International Journal of Production Research

ISSN: 0020-7543 (Print) 1366-588X (Online) Journal homepage: www.tandfonline.com/journals/tprs20

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To cite this article: Ming Liu, Xin Liu, Feng Chu, Feifeng Zheng & Chengbin Chu (2020) Robust disassembly line balancing with ambiguous task processing times, International Journal of Production Research, 58:19, 5806-5835, DOI: 10.1080/00207543.2019.1659520

To link to this article: https://doi.org/10.1080/00207543.2019.1659520

International Journal of Production Research, 2020
Vol. 58, No. 19, 5806–5835, https://doi.org/10.1080/00207543.2019.1659520

Robust disassembly line balancing with ambiguous task processing times

Ming Liu[a], Xin Liu[a], Feng Chu[b,c*], Feifeng Zheng[d] and Chengbin Chu[e,f]

[a]*School of Economics & Management, Tongji University, Shanghai, People's Republic of China;* [b]*School of Economics and Management, Fuzhou University, Fuzhou, People's Republic of China;* [c]*IBISC, Univ Évry, University of Paris-Saclay, Évry, France;* [d]*Glorious Sun School of Business & Management, Donghua University, Shanghai, People's Republic of China;* [e]*ESIEE Paris, Université Paris-Est, Noisy-le-Grand Cedex 93162, France;* [f]*Université Paris-Est, Laboratoire d'Informatique Gaspard-Monge UMR8049, UPEMLV, ESIEE Paris, ENPC, CNRS, 93162 Noisy-le-Grand Cedex, France*

(*Received 10 October 2018; accepted 12 August 2019*)

Disassembly line balancing problem (DLBP), which is to select disassembly process, open workstations and assign selected tasks to opened workstations, plays an important role in the recycling of End Of Life products. In real-world disassembly operations, task processing times are usually stochastic due to various factors. Most related works address the uncertain processing times by assuming that the probability distribution is known and the task processing times are independent of each other. In practice, however, it is difficult to get the complete distributional information and there is always underlying correlation between the uncertain processing times. This paper investigates the DLBP with partial uncertain knowledge, i.e. the mean and covariance matrix of task processing times. A new distributionally robust formulation with a joint chance constraint is proposed. To solve the problem, an approximated mixed integer second-order cone programming (MI-SOCP) model is proposed, and a two-stage parameter-adjusting heuristic is further developed. Numerical experiments are conducted, to evaluate the performance of the proposed method. We also draw some managerial insights and consider an extension problem.

Keywords: disassembly line; stochastic optimisation; correlated task processing time; robust; uncertainty

1. Introduction

Recycling End of Life (EOL) products, which mainly includes the collecting, disassembling, remanufacturing, storing and disposal of EOL products (Ilgin and Gupta 2010), can realise the reuse of resources, saving energy and reducing emissions as well. Higher requirement on environmental protection and resource reutilisation is put forward, and recycling industry is becoming emphasised (Tian et al. 2017; Tian, Zhou, and Li 2018b). Disassembly process, which plays an important role in EOL product recycling, is to decompose an EOL product into components, subassemblies and other subgroups (Moore, Güngör, and Gupta 2001). Thus it is crucial that disassembly line is well designed and balanced, such that the system cost is minimised or the profit is maximised. The disassembly line design is called the disassembly line balancing problem (DLBP). There have been many works addressing the DLBP since it is first introduced by Gupta and Güngör (1999).

Early studies mainly focus on deterministic DLBPs (Güngör and Gupta 2001; Mcgovern and Gupta 2007; Altekin, Kandiller, and Ozdemirel 2008). However, the decomposition tasks have the following features: (i) the types of EOL products are not constant, (ii) the shapes of EOL products may vary, (iii) the production environment, which is not constant, greatly affects the productivity (Bentaha, Battaïa, and Dolgui 2015a). Therefore, the task processing times are often uncertain and studying stochastic DLBP is more realistic due to the above characteristics.

Most existing works investigate stochastic DLBPs by assuming that the probability distribution of uncertain parameters can be obtained (Bentaha, Battaïa, and Dolgui 2014b, 2014a; Bentaha, Dolgui, and Battaïa 2015c; Bentaha et al. 2018). Nevertheless, according to Wagner (2008) and Delage and Ye (2010), the complete information on uncertainties is not always available or cannot be fully estimated due to the lack or the poor quality of historical data. For example, the renewal and regeneration of electronic products is rapid and accelerating, and the probability distribution of task processing times cannot be well estimated due to that the historical data are very sparse and not representative. The number of researches studying stochastic DLBP with partial distributional information is very rare (Zheng et al. 2018).

Besides, most related researches usually assume that the task processing times are independent of each other. However, in practice, there is usually underlying correlations (Agrawal et al. 2012), such as that (i) unpredicted damage caused by the

*Corresponding author. Email: feng.chu@univ-evry.fr

previous task may prolong or shorten the processing time of the next task, and (ii) for different tasks, manual processing effectiveness and motivation may influence task processing times. Ignoring the underlying correlations may lead to great loss in practice. For example, if two tasks with large positive correlation between their processing times are assigned to one workstation, the operating time of the workstation may fluctuate largely, leading to the decrease in solution quality. Motivated by the above observation, this work investigates a stochastic DLBP with only partial distributional information, i.e. the mean and covariance matrix of task processing times. For the problem, we introduce a new formulation with joint chance constraint, and develop a two-stage parameter-adjusting heuristic as solution method. The contribution of this work mainly includes:

(1) Differing from Zheng et al. (2018) that assumes the independence between task processing times, this paper studies a new stochastic disassembly line balancing problem with correlated task processing times, in which only partial distributional information (i.e. the mean and covariance matrix) is known.
(2) For the problem, a distributionally robust joint chance-constrained formulation is proposed. Since it is intractable to directly solve the joint chance-constrained programmes, an approximated mixed integer second-order cone programming (MI-SOCP) formulation is then developed.
(3) To efficiently solve the problem, a two-stage parameter-adjusting heuristic is developed, in which the first stage decides the number of workstations and adjusts the parameters and the second stage determines the task-to-workstation assignment.
(4) We also consider the extension problem, by considering the multiple product types and integrating the workstation-to-product-type assignment with the disassembly line balancing, and propose a new distributionally robust formulation.

Numerical experiments on instances with different scales are conducted, to evaluate the performance of the proposed heuristic. Sensitivity analyses have been conducted to analyse the impact of different parameters, i.e. the preset risk level α, the standard deviation, the correlation coefficients of tasks with precedence relation and the cycle time.

The remainder of this paper is organised as follows. Section 2 gives a brief literature review. In Section 3, problem description is given and a new distributionally robust model is proposed. In Section 4, a two-stage parameter-adjusting heuristic is developed. Computational results are reported and analysed in Section 5. Section 6 provides an extension of the model and Section 7 summarises this work and suggests future research directions.

2. Literature review

The deterministic DLBP has been well investigated in literature (Güngör and Gupta 2002; Habibi et al. 2016; Ilgin, Akçay, and Araz 2017; Ren et al. 2017; Mete et al. 2018; Tian et al. 2018a; Fang et al. 2019; Li et al. 2019). Since our study falls within the scope of stochastic DLBP, in the following, we first review existing researches on DLBP and robust approaches in the assembly line balancing problem (ALBP). Then we review the literature investigating the solution approaches for stochastic optimisation problems with ambiguous uncertainty sets.

2.1. DLBP with uncertain task times

DLBP with stochastic task processing times has been investigated by many researchers (Özceylan et al. 2018). Most existing works handle the uncertainty with known probability distribution and under the assumption that the task processing times are independent.

Agrawal and Tiwari (2008) study an U-shaped DLBP with normally distributed task processing times, and develop a collaborative ant colony optimisation approach. Bentaha, Battaïa, and Dolgui (2012) investigate a stochastic DLBP with known probability distributions of task processing times to minimise the cost, and propose a stochastic linear mixed integer programming formulation. Bentaha, Battaïa, and Dolgui (2013b) consider a stochastic DLBP with normally distributed task processing times to minimise the system cost, and propose an L-shaped algorithm. Aydemir-Karadag and Turkbey (2013) investigate a multi-objective stochastic DLBP with parallel stations and known probability distributions of task processing times, to optimise the line balance and design costs simultaneously. Genetic algorithm (GA) is proposed to obtain Pareto-optimal solutions. Bentaha, Battaïa, and Dolgui (2014b) consider a stochastic DLBP with known probability distributions of uncertain task processing times, to minimise the total line cost. An SAA based mixed integer programming (MIP) model is proposed, and the L-shaped algorithm is then developed. Bentaha et al. (2014c) study a stochastic DLBP with known probability distributions of task processing times, to maximise the system profit. An SAA based MIP formulation is established. Bentaha, Battaïa, and Dolgui (2015a) investigate a stochastic DLBP with hazardous components and normally distributed task processing times, to minimise the workstation operation cost and cost for workstations handling hazardous components.

An MIP formulation with a joint probabilistic constraint is proposed, and lower and upper-bounding schemes to approximately solve the problem are developed. Bentaha et al. (2015b) consider a stochastic DLBP with hazardous components and normally distributed task processing times, to maximise the revenue with balanced workload. An MIP formulation with a joint chance constraint is proposed, and a second-order conic approximation is proposed. Various lower and upper-bounding schemes are proposed to approximately solve the problem. Altekin, Bayndr, and Gümüşkaya (2016) investigate a stochastic DLBP with normally distributed task processing times, to maximise the expected profit. An MIP formulation and a full enumeration scheme are proposed. Altekin (2017) considers a stochastic DLBP with normally distributed processing times, to minimise the number of opened stations. Five piecewise linear MIP models are evaluated and compared.

Zheng et al. (2018) investigate a stochastic DLBP with hazardous components, and task processing times are regarded to be uncertain and only partial distributional information is known beforehand, i.e. the mean, standard deviation and upper bounds of task processing times. Besides, in their paper, it is assumed that the task processing times are independent from each other. They propose a new decomposition colour graph to describe possible disassembly processes, and construct a distribution-free model with a joint chance constraint for the problem. Differing from Zheng et al. (2018), this work (i) considers that the task times are correlated, (ii) assumes that only the mean and covariance matrix of task times are known, and (iii) investigates an extension problem, by considering the multiple product types and integrating the workstation-to-product-type assignment with the disassembly line balancing.

2.2. Robust approaches in the ALBP

As ALBP is related to DLBP, in this part we review the robust approaches in the ALBP. Most existing works considering the robust ALBP focus on the min–max relative regret optimisation or finding robust solutions that perform well under all possible scenarios (Battaïa and Dolgui 2013).

