conservation & Recycling*, *134*, 112–120. https://doi.org/10.1016/j.resconrec.2018.02.032

Zhou, F., Lim, M. K., He, Y., Lin, Y., & Chen, S. (2019). End-of-life vehicle (ELV) recycling management: Improving performance using an ISM approach. *Journal of Cleaner Production*, *228*, 231–243. https://doi.org/10.1016/j.jclepro.2019.04.182

Zhou, F., Lim, M. K., He, Y., & Pratap, S. (2019). What attracts vehicle consumers' buying A Saaty scale-based VIKOR (SSC-VIKOR) approach from after-sales textual perspective? *Industrial Management & Data Systems*, *120*(1), 57–78. https://doi.org/10.1108/IMDS-01-2019-0034

Zhou, F., Lin, Y., Wang, X., Zhou, L., & He, Y. (2016). ELV recycling service provider selection using the hybrid MCDM method: A case application in China. *Sustainability*, *8*(5), 482–496. https://doi.org/10.3390/su8050482

Zhou, F., & Ma, P. (2019). End-of-life vehicle (ELV) recycling management practice based on 4R procedure. In: *6th IEEE International Conference on Industrial Engineering and Applications, ICIEA 2019, April 12, 2019 - April 15, 2019* (pp. 230–234). Institute of Electrical and Electronics Engineers Inc.

Zhou, F., Ma, P., He, Y., Pratap, S., Yu, P., & Yang, B. (2020). Lean production of ship-pipe parts based on lot-sizing optimization and PFB control strategy. *Kybernetes* (ahead-of-print). https://doi.org/10.1108/K-06-2019-0389

Zhou, F., Wang, X., Goh, M., Zhou, L., & He, Y. (2019). Supplier portfolio of key outsourcing parts selection using a two-stage decision making framework for Chinese domestic auto-maker. *Computers & Industrial Engineering*, *128*, 559–575. https://doi.org/10.1016/j.cie.2018.12.014

Zhou, F., Wang, X., Lim, M. K., He, Y., & Li, L. (2018). Sustainable recycling partner selection using fuzzy DEMATEL-AEW-FVIKOR: A case study in small-and-medium enterprises (SMEs). *Journal of Cleaner Production*, *196*, 489–504. https://doi.org/10.1016/j.jclepro.2018.05.247

Zhou, F. L., Wang, X., He, Y. D., & Goh, M. (2017). Production lot-sizing decision making considering bottleneck drift in multi-stage manufacturing system. *Advances in Production Engineering & Management*, *12*(3), 213–220. https://doi.org/10.14743/apem2017.3.252

Zhou, L., Baldacci, R., Vigo, D., & Wang, X. (2018). A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution. *European Journal of Operational Research*, *265*(2), 765–778. https://doi.org/10.1016/j.ejor.2017.08.011

Zhou, L., Lin, Y., Wang, X., & Zhou, F. (2019). Model and algorithm for bilevel multisized terminal location-routing problem for the last mile delivery. *International Transactions in Operational Research*, *26*(1), 131–156. https://doi.org/10.1111/itor.12399

Zussman, E., & Zhou, M. (1999). A methodology for modeling and adaptive planning of disassembly processes. *IEEE Transactions on Robotics and Automation*, *15*(1), 190–194. https://doi.org/10.1109/70.744614