Xu and Xiao (2009) consider a mixed ALBP with uncertain task processing times, to optimise the min–max related robust criteria and an α-worst scenario based robust criteria. Xu and Xiao (2011) study the robust ALBP and propose a lexicographic-order on the α-worst scenario. Dolgui and Kovalev (2012) consider a robust line balancing problem with uncertain task times belonging to a given set of scenarios, to minimise the cycle time, i.e. the maximal total execution time of the same station, for the worst scenario. They prove that several special cases are strongly NP-hard. Chica et al. (2013) define a set of scenarios and propose new robustness functions, which are based on the stations overload uncertain demand and are used as a posteriori information for the non-dominated solutions. HazıR and Dolgui (2013) investigate an ALBP with given interval of task processing times, to minimise the cycle time, i.e. the maximum of station times. From the risk-averse perspective, two robust minmax optimisation formulations considering extreme cases are proposed, and a decomposition based algorithm is then developed. Moreira et al. (2015) study a robust ALBP with uncertain task processing times, in which the task times are worker-dependent and within given intervals. The objective is to minimise the number of stations, and a desired robust measure is respected by controlling a budget of uncertainty for each worker. They propose two MIP formulations and a constructive heuristic. Chica et al. (2016) investigate a robust time and space assembly line balancing problem with uncertain demand. They propose a multiobjective formulation by considering a set of demand scenarios, and develop two multiobjective evolutionary algorithms.

2.3. Distributionally robust approaches

Literature, considering the stochastic optimisation programmes with correlated uncertain parameters under partial known probability distribution, usually focuses on developing distributionally robust stochastic programming models (Wagner 2008; Agrawal et al. 2012). Most existing works investigate the distributionally robust approach via addressing (i) chance constraints to handle marginal distributions and (ii) joint chance constraint to handle the correlation between stochastic variables (Hanasusanto et al. 2015).

Wagner (2008) considers a general stochastic optimisation problem with chance constraint under unknown probability. Given different partial distributional information, different approximated formulations are developed. Delage and Ye (2010) propose a new ambiguous set that is assumed to include the true underlying probability distributions of uncertain variables, by considering the inevitable estimation errors of mean and covariance matrix. A new approximation method is proposed for the chance constraint in the data-driven settings. Jiang and Guan (2016) study data-driven stochastic programmes with distributionally robust chance constraints (DCCs). Two confidence sets for the ambiguous distribution are constructed, namely the moment-based and density-based confidence sets. An approximated reformulation for DCCs is derived. Zhang, Shen, and Erdogan (2017) investigate the allocation of surgery blocks to operating rooms under uncertain surgery durations, under mean and covariance matrix of surgery durations known. A 0–1 SOCP approximation is developed for the problem.

There have been various researches considering distributionally robust joint chance constraint, which requires all the constraints satisfied with a least probability. Chen et al. (2010) propose a general approach to address joint chance-constrained optimisation problems, which is based on Bonferroni's inequality. Chung, Yao, and Zhang (2012) consider transportation planning and operations under uncertain demand with partial distributional information. An approximated formulation based on Bonferroni's inequality to the joint chance-constrained formulation is proposed. Zymler, Kuhn, and Rustem (2013) study the distributionally robust joint chance constraint under partial distribution information. Tractable semidefinite programming based approximations for the joint chance constraint are proposed. Sun et al. (2014) develop a new distributionally robust joint chance-constrained optimisation model for a dynamic network design problem under demand uncertainty.

To the best of our knowledge, concluding, there is no result for the stochastic DLBP with only mean and covariance matrix of task processing times, where the processing times of different tasks are correlated.

3. Problem description and formulation

In this section, we first give the problem description and then construct an ambiguity set to portray the partial known distribution, then propose a new distributionally robust joint chance-constrained formulation for the problem.

3.1. Problem description

The DLBP aims at determining one disassembly process for the EOL products and assigning the disassembly tasks to workstations with given sequence. This work addresses a new stochastic DLBP with only partial distributional knowledge, and assumes that there is correlation between the processing times of different tasks.

To better describe the problem, an example of compass separation process (Bentaha, Battaïa, and Dolgui 2014b) is given and illustrated in Figure 1: a compass can be disassembled into seven components, i.e. wheel, left leg, right leg, left fixation screw, lead, tip and right fixation screw. Following Zheng et al. (2018), a decomposition colour graph, which is adapted from the AND/OR graph in Lambert (1999), Koc, Sabuncuoglu, and Erel (2009) and Bentaha, Battaïa, and Dolgui (2014b), is applied to characterise the example (see Figure 2). There are three possible disassembly processes coloured in red, blue and purple, respectively. In the decomposition colour graph $G = (V, A)$, a vertex of type $\square$ denotes a status or subassembly, and a vertex of type $\bigcirc$ implies a disassembly task. $S = \{\square\}$ and $T = \{\bigcirc\}$ are used to denote the set of statuses and the set of tasks, respectively. In particular, the source vertex of the graph S_0 denotes the beginning status of an EOL product, and S_6 denotes the status with all required separated components disassembled. Note that one task can be a candidate for different disassembly process, for example, task T_8 in Figure 2 is included in disassembly process 1 (coloured in red) and disassembly process 2 (coloured in blue). Cycle time constraint restricts that the total processing time of tasks processed on one workstation cannot exceed given cycle time (Battaïa and Dolgui 2013).

The problem is to determine the opened workstations, the disassemble process and the assignment of disassembly task such that (1) the precedence constraints of tasks should be satisfied, (2) one workstation can process more than one tasks, (3) only one disassembly process is finalised, (4) the workstations are in an ordered sequence.

3.2. Ambiguity set

It is difficult to access the exact probability of task processing times, thus under the partial known distributional information (i.e. the mean and covariance matrix), an ambiguity set is applied to characterise the possible probability distributions (Delage and Ye 2010). Given a set of samples of independent historical task processing times $\{\boldsymbol{t}^r\}_{r=1}^{|R|}$, where $\boldsymbol{t}^r = [t_1^r, t_2^r, \ldots, t_{|T|}^r]^\mathsf{T}$ denotes the task processing time vector and R denotes the set of samples indexed by r. The empirical value of the mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ of task processing times can be estimated as

$$\boldsymbol{\mu} = \frac{1}{|R|}\sum_{r=1}^{|R|}\boldsymbol{t}^r, \quad \boldsymbol{\Sigma} = \frac{1}{|R|}\sum_{r=1}^{|R|}(\boldsymbol{t}^r - \boldsymbol{\mu}) \cdot (\boldsymbol{t}^r - \boldsymbol{\mu})^\mathsf{T},$$

where $(\cdot)^\mathsf{T}$ denotes the transposition of the vector in parentheses. According to Delage and Ye (2010), the ambiguity set of all possible probability distributions of task processing times, i.e. $\mathcal{P}(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \gamma_1, \gamma_2)$, can be described as

$$\mathcal{P}(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \gamma_1, \gamma_2) = \left\{\mathbb{P} : \begin{array}{c} (\mathbb{E}_\mathbb{P}[\boldsymbol{t}] - \boldsymbol{\mu})^\mathsf{T}\boldsymbol{\Sigma}^{-1}(\mathbb{E}_\mathbb{P}[\boldsymbol{t}] - \boldsymbol{\mu}) \le \gamma_1, \\ \mathbb{E}_\mathbb{P}[(\boldsymbol{t} - \boldsymbol{\mu})(\boldsymbol{t} - \boldsymbol{\mu})^\mathsf{T}] \preceq \gamma_2\boldsymbol{\Sigma} \end{array}\right\},$$

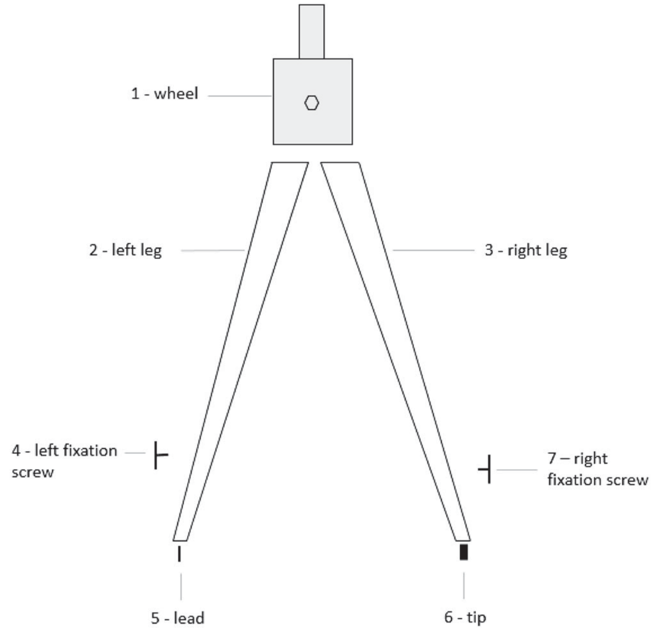

Figure 1. A compass example (Bentaha, Battaïa, and Dolgui 2014b).

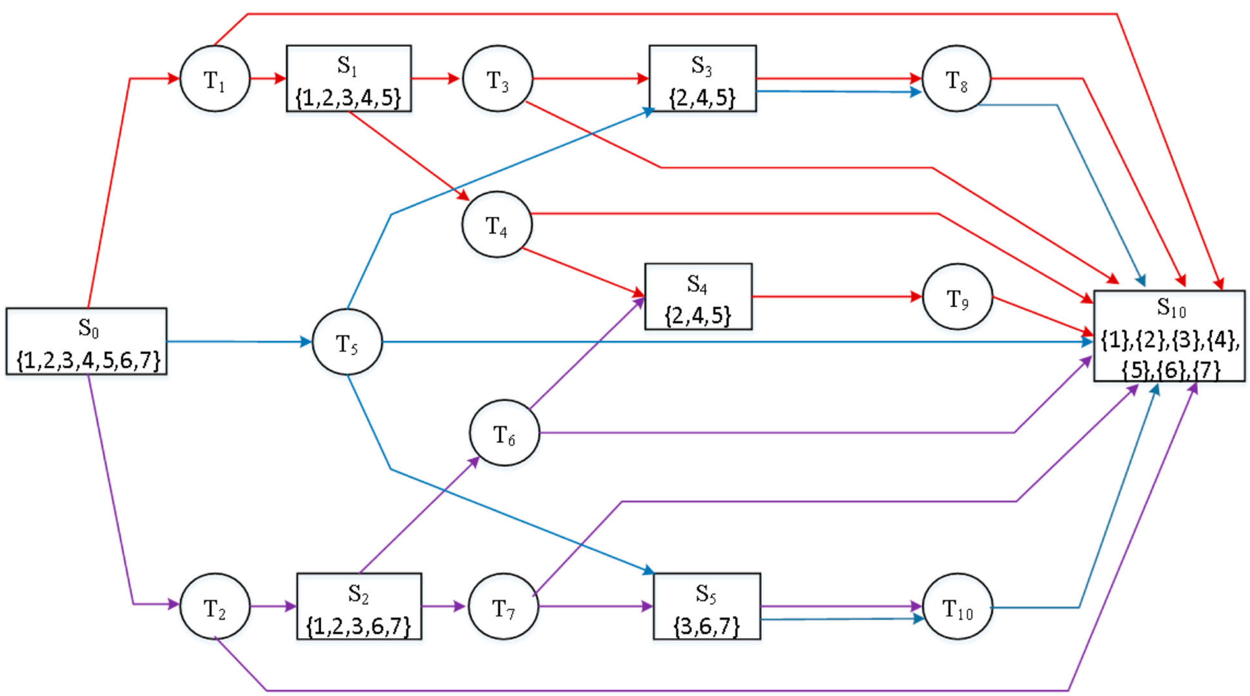

Figure 2. The decomposition colour graph of compass disassembly process (Bentaha, Battaïa, and Dolgui 2014b).

where $\gamma_1 \geq 0$ and $\gamma_2 \geq 0$ are two parameters of ambiguity set $\mathcal{P}(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \gamma_1, \gamma_2)$, restricting that (i) the true mean vector of task processing times lies in an ellipsoid of radius γ_1 centred at $\boldsymbol{\mu}$, and (ii) the true covariance of task processing times is in a positive semi-definite cone bounded by $\gamma_2 \boldsymbol{\Sigma}$.

A risk level α is introduced and predetermined by the decision makers, which is the maximum probability of not meeting all cycle time constraints. In the following, x_{ij} is a binary variable, which is equal to 1 if task $i \in T$ is assigned to workstation $j \in J$, and t_i is an uncertain parameter denoting the processing time of task $i \in T$ and C represents the cycle time. Then a joint chance constraint ensuring a least probability $1-\alpha$ of all cycle time constraints jointly satisfied is introduced as

$$\inf_{\mathbb{P}\in\mathcal{P}} \mathrm{Prob}_{\mathbb{P}}\Big(\sum_{i\in T} x_{ij}\cdot t_i \le C,\ \forall j\in J\Big) \ge 1-\alpha, \tag{1}$$

where $\mathrm{Prob}_{\mathbb{P}}(\cdot)$ denotes the probability of the event in brackets under any given probability distribution $\mathbb{P}\in\mathcal{P}$, and $\mathcal{P}$ is the ambiguity set of distributions, and $\inf_{\mathbb{P}\in\mathcal{P}}$ denotes the worst-case scenario, i.e. the robustness. Constraint (1) guarantees that the probability of jointly satisfying all cycle time constraints is no less than $1-\alpha$.

3.3. The distributionally robust formulation

In the following, we give basic notations, define decision variables, and propose a distributionally robust formulation **[P1]** for the DLBP with ambiguous and correlated task processing times.

Parameters:

- T: Set of tasks indexed by i, i.e. $T=\{1,2,\dots,|T|\}$.
- H: Set of hazardous tasks, which is a subset of T.
- S: Set of subassembly nodes (statuses) indexed by k, i.e. $S=\{0,1,\dots,|S|\}$, where 0 denotes the beginning status of an EOL product, and $|S|$ denotes the status with all required separated components disassembled.
- J: Set of workstations indexed by j,l, i.e. $J=\{1,2,\dots,|J|\}$.
- P_k: Set of preceding tasks of subassembly node $k\in S$.
- Q_k: Set of successor tasks of subassembly node $k\in S$.
- C: Cycle time.
- C_f: Operating cost for each workstation per time unit.
- C_h: Cost for a workstation handling hazardous tasks per time unit.
- α: Maximum probability for not satisfying all cycle time constraints.
- t_i: Stochastic processing time of task $i\in T$.

Decision variables:

- x_{ij}: Binary variable, equal to 1 if task $i\in T$ is assigned to workstation $j\in J$, 0 otherwise.
- y_j: Binary variable, equal to 1 if workstation $j\in J$ is opened, 0 otherwise.
- z_j: Binary variable, equal to 1 if a hazardous task is assigned to workstation $j\in J$, 0 otherwise.

Distributionally robust formulation [P1]:

$$\min \quad C\cdot\left(C_f\cdot\sum_{j\in J} y_j + C_h\cdot\sum_{j\in J} z_j\right)$$

s.t. Constraint (1)

$$\sum_{i\in Q_k}\sum_{j\in J} x_{ij} = 1, \quad k=0, \tag{1}$$

$$\sum_{j\in J} x_{ij} \le 1, \quad \forall i\in T, \tag{3}$$

$$y_j \ge x_{ij}, \quad \forall i\in T, j\in J, \tag{4}$$

$$\sum_{j\in J} j\cdot x_{ij} \le \sum_{j\in J} y_j, \quad \forall i\in T, \tag{5}$$

$$\sum_{i\in Q_k}\sum_{j\in J} x_{ij} = \sum_{i\in P_k}\sum_{j\in J} x_{ij}, \quad \forall k\in S\backslash\{0,|S|\}, \tag{6}$$

$$\sum_{i\in Q_k} x_{iv} \le \sum_{i\in P_k}\sum_{j=1}^{v} x_{ij}, \quad \forall v\in J, k\in S\backslash\{0,|S|\}, \tag{7}$$

$$z_j \ge x_{ij}, \quad \forall i\in H,\ j\in J, \tag{8}$$

$$x_{ij}, y_j, z_j \in \{0,1\}, \quad \forall i\in T,\ j\in J. \tag{9}$$

The objective function implies to minimise the total cost associated with operating workstations, i.e. $C \cdot C_f \cdot \sum_{j\in J} y_j$, and handling hazardous tasks, i.e. $C \cdot C_h \cdot \sum_{j\in J} z_j$.

Constraint (2) ensures that there is only one disassembly process to be selected. Constraint (3) implies that a task $i \in T$ can be assigned to at most one workstation. Constraint (4) determines the opened workstations. Constraint (5) respects the given sequence of workstations, where the total number of opened workstations is $\sum_{j\in J} y_j$ and each task should be assigned to the first $\sum_{j\in J} y_j$ workstations. Constraint (6) ensures that there is only one predecessor and one successor for a subassembly node in a disassembly process, i.e. the flow conservation. Constraint (7) implies the precedence restrictions, i.e. for a subassembly node, its preceding task should be assigned to the workstation with index lower than or equal to the workstation processing its successor tasks. Since there is no predecessor of the initial subassembly node 0 and no successor of the last subassembly node $|S|$, thus they are not included in Constraint (7). Constraint (8) ensures the workstation handling hazardous tasks. Constraint (9) gives the restrictions on the decision variables.

4. Solution approaches

The proposed distributionally robust model is difficult to solve due to the joint chance constraint (Xie and Ahmed 2018b). In this section, we first approximate the joint chance constraint via the Bonferroni's inequality. Motivated by the observation that the classic Bonferroni's approximation may produce solutions with poor quality in some cases and the problem characteristics, a two-stage parameter-adjusting heuristic is then proposed to efficiently solve the problem.

4.1. The Bonferroni approximation

As correlation is allowed in this work, the popular method for handling the joint chance constraint, i.e. $\text{Prob}\left(\sum_{i\in T} x_{ij}\cdot t_i \le C,\ \forall j\in J\right) = \prod_{j\in J}\text{Prob}\left(\sum_{i\in T} x_{ij}\cdot t_i \le C\right)$, which is based on the independence of task processing times, is not applicable for the problem. Thus we apply a general and widely applied method, i.e. the Bonferroni approximation (Chen et al. 2010; Chung, Yao, and Zhang 2012): the joint chance constraint, i.e. Constraint (1), can be approximated by

$$\inf_{\mathbb{P}\in\mathcal{P}} \text{Prob}_{\mathbb{P}}\left(\sum_{i\in T} x_{ij}\cdot t_i \le C\right) \ge 1-\alpha_j, \quad \forall j\in J. \tag{10}$$

The proof for such an approximation is provided as follows.

For Constraint (1), i.e. $\inf_{\mathbb{P}\in\mathcal{P}}\text{Prob}_{\mathbb{P}}\left(\sum_{i\in T} x_{ij}\cdot t_i \le C,\ \forall j\in J\right) \ge 1-\alpha$, we first use Φ to denote the associated event $\left\{\sum_{i\in T} x_{ij}\cdot t_i \le C,\ \forall j\in J\right\}$, and $\bar{\Phi}$ to denote its complementary event $\left\{\sum_{i\in T} x_{ij}\cdot t_i > C, \exists j\in J\right\}$ (i.e. $\bigcup_{j\in J}\left\{\sum_{i\in T} x_{ij}\cdot t_i > C\right\}$). Accordingly, the considered joint chance constraint is equivalent to

$$\text{If}\quad \inf_{\mathbb{P}\in\mathcal{P}} \text{Prob}_{\mathbb{P}}\left(\sum_{i\in T} x_{ij}\cdot t_i \le C,\ \forall j\in J\right) \ge 1-\alpha,$$

$$\text{we have}\ \inf_{\mathbb{P}\in\mathcal{P}} \text{Prob}_{\mathbb{P}}(\Phi) \ge 1-\alpha \quad \text{and} \quad \inf_{\mathbb{P}\in\mathcal{P}}\left\{1-\text{Prob}_{\mathbb{P}}(\bar{\Phi})\right\} \ge 1-\alpha.$$

Naturally, we have

$$1+\inf_{\mathbb{P}\in\mathcal{P}}\left\{-\text{Prob}_{\mathbb{P}}(\bar{\Phi})\right\} \ge 1-\alpha \quad \text{and} \quad 1-\sup_{\mathbb{P}\in\mathcal{P}}\text{Prob}_{\mathbb{P}}(\bar{\Phi}) \ge 1-\alpha.$$

Finally, we can have

$$\sup_{\mathbb{P}\in\mathcal{P}}\text{Prob}_{\mathbb{P}}(\bar{\Phi}) \le \alpha \quad \text{and} \quad \sup_{\mathbb{P}\in\mathcal{P}}\text{Prob}_{\mathbb{P}}\left(\bigcup_{j\in J}\left\{\sum_{i\in T} x_{ij}\cdot t_i > C\right\}\right) \le \alpha,$$

where $\sup_{\mathbb{P}\in\mathcal{P}}$ denotes the supremum of the probability. Following Boole's inequality, we have

$$\text{Prob}\left(\bigcup_{j\in J}\left\{\sum_{i\in T} x_{ij}\cdot t_i > C\right\}\right) \le \sum_{j\in J}\text{Prob}\left(\sum_{i\in T} x_{ij}\cdot t_i > C\right).$$

If the individual risk levels α_j, such that $\sup_{\mathbb{P}\in\mathcal{P}} \text{Prob}_{\mathbb{P}}\left(\sum_{i\in T} x_{ij}\cdot t_i > C\right) \le \alpha_j$, $\forall j \in J$, are given and restricted by $\sum_{j\in J}\alpha_j \le \alpha$, we have

$$\text{Prob}\left(\bigcup_{j\in J}\left\{\sum_{i\in T} x_{ij}\cdot t_i > C\right\}\right) \le \sum_{j\in J}\text{Prob}\left(\sum_{i\in T} x_{ij}\cdot t_i > C\right) \le \sum_{j\in J}\alpha_j \le \alpha.$$

That is, Constraint (1) can be approximated by Constraint (10).

Therefore, formulation **[P1]** can be approximated by the following model:

$$[\mathbf{P2}]: \quad \min\ C\cdot\left(C_f\cdot\sum_{j\in J} y_j + C_h\cdot\sum_{j\in J} z_j\right)$$

$$\text{s.t.} \quad (2)\text{–}(9),\ (10)$$

$$\sum_{j\in J}\alpha_j \le \alpha, \tag{11}$$

$$\alpha_j > 0, \quad \forall j \in J. \tag{12}$$

4.2. An approximated MI-SOCP model

In the following, two column vectors $\boldsymbol{x}_j = [x_{1j}, x_{2j}, \ldots, x_{|T|,j}]^\top$ and $\boldsymbol{t} = [t_1, t_2, \ldots, t_{|T|}]^\top$ are introduced to rewrite Constraint (11) as

$$\inf_{\mathbb{P}\in\mathcal{P}} \text{Prob}_{\mathbb{P}}\left(\boldsymbol{t}^\top\boldsymbol{x}_j \le C\right) \ge\ 1-\alpha_j, \quad \forall j \in J. \tag{13}$$

According to Zhang, Shen, and Erdogan (2017), individual chance constraints (11) and (14) can be further approximated by the following inequality:

$$\sqrt{\frac{1}{1-a-b}}\cdot\left(1+\sqrt{\frac{\alpha_j\cdot b}{1-\alpha_j}}\right)\cdot\sqrt{\boldsymbol{x}_j^\top\boldsymbol{\Sigma}\boldsymbol{x}_j} \le \sqrt{\frac{\alpha_j}{1-\alpha_j}}\cdot\left(C-\boldsymbol{\mu}^\top\boldsymbol{x}_j\right), \quad \forall j \in J, \tag{14}$$

where parameters a, b, γ_1 and γ_2 are restricted to

$$\gamma_1 = \frac{b}{1-a-b}, \quad \gamma_2 = \frac{1+b}{1-a-b}.$$

Accordingly, the distributionally robust model can be further approximated by the following mixed integer second-order cone programming (MI-SOCP) formulation denoted as **[P3]**:

$$[\mathbf{P3}]: \quad \min\ C\cdot\left(C_f\cdot\sum_{j\in J} y_j + C_h\cdot\sum_{j\in J} z_j\right)$$

$$\text{s.t.} \quad (2)\text{–}(9),\ (14).$$

MI-SOCP problems have been investigated by various works (Alizadeh and Goldfarb 2003; Bonnans and Héctor 2005). According to Sun et al. (2014), the approximation quality depends heavily on the selection of individual risk level α_j, which is still non-convex (Nemirovski and Shapiro 2006). Most existing works address the obstacle by a simplest way, i.e. $\alpha_j = \frac{\alpha}{|J|}$, $\forall j \in J$, where $|J|$ is the number of workstations. But the above method of finding the individual risk level α_j may have its disadvantages, such as (i) the problem may be infeasible with identical individual risk levels, (ii) the system cost may be sacrificed. For example, if the selected disassembly process contains four tasks and there are 10 workstations in total, and the selected tasks can be assigned to at most four workstations, i.e. the first four workstations according to Constraint (5). Then the remaining six workstations are not opened, thus their cycle time constraints are satisfied with probability equal to 100%. Therefore, we develop a two-stage parameter-adjusting heuristic in order to find a more cost-saving combination of individual risk levels in a simple and efficient way.

4.3. Two-stage parameter-adjusting heuristic

From Constraint (5), it can be obtained that if the number of selected workstations is $|J_0|$, they must be the first $|J_0|$ ones. Based on such an observation, we design a heuristic named as *two-stage parameter-adjusting heuristic*, to find a better combination of individual risk levels among possible combinations and obtain high-quality task-to-workstation assignment.

The heuristic is based on two stages: (1) we select the first $|J'|$ workstations, and estimate their individual risk levels such that $\sum_{j\in\{1,2,\ldots,|J'|\}} \alpha_j = \alpha$, and (2) under the individual risk levels obtained in the first stage, formulation [**P3**] is solved by calling CPLEX, to output the optimal task-to-workstation assignment. For the estimation of individual risk levels in the first stage, two methods are applied, by evenly dividing α (i.e. $\alpha_j = \frac{\alpha}{|J'|},\ \forall j \in \{1,2,\ldots,|J'|\}$) and arithmetic progression with identical difference Δ_1 (i.e. $\alpha_1, \alpha_2 = \alpha_1 + (2-1)\cdot\Delta_1, \ldots, \alpha_{|J'|} = \alpha_1 + (|J'|-1)\cdot\Delta_1$) (see Appendix 1).

Algorithm 1: Two-stage parameter-adjusting heuristic

Input: Parameters for the problem: $T,\ S,\ H,\ J,\ C_f,\ C_h,\ \alpha,\ \boldsymbol{\mu},\ \boldsymbol{\Sigma},\ \Delta_1,\ \Delta_2,\ P_k,\ Q_k,\ \forall k \in S$.
$S = \emptyset$; (Set of feasible solutions)
$Obj = \emptyset$; (Set of obtained objective values)
while α **do**
    for $t = 0 : |J|-1$ **do**
        (1) $\alpha_j^t = \frac{\alpha}{|J|-t},\ \forall j \in \{1,2,...,|J|-t\}$;
            Solve [**P3**] by calling CPLEX;
            Obtain the optimal solution s_1^t and its objective value obj_1^t;
            $S = S \cup s_1^t$ and $Obj = Obj \cup obj_1^t$;
        (2) $\alpha_j^t = \alpha_1 + (j-1)\cdot\Delta_1,\ \forall j \in \{1,2,...,|J|-t\}$;
            Solve [**P3**] by calling CPLEX;
            Obtain the optimal solution s_2^t and its objective value obj_2^t;
            $S = S \cup s_2^t$ and $Obj = Obj \cup obj_2^t$;
        if *No feasible solutions* **then**
            Continue;
        end
    end
    if *No feasible solutions* **then**
        $\alpha = \alpha + \Delta_2$;
        else
            Break;
        end
    end
end
Compare the values in *Obj* and obtain solutions with minimal objective value.
If multiple solutions are obtained, then a heuristic rule based on min–max correlation is applied to determine a task-to-workstation assignment.
Output: Form a disassembly process.

The heuristic is illustrated in Algorithm 1, in which S and *Obj* denote the sets of obtained solutions and their objective values, respectively. During the tth iteration ($0 \le t \le |J|-1$), we select the first $|J'| = |J| - t$ workstations, and (i) calculate their individual risk levels as $\alpha_j = \frac{\alpha}{|J'|},\ \forall j \in \{1,2,\ldots,|J'|\}$ (i.e. by the first method), then solve formulation [**P3**] by calling CPLEX and obtain the optimal solution s_1^t and its objective obj_1^t, and (ii) calculate the individual risk level as $\alpha_j = \alpha_1 + (j-1)\cdot\Delta_1,\ \forall j \in \{1,2,\ldots,|J'|\}$, and solve [**P3**] by calling CPLEX and obtain the optimal solution s_2^t with objective obj_2^t. As formulation [**P3**] is a conservative approximation, preset risk level α with a larger value is required to satisfy Constraint (14). If no feasible solutions can be found under the current value of α, then α will be updated as $\alpha = \alpha + \Delta_2$, where Δ_2 is the step size of α, helping to find feasible solutions. The process continues until the stop criterion is met.

Then by comparing the objective values in *Obj*, solutions with minimal objective value can be obtained. If we get more than one solution with minimal objective value, the key remaining work is how to determine a task-to-workstation assignment, to form a disassembly process. It is understanding that if there is a large positive correlation between the processing times of two tasks, their processing times may take large or small values at the same time. That is, the assignment of two tasks with a large positive correlation to one workstation may lead to a large fluctuation range of the operating time of the workstation. Therefore, we develop a heuristic rule, based on min–max correlation, to refine the two-stage parameter-adjusting heuristic and to determine a task-to-workstation assignment: (i) for each candidate solution, we first calculate the maximum correlation coefficient among all tasks assigned to each single workstation, and then obtain the maximum correlation coefficients among all workstations; (ii) then the maximum correlation coefficients of all solutions are compared, and the solution with the minimal maximum correlation coefficient is selected.

5. Computational experiments

In this section, the performance of the proposed heuristic is evaluated and compared with three existing methods, i.e. the adapted deterministic approach (Battaïa and Dolgui 2013, see Appendix 3), the adapted sampling average approximation (SAA) method (Bentaha, Battaïa, and Dolgui 2014b, see Appendix 2), the distribution-free model in Zheng et al. (2018) and the method based on the assumption of normally distributed task times (Bentaha et al. 2015b). Note that the deterministic approach and the distribution-free model are based on the assumption that the task processing times are independent from each other, thus the two methods are implemented by only utilising the mean and standard deviation of each task processing time, to obtain solutions. Approaches are coded in MATLAB_2014b and formulations are solved by calling CPLEX 12.6 solver. All computational experiments are conducted on a personal computer with Core I5 and 3.30 GHz processor and 8 GB RAM under Windows 7 operating system. Besides, each instance is tested 10 times via each approach, to obtain its average results.

5.1. *Out-of-sample test*

To compare the different approaches, we test their obtained solutions in a large set of scenarios, i.e. the out-of-sample test (Zhang, Jiang, and Shen 2016; Zhang, Shen, and Erdogan 2017; Zhang, Jiang, and Shen 2018). In each scenario, task times are randomly generated following a Lognormal distribution, satisfying the given information, which represents the realisation of task processing times (Xie and Ahmed 2018a). The number of tested scenarios is set to be 50,000 in this work. For each method, based on its obtained task-to-workstation assignment:

(1) Under each scenario in the 50,000 ones, the total processing time of the tasks assigned to each workstation can be easily calculated, and the violation of the cycle time constraints can be then obtained.
(2) Then we evaluate each method's out-of-sample performance, by calculating and estimating the following criteria:
    (i) the (out-of-sample) coverage level by $\frac{n}{50{,}000\times|J|}\times 100\%$, in which n denotes the number of workstations respecting the cycle time under all tested 50,000 scenarios;
    (ii) the (out-of-sample) service level by $\frac{s}{50{,}000}\times 100\%$, where s denotes the number of scenarios without violating the joint chance constraint.

5.2. *An illustrative example*

A preliminary discussion has been conducted to adjust the parameters for the proposed approach. For the two-stage parameter-adjusting heuristic, γ_1, γ_2, θ_1, θ_2 and Δ_2 are set to be 0.2%, 0.4%, 0.95%, 0.05% and 0.02%, and the value of Δ_1 is set to be $-(\alpha - |J'|\cdot\frac{\alpha}{|J|})\cdot\frac{2}{|J'|\cdot(|J'|-1)}$ (see Appendix 1), where $|J'|$ denotes the number of selected workstations in the first stage during each iteration. For the SAA, θ and $|\Omega|$ are set to be 50 and 500 in the following.

An illustrative example based on a small-scale benchmark instance is investigated, to compare the solutions obtained by different approaches. As in line with Zheng et al. (2018), the illustrative example is based on the hand light instance introduced in Bentaha, Battaïa, and Dolgui (2015a). The input data of the illustrative example are detailed in Table 1, where there are 10 tasks and 5 workstations. Besides, the mean and standard deviation of each task processing time and the correlation coefficient matrix are presented in Table 2. Note that the covariance matrix can be calculated through the standard deviation and the correlation coefficient matrix.

Table 3 reports the computational results obtained by the tested approaches. Task-to-workstation assignments obtained by the deterministic approach, the SAA, the distribution-free model, the method based on the normal distribution assumption and the two-stage parameter-adjusting heuristic are reported by columns 2–6, columns 7–11, columns 12–16, columns 17–21 and columns 22–16, respectively. In each row $i \in \{1, 2, \ldots, 10\}$, a number '1' denotes that disassembly task i is assigned to workstation $j \in \{1, 2, \ldots, 5\}$, i.e. $x_{ij} = 1$. Note that workstation j is not selected if there is no task assigned to it.

Accordingly, it can be observed from Table 3 that the task-to-workstation assignment obtained by the deterministic approach is the same with that of the SAA: tasks 2, 4, 9 and 10 are assigned to workstation 1, and tasks 6 and 7 are assigned

Table 1. Input data of the illustrative example.

Parameter	Value
Number of tasks ($\|T\|$)	10
Maximal number of workstations ($\|J\|$)	5
Cycle time (C)	90
Hazardous task	T_7
Cost for each workstation per time unit (C_f)	3
Cost for handling hazardous operation per time unit (C_h)	2
Preset risk level (α)	15%

Table 2. The mean, standard deviation and correlation coefficient matrix of the illustrative example.

			Correlation coefficient matrix									
Task	μ_i	σ_i	1	2	3	4	5	6	7	8	9	10
1	50	10	1.0000	0.8695	0.8681	0.8608	0.8274	0.8272	0.8166	0.8254	0.8670	0.8962
2	11	2.2	0.8695	1.0000	0.8841	0.9000	0.8500	0.8236	0.8392	0.8372	0.8719	0.8920
3	22	4.4	0.8681	0.8841	1.0000	0.8991	0.8847	0.8762	0.8625	0.8968	0.9267	0.9596
4	20	4	0.8608	0.9000	0.8991	1.0000	0.8752	0.8453	0.8657	0.8559	0.8948	0.9130
5	45	9	0.8274	0.8500	0.8847	0.8752	1.0000	0.8269	0.8260	0.8406	0.8623	0.8932
6	61	12.2	0.8272	0.8236	0.8762	0.8453	0.8269	1.0000	0.8213	0.8465	0.8690	0.8833
7	10	2	0.8166	0.8392	0.8625	0.8657	0.8260	0.8213	1.0000	0.8269	0.8530	0.8663
8	35	7	0.8254	0.8372	0.8968	0.8559	0.8406	0.8465	0.8269	1.0000	0.8699	0.8835
9	25	5	0.8670	0.8719	0.9267	0.8948	0.8623	0.8690	0.8530	0.8699	1.0000	0.9522
10	30	6	0.8962	0.8920	0.9596	0.9130	0.8932	0.8833	0.8663	0.8835	0.9522	1.0000

to workstation 2. The objective value and the coverage level are 720% and 90.69%, respectively. However, the service level of the deterministic approach and the SAA is 60.78%, which fails to meet the requirement (i.e. $1-\alpha = 85\%$). Besides, by solving the distribution-free model, tasks 1 and 3 are assigned to workstation 1, and tasks 6 and 7 are assigned to workstation 2, and tasks 9 and 10 are assigned to workstation 3. The coverage level and the service level obtained by the distribution-free model are 96.81% and 87.21%, which are both higher than those of the deterministic approach and the SAA. In addition, the solution approach based on the normal distribution assumption obtains the following task-to-workstation assignment: tasks 2 and 5 are assigned to workstation 1, and tasks 7, 8 and 9 are assigned to workstation 2 and task 10 is assigned to workstation 3. The objective value is 990, which is the same with that of the distribution-free model. The coverage level and the service level are 98.6% and 93.11%, about 1.86% and 6.77% larger than those obtained by the distribution-free model.

Moreover, the two-stage parameter-adjusting heuristic outputs a solution in 3.6 s, in which tasks 2 and 5 are assigned to workstation 1, and tasks 7 and 8 are assigned to workstation 2, and tasks 9 and 10 are handled by workstation 3. However, its obtained coverage level and service level are 99.79% and 99.12%, which are higher than those obtained by other tested approaches. The reason may be that tasks 9 and 10 are selected by all tested methods, and the correlation coefficient between the processing times of tasks 9 and 10 is 0.9569, which is very close to 1. Thus their processing times may take large values at the same time. Via the deterministic approach, the SAA and the distribution-free model, tasks 9 and 10 are assigned to one workstation, and the operating time of the workstation may fluctuate largely, leading to the reduction of service level.

In sum, for the illustrative example, it can be obtained from Table 3 that the two-stage parameter-adjusting heuristic can obtain high-quality solutions, in terms of the service level and coverage level, within a reasonable time. In addition, if the correlation coefficient between the processing times of two tasks is very large (e.g. very close to 1), they may take large values at the same time, thus processing them on different workstations may improve the service level.

5.3. Numerical experiments on randomly generated instances

In the following part, numerical experiments on several instances of different scales are conducted. The input data of the instances are reported in Table 4, in which instances in rows 1–8 are benchmarks and named with the abbreviations of the author names' initials and the year of the literature, the data of benchmark instances can be found in Bentaha, Dolgui, and Battaïa (2015d). Instances in rows 9–16 are generated by extending and generalising the disassembly processes of the first eight benchmarks. Take instance BBD12 with three disassembly processes shown in Figure 2 as an example, by Generalisation we mean that three disassembly processes with the same task precedence constraints are added to BBD12,

Table 3. Task-to-workstation assignments for the illustrative example.

	Deterministic approach					The SAA					Distribution-free model					Normal distribution assumption					Two-stage parameter-adjusting heuristic				
Tasks Workstations	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1											1														
2	1					1										1					1				
3											1														
4	1					1																			
5																1					1				
6		1					1					1													
7		1					1					1					1					1			
8																	1					1			
9	1					1							1				1						1		
10	1					1							1					1					1		
Objective (Cost)			720					720					990					990					990		
Coverage level			90.69%					90.69%					96.81%					98.6%					99.99%		
Service level			60.78%					60.78%					87.21%					93.11%					99.96%		
Time (s)			0.5					12.8					0.5					0.6					3.6		

Table 4. Data set of the tested instances.

Set	Instance	Product	Generation mode	$\vert T\vert$	$\vert J\vert$	$\vert S\vert$	C
1	BBD12	Compass	Bentaha, Battaïa, and Dolgui (2012)	10	3	7	0.71
2	TZC02	Hand light	Bentaha, Battaïa, and Dolgui (2015a)	10	5	9	90
3	L99b	Ball-point pen	Lambert (1999)	20	9	15	10
4	KSE09	Sample product	Koc, Sabuncuoglu, and Erel (2009)	23	6	15	20
5	BBD13b	Piston and connecting rod	Bentaha, Battaïa, and Dolgui (2013a)	25	4	13	120
6	L99a	Radio set	Lambert (1999)	30	9	20	50
7	BAO2015	Rigid caster	Bentaha, Dolgui, and Battaïa (2015d)	32	4	16	90
8	MJKL11	Automatic pencil	Ma et al. (2011)	37	10	24	40
9	BBD12*	–	Generalisation of BBD12	20	3	12	0.71
10	TZC02*	–	Generalisation of TZC02	20	5	16	90
11	L99b*	–	Generalisation of L99b	40	9	28	10
12	KSE09*	–	Generalisation of KSE09	46	6	28	20
13	BBD13b*	–	Generalisation of BBD13b	50	4	24	120
14	L99a*	–	Generalisation of L99a	60	9	20	50
15	BAO2015*	–	Generalisation of BAO2015	64	4	30	90
16	MJKL11*	–	Generalisation of MJKL11	74	10	46	40

leading to BBD12*. In columns 5–8 of Table 4, $|T|$, $|J|$, $|S|$, C are used to denote the number of tasks, the maximal number of workstations, the number of disassembly nodes and the cycle time, respectively. Besides, the mean task processing times μ_i are randomly and uniformly generated from interval $[\min_{i\in T} t_i^0, \max_{i\in T} t_i^0]$, where t_i^0 denotes the task processing times given by benchmark instances. In the following, unless otherwise specified, (i) the standard deviation of each task processing time is set to be $\sigma_i = 0.2\mu_i$; (ii) the correlation coefficient between any two different tasks is randomly and uniformly generated from interval [0.8, 1]; (iii) the fixed unit time cost C_f for each workstation and the fixed unit time cost C_h for handling hazardous operation C_h are set to be 3 and 2, respectively; and (iv) 25% of the tasks are assumed to be hazardous, as in line with Zheng et al. (2018).

Computational results under $\alpha = 15\%$ are reported in Table 5. Service levels are presented in Figure 3, where the red dashed line denotes the required $1 - \alpha = 85\%$. For the deterministic approach, it can be obtained that it outputs the solution for each instance in the shortest time, and the obtained objective value is also the smallest. However, the quality of the solutions obtained by the deterministic approach is the worst, with the average coverage level 95.46% and the average service level 76.63%. Especially, it can be observed from Figure 3 that the service level obtained by the deterministic approach usually fails to meet the required $1 - \alpha = 85\%$, such as instances 3, 5, 6, 7, 8, 10, 11, 14, 15 and 16. Compared with the deterministic approach, the SAA outputs larger objective value within a longer computational time. The average coverage level and the average service level obtained by the SAA are 98.67% and 90.84%, both of which are higher than those of the deterministic approach. However, the SAA fails to reach the requirement for instances 6, 10, 11, 14 and 16. In addition, the average coverage level and the service level obtained by the distribution-free model are 99.06% and 93.44%, which are both higher than those of the deterministic approach and the SAA. However, the distribution-free model is unstable in terms of the service level, as it obtains the highest service level 99.99% for instances 4 and 15 and the lowest service level 82.15% for instance 10, and it fails to reach the required service level for instance 10 and 11. The solution approach under normal distribution assumption obtains average coverage level 98.21% and average service level 92.81, both smaller than those of the SAA. Likewise, the solution approach under normal distribution assumption is unstable as well, and it fails to meet the required service level for instances 10, 11 and 15. Moreover, the average coverage level and the average service level obtained by the two-stage parameter-adjusting heuristic are 99.57% and 98.15%, which are both higher than those obtained by the other three approaches. The two-stage parameter-adjusting heuristic can ensure the requirement on the service level for each instance as well.

Computational results obtained under $\alpha = 10\%$ are reported in Table 6, and the service levels are illustrated in Figure 4. As computational times for each instance via each solution method are very similar to those under $\alpha = 15\%$, thus they are omitted in the following. We can observe that with the decrease of α, (i) the objective values obtained by the deterministic approach, the SAA and the solution approach based on normal distribution assumption change little, and (ii) the average objective value obtained by the distribution-free model and the two-stage parameter-adjusting heuristic increase, and (iii) the coverage levels and the service levels obtained by all approaches increase. Besides, the average service level obtained by the deterministic approach is 76.14%, which is lower than those of other approaches. The SAA fails to satisfy the required service level for instances 10, 11 and 16. The distribution-free model fails to reach the required service level for instances 7, 10, 11, 14 and 16, and the method based on normal distribution assumption fails to meet the requirement for instances 10,

Table 5. Computational results of instances of different scales under $\alpha = 15\%$.

Set	Deterministic approach				The SAA				Distribution-free model				Normal distribution assumption				Two-stage parameter-adjusting heuristic			
	Obj	Coverage level (%)	Service level (%)	Time	OObj	Coverage level (%)	Service level (%)	Time	Obj	Coverage level (%)	Service level (%)	Time	Obj	Coverage level (%)	Service level (%)	Time	Obj	Coverage level (%)	Service level (%)	Time
1	4.26	99.35	98.08	0.2	4.26	99.39	98.20	2.3	4.26	99.69	98.13	0.7	4.26	99.38	98.14	0.59	4.26	99.44	98.25	0.9
2	810	99.39	97.04	0.4	810	99.97	99.90	3.8	810	99.31	97.06	8.6	810	99.29	96.89	0.6	810	99.98	99.94	2.1
3	110	93.79	54.29	0.8	110	99.10	94.96	10.2	110	98.57	90.06	3.2	90	99.05	94.73	1.4	120	99.90	99.36	15.4
4	100	99.96	99.76	0.6	100	99.99	99.99	5.9	100	99.99	99.99	1.1	100	99.99	99.99	0.9	100	99.99	99.99	5.3
5	720	92.08	68.30	0.7	720	99.98	99.94	4.0	720	99.98	99.94	1.0	720	99.99	99.98	1.3	720	99.99	99.98	3.6
6	400	92.30	57.95	1.2	420	94.28	69.33	14.7	450	99.60	96.68	2.1	450	98.15	83.91	2.2	450	99.81	98.31	22.2
7	2.4	97.15	88.60	0.5	2.4	97.58	90.32	4.0	2.4	97.16	88.66	1.2	2.4	97.62	90.49	0.6	2.4	97.61	90.45	4.0
8	385	95.36	54.10	1.4	455	99.43	95.81	37.5	455	99.41	95.84	1.2	455	99.45	96.06	3.5	455	99.62	96.73	51.0
9	4.26	99.90	99.78	0.4	4.59	99.01	94.13	2.6	4.59	98.94	93.68	0.9	4.26	99.03	97.09	0.6	4.26	99.06	97.18	3.7
10	540	94.04	81.99	0.6	540	96.99	81.94	4.6	540	97.04	82.15	17.8	540	94.09	82.18	0.8	810	99.52	98.21	4.6
11	110	90.05	55.40	1.5	110	98.16	84.19	24.0	110	98.16	83.92	6.1	110	95.05	78.26	4.1	140	99.92	99.52	48.1
12	60	99.79	98.76	0.9	60	99.90	98.86	9.6	60	99.89	98.67	8.3	60	99.78	98.68	1.2	60	99.76	98.90	13.5
13	600	97.61	90.44	1.0	600	99.38	95.00	6.3	600	98.77	90.20	11.2	600	97.56	90.26	1.8	600	98.74	95.24	7.7
14	400	91.75	54.08	2.1	460	97.67	76.60	34.1	450	99.62	94.89	33.8	450	99.08	94.74	10.2	550	99.75	97.96	82.0
15	4.8	93.58	74.32	1.1	4.8	99.99	99.99	7.3	4.8	99.99	99.99	2.4	4.8	93.92	83.37	2.4	4.8	99.99	99.99	7.2
16	385	91.20	53.19	3.2	420	97.96	74.20	76.4	525	98.88	85.11	53.1	595	99.91	99.12	15.9	595	99.99	99.99	98.6
Average	289.7	95.46	76.63	1.0	301.3	98.67	90.84	15.5	309.1	99.06	93.44	9.5	312.2	98.21	92.74	3.0	339.1	99.57	98.13	23.1

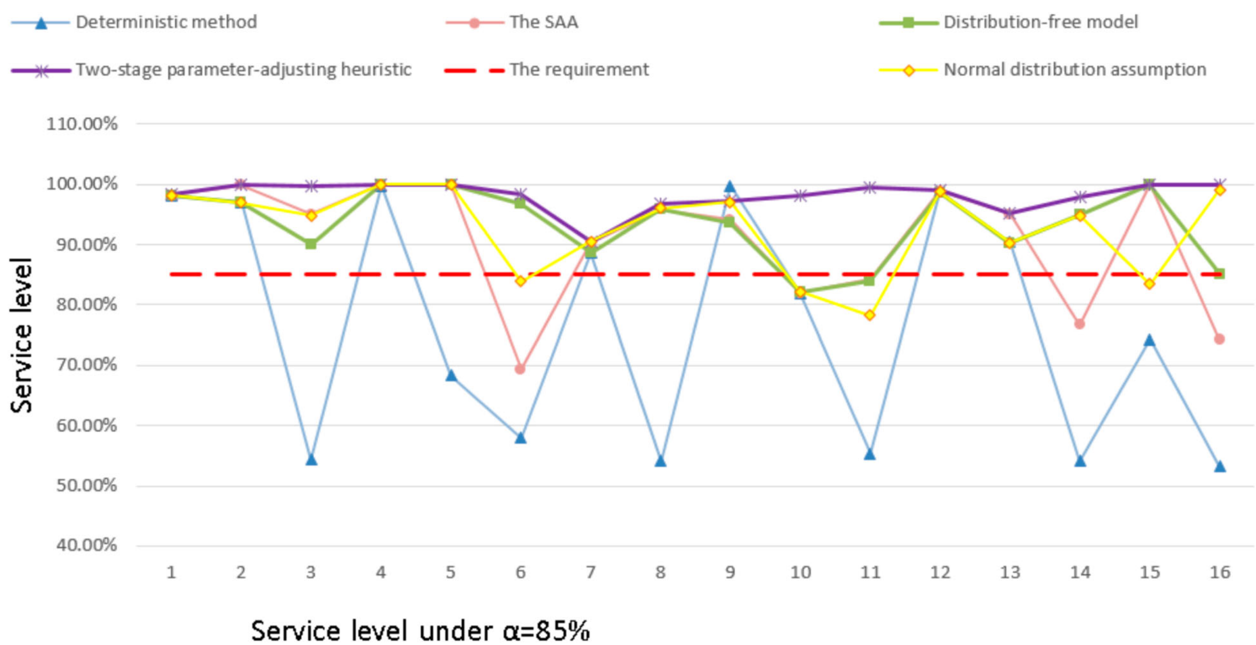

Figure 3. Service levels obtained under $\alpha = 15\%$.

11 and 14. In addition, the two-stage parameter-adjusting heuristic obtains the highest average service level 99.18%, and it can satisfy the requirement on the service level for each instance.

Moreover, computational results obtained under $\alpha = 5\%$ are presented in Table 7, and the service levels under $\alpha = 5\%$ are painted in Figure 5. We can observe that the average objective values obtained by the deterministic approach, the SAA and the distribution-free model have almost unchanged. Whereas, the four existing approaches perform worse in terms of the coverage level and service level, as the numbers of instances in which the requirements are not satisfied by the deterministic approach, the SAA and the distribution-free model are 11, 7 and 7, respectively. Besides, the method based on normal distribution assumption fails to meet the service level requirement for 11 instances, i.e. instances 2, 3, 6, 7, 8, 10, 11, 13, 14, 15 and 16. It can be obtained that the objective value obtained by the two-stage parameter-adjusting heuristic under $\alpha = 5\%$ is 443.5, which is 25.04% larger than that under $\alpha = 10\%$. However, the two-stage parameter-adjusting also satisfies the required service level for each instance.

In sum, we can observe that (i) the two-stage parameter-adjusting heuristic outputs solutions with larger objective values, as it is based on conservative approximation; (ii) the two-stage parameter-adjusting heuristic is quite stable and performs well for all instances under $\alpha = 15\%$, 10% and 5%, in terms of the coverage level and service level; (iii) though the deterministic approach, the SAA, the distribution-free model and the method based on normal distribution assumption obtain solutions with smaller objective values, they usually fail to meet the required service level; (iv) with the decrease of α, the obtained objective values of the deterministic approach, the SAA and the distribution-free model change little, (v) with the decrease of α, the distribution-free model fails to reach the requirement on the service level with higher frequency.

5.4. Sensitivity analyses

In this subsection, sensitivity analyses on instance L99b with 20 disassembly tasks, 9 workstations and 15 disassembly nodes are conducted. The input data are generated in the way detailed above, such that (1) the mean processing time of each disassembly task is randomly and uniformly generated from interval $[1, 5]$ according to benchmark L99b (Lambert 1999); (2) disassembly tasks 1, 3, 5, 7 and 12 are assumed to be hazardous; (3) the fixed unit time costs for each workstation C_f and handling hazardous tasks C_h are set to be 3 and 2. In the following, unless otherwise specified, (i) the standard deviation of each task processing time is set as $\sigma_i = 0.2 \times \mu_i$; (ii) there is correlation between any two task processing times, and the correlation coefficients are randomly and uniformly generated from interval $[0.8, 1]$; (iii) the cycle time is 10. It can be obtained from above that the deterministic approach, the SAA and the approach based on normal distribution assumption obtain solutions with worse quality than the distribution-free model and the two-stage parameter-adjusting heuristic. Thus we conduct the sensitivity analyses by solving the problem via the distribution-free model and the two-stage parameter-adjusting heuristic.

Table 6. Computational results of instances of different scales under $\alpha = 10\%$.

	Deterministic approach			The SAA			Distribution-free model			Normal distribution assumption			Two-stage parameter-adjusting heuristic		
Set	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)
1	4.26	99.41	98.22	4.26	99.37	98.13	4.26	99.39	98.20	4.26	99.44	98.33	4.26	99.37	98.13
2	810	99.29	97.01	810	99.97	99.88	810	99.29	96.94	810	99.29	96.89	810	99.97	99.91
3	110	93.78	54.27	110	99.08	94.95	110	98.58	90.10	90	99.06	94.73	140	99.97	99.83
4	100	99.99	99.99	100	99.99	99.99	100	99.99	99.99	100	99.99	99.99	100	99.99	99.99
5	720	94.07	68.06	720	99.98	99.95	720	99.98	99.94	720	99.74	98.96	720	99.99	99.96
6	400	92.34	58.55	450	99.68	97.35	450	99.59	96.63	450	99.69	97.49	550	99.92	99.49
7	2.4	97.21	88.86	2.4	97.52	90.06	2.4	97.13	88.53	2.4	97.62	90.04	4.8	99.99	99.99
8	385	95.64	56.45	455	99.41	95.84	455	99.42	95.92	455	98.82	90.01	560	99.99	99.98
9	4.26	98.99	96.97	4.26	98.96	96.88	4.59	99.01	97.04	4.26	99.03	97.09	5.68	99.26	98.46
10	540	94.14	82.30	540	94.19	82.39	540	94.06	82.11	540	94.09	82.18	810	99.99	99.95
11	110	92.87	56.26	110	96.36	84.07	110	96.30	83.81	110	96.25	80.63	160	99.98	99.88
12	60	99.77	98.62	60	99.76	98.55	60	99.78	98.70	60	99.78	98.68	60	99.78	98.66
13	600	98.74	94.95	600	98.71	94.83	600	98.72	94.87	600	98.77	95.08	600	98.69	94.76
14	400	93.92	53.99	450	99.07	94.82	450	98.06	87.42	450	97.9	84.27	450	99.75	97.94
15	4	89.95	59.81	4.8	99.99	99.98	4.8	99.99	99.99	4.8	99.99	99.99	4.8	99.99	99.99
16	385	92.61	53.96	420	95.95	76.33	525	98.40	85.37	595	99.81	98.72	595	99.99	99.99
Average	289.7	95.79	76.14	302.5	98.62	94.00	309.1	98.60	93.47	312.2	98.70	93.94	348.4	99.79	99.18

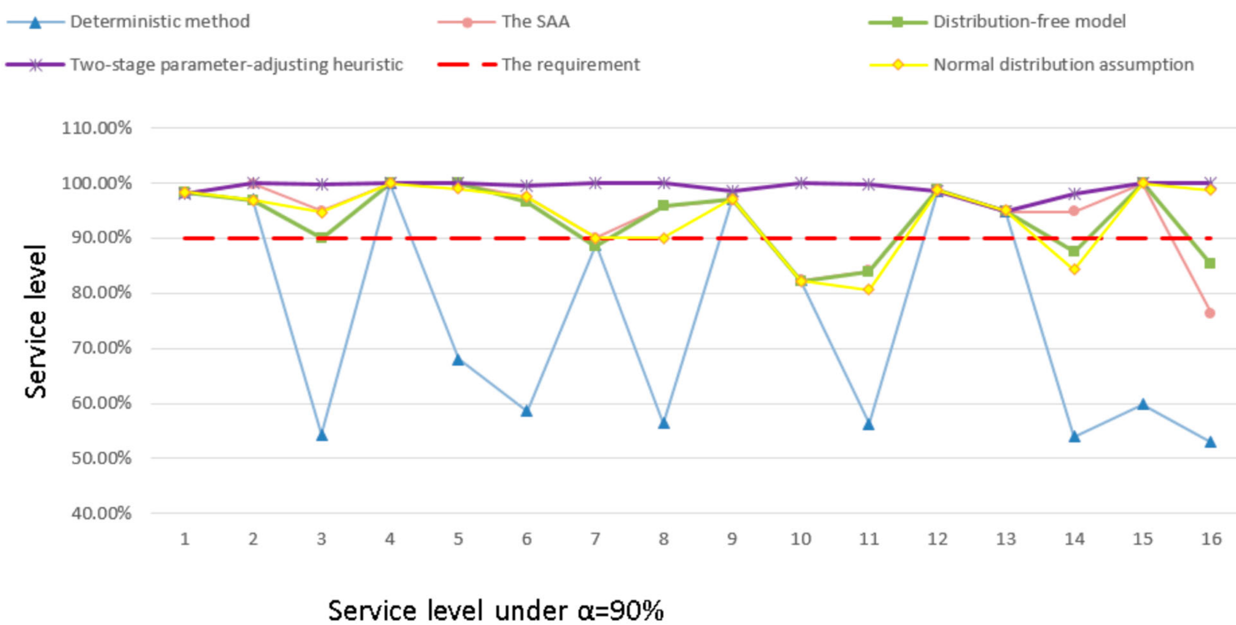

Figure 4. Service levels obtained under $\alpha = 10\%$.

We first examine the impact of the standard deviation, and the standard deviation of each task processing time is set from 0, $0.1 \times \mu_i$, $0.2 \times \mu_i$, $0.3 \times \mu_i$, $0.4 \times \mu_i$, $0.5 \times \mu_i$ and $0.6 \times \mu_i$. Numerical results are reported in Table 8, in which $|J_1^*|$ in the second column and $|J_2^*|$ in the sixth column denote the numbers of selected workstations obtained by the distribution-free model and the two-stage parameter-adjusting heuristic. Figure 6 is presented, to better analyse the impact of the standard deviation on the service level. For the two methods, with the increase of the standard deviation σ_i, the numbers of selected workstations increase in general, as shown in Table 8. The reason may be that there are more task processing times with larger values, thus more workstations should be selected, respecting the cycle time constraints. From Figure 6, we observe that with the increase of σ_i, the service level obtained by the two-stage parameter-adjusting heuristic decrease slightly. As the service level measures the probability of cycle time constraints respected by all workstations, it is understanding that the service level decrease when larger processing times exist. However, for the distribution-free model, it can be obtained from Figure 6 that the service level fluctuates considerably. That may be because the distribution-free model is based on the assumption that the task processing times are independent from each other, but when the standard deviation σ_i increases, the covariance between any two task processing times is getting larger, leading to the unstability.

The impact of the correlation coefficient between disassembly tasks with precedence relation in each disassembly process is then analysed. Correlation coefficients between disassembly tasks with precedence relation in each disassembly process are randomly and uniformly generated from intervals $[-1, -0.8]$, $[-0.8, -0.6]$, $[-0.6, -0.4]$, $[-0.4, -0.2]$, $[-0.2, 0]$, $[0, 0]$, $[0, 0.2]$, $[0.2, 0.4]$, $[0.4, 0.6]$, $[0.6, 0.8]$, and $[0.8, 1]$. Numerical results are illustrated in Table 9, and service levels are illustrated in Figure 7. We observe from Table 9 that for both of the two methods, the numbers of selected workstations have hardly changed under different correlation coefficient ranges. Besides, the two-stage parameter-adjusting heuristic outperforms the distribution-free model in terms of the coverage level and the service level. For example, under correlation coefficients of tasks with precedence relation in $[-1, -0.8]$, the service level obtained by the two-stage two-stage parameter-adjusting heuristic is 99.84%, which is about 7.89% higher than that of the distribution-free model. In addition, from Figure 7 and Table 9, it can be obtained that with the increase of the correlation coefficients, the service levels output by the two methods decrease. The reason may be that when the correlation coefficient of tasks with precedence relation increases, the processing times of tasks with precedence relation may take large values at the same time. Note that the service level obtained by the distribution-free model decreases faster, and fails to reach 90% under correlation coefficients of tasks with precedence relation in [0.4,0.6], [0.6,0.8] and [0.8,1].

The sensitivity of the solutions with the cycle time is further studied, and the cycle time is set from 13, $12, \ldots, 7$. Numerical results are reported in Table 10, and Figure 8 is drawn to better illustrate the service levels. It can be obtained from Table 10 that for the two methods, the numbers of selected workstations increase in general. That may be because when the cycle time is getting larger, one workstation can operate more tasks without violating the cycle time constraint. Besides, the service level obtained by the two-stage parameter-adjusting heuristic changes quite slightly under different cycle times,

Table 7. Computational results of instances of different scales under $\alpha = 5\%$.

Set	Deterministic approach			The SAA			Distribution-free model			Normal distribution assumption			Two-stage parameter-adjusting heuristic		
	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)	Obj	Coverage level (%)	Service level (%)
1	4.26	99.44	98.38	4.26	99.40	98.21	4.26	99.37	98.14	4.26	99.44	98.33	4.26	99.43	98.30
2	810	99.38	97.31	810	99.96	99.85	810	99.29	96.97	810	98.67	93.47	1350	99.99	99.99
3	110	90.32	50.62	110	99.05	94.78	110	98.56	89.92	90	99.06	94.73	160	99.99	99.99
4	100	99.99	99.99	100	99.99	99.99	100	99.99	99.99	100	99.99	99.99	100	99.99	99.99
5	720	92.13	68.51	720	99.98	99.94	720	99.98	99.94	720	99.98	99.96	720	99.99	99.99
6	400	92.29	58.00	450	99.67	97.29	450	99.60	96.63	450	98.53	87.62	700	99.99	99.99
7	2.4	97.15	88.61	2.4	97.57	90.28	2.4	97.15	88.62	2.4	97.62	90.49	4.8	99.99	99.99
8	385	95.64	56.36	455	99.41	95.71	455	99.42	95.88	455	98.81	90.01	560	99.99	99.98
9	4.26	99.04	97.13	4.26	98.98	96.94	4.26	99.02	97.07	4.26	99.03	97.09	6.39	99.99	99.99
10	540	94.06	82.04	540	94.11	82.26	540	94.08	82.12	540	94.09	82.18	1080	99.99	99.98
11	110	91.86	56.05	110	96.37	84.00	110	96.33	83.96	110	96.33	84.04	190	99.99	99.99
12	60	99.79	98.73	60	99.74	98.44	60	99.79	98.74	60	99.78	98.68	60	99.80	98.81
13	600	98.66	94.63	600	98.69	94.76	600	98.72	94.88	600	98.77	95.08	960	99.99	99.99
14	400	91.90	54.41	450	99.07	94.78	450	98.07	87.49	450	99.08	94.74	600	99.99	99.99
15	4	88.94	55.74	4.8	99.99	99.99	4.8	99.99	99.99	4.8	96.84	91.25	4.8	99.99	99.99
16	385	91.86	53.11	420	95.94	74.01	525	98.41	85.36	595	99.29	93.63	595	99.99	99.99
Average	289.7	95.15	75.60	302.5	98.62	93.83	309.1	98.61	93.48	312.2	98.46	93.21	443.5	99.94	99.81

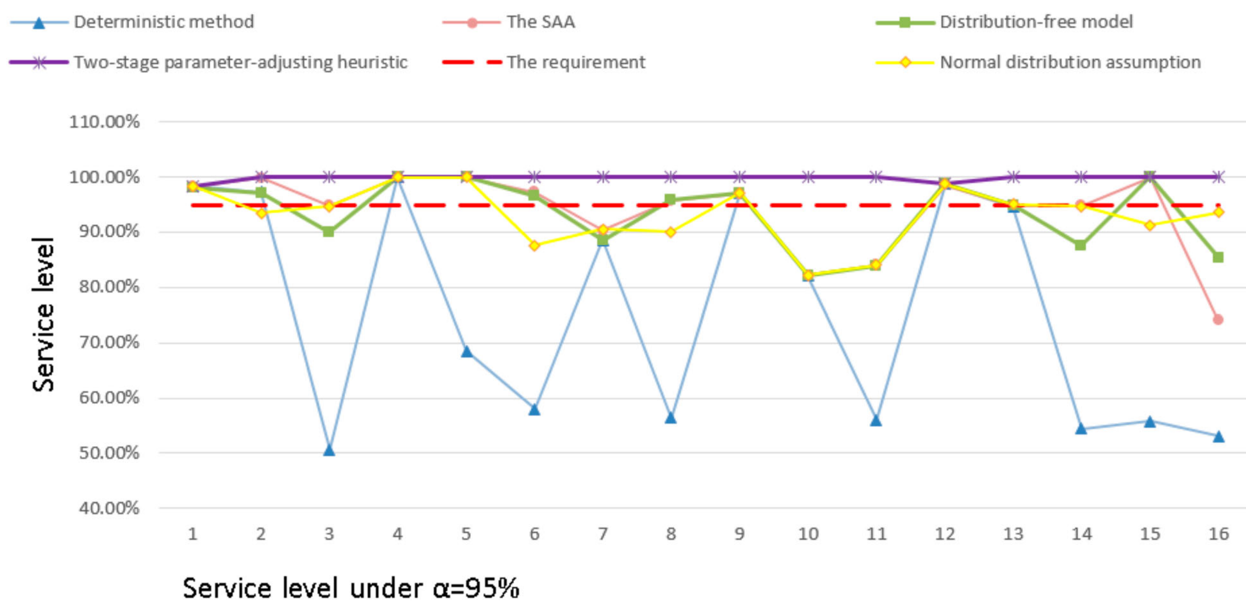

Figure 5. Service levels obtained under $\alpha = 5\%$.

Table 8. The impact of the standard deviation σ_i of each task processing time.

	Distribution-free model				Two-stage parameter-adjusting heuristic			
$\sigma_i(\times\mu_i)$	$\lvert J_1^*\rvert$	Obj	Coverage level (%)	Service level (%)	$\lvert J_2^*\rvert$	Obj	Coverage level (%)	Service level (%)
0	3	90	99.99	99.99	3	90	99.99	99.99
0.1	3	90	99.80	98.23	3	90	99.96	99.80
0.2	3	90	96.43	83.51	4	120	99.99	99.99
0.3	3	90	96.81	85.51	4	120	99.88	99.45
0.4	4	120	98.44	92.75	6	180	99.94	99.55
0.5	4	120	95.70	82.20	6	180	99.55	97.27
0.6	4	120	96.52	84.61	6	180	99.34	95.73

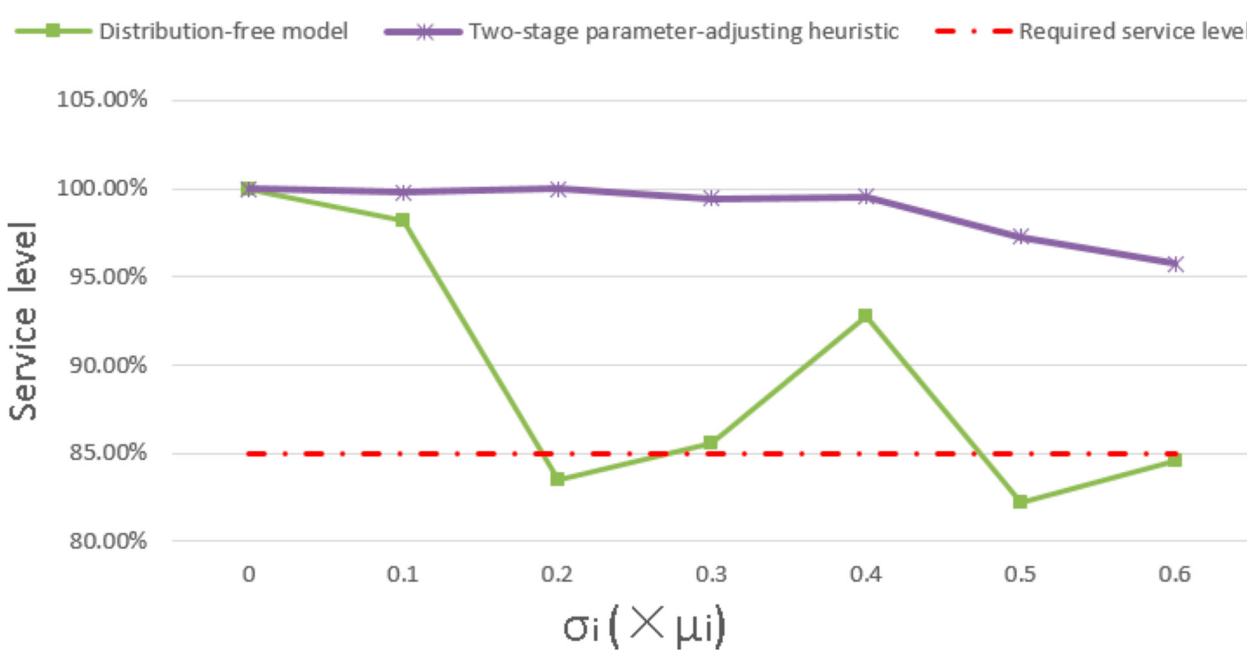

Figure 6. The impact of the standard deviation on the service level.

Table 9. The impact of correlation coefficients of tasks with precedence relation.

	Distribution-free model				Two-stage parameter-adjusting heuristic			
Range of correlation coefficients	$\lvert J_1^* \rvert$	Obj	Coverage level (%)	Service level (%)	$\lvert J_2^* \rvert$	Obj	Coverage level (%)	Service level (%)
$[-1, -0.8]$	3	90	99.10	91.96	3	90	99.98	99.84
$[-0.8, -0.6]$	3	90	99.08	91.73	3	90	99.95	99.56
$[-0.6, -0.4]$	3	90	99.05	91.46	3	90	99.97	99.72
$[-0.4, -0.2]$	3	90	99.02	91.24	3	90	99.91	99.22
$[-0.2, 0]$	3	90	98.96	90.77	3	90	99.90	99.14
$[0, 0]$	3	90	98.94	90.67	3	90	99.80	98.23
$[0, 0.2]$	3	90	98.91	90.43	3	90	99.89	99.01
$[0.2, 0.4]$	3	90	98.86	90.10	3	90	99.86	98.72
$[0.4, 0.6]$	3	90	98.79	89.64	3	90	99.86	98.62
$[0.6, 0.8]$	3	90	98.73	89.27	3	90	99.82	98.35
$[0.8, 1]$	3	90	98.68	88.99	3	90	99.83	98.23

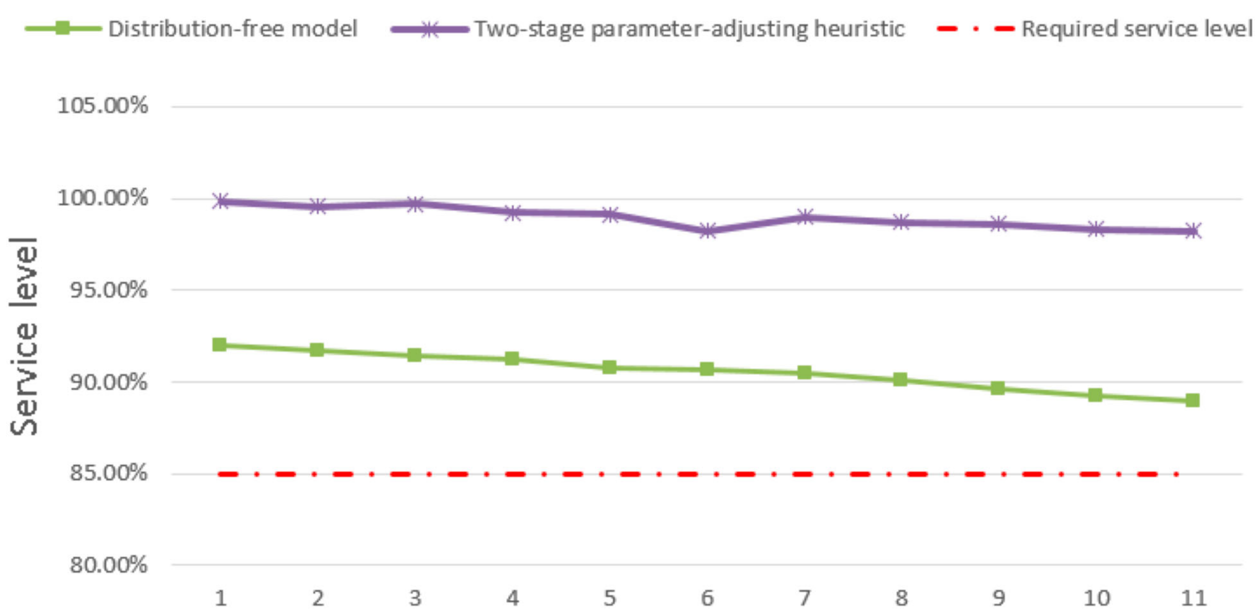

Figure 7. Impact of the correlation coefficients of tasks with precedence relation on the service level.

while the service level output by the distribution-free model fluctuates considerably. The reason may be that the number of workstations selected by the two-stage parameter-adjusting heuristic increases faster according to the change of cycle time rapidly.

In sum, we can observe that (i) the two-stage parameter-adjusting heuristic performs better with its higher coverage level and service level; (ii) as the two-stage parameter-adjusting heuristic is based on the conservative approximation technology, it usually sacrifices the system cost; (iii) the distribution-free model usually fails to meet the required customer service level; (iv) with the increase of the standard deviation of each task processing time, the numbers of selected workstations obtained by the two-stage parameter-adjusting heuristic and the distribution-free model increase in general; (v) with the increase of the standard deviation of each task processing time, the service level obtained by the two-stage parameter-adjusting heuristic decrease slightly, while that obtained by the distribution-free model fluctuates considerably; (vi) when the correlation coefficient between processing times of consecutive tasks increases, the service levels output by the two-stage parameter-adjusting heuristic and the distribution-free model decrease, as the processing times of tasks may take large values at the same time; (vii) when the cycle time decreases, the numbers of selected workstations obtained by the two-stage parameter-adjusting heuristic and the distribution-free model increase in general, and the distribution-free model is unstable in terms of the service level. Thus we recommend the two-stage parameter-adjusting heuristic as solution method, to ensure the requirement on the service level satisfied.

From the above observation, we provide the following suggestions for decision makers:

Table 10. The impact of cycle time C.

	Distribution-free model				Two-stage parameter-adjusting heuristic			
C	$\vert J_1^*\vert$	Obj	Coverage level (%)	Service level (%)	$\vert J_2^*\vert$	Obj	Coverage level (%)	Service level (%)
13	3	117	98.93	90.40	3	117	99.99	99.93
12	3	108	99.05	91.51	3	117	99.99	99.91
11	3	99	99.49	96.94	3	99	99.85	99.03
10	3	90	96.43	83.51	4	120	99.99	99.99
9	4	108	98.45	91.55	4	108	99.96	99.73
8	4	96	97.35	85.98	4	96	99.65	98.20
7	4	84	96.54	84.77	5	140	99.95	99.60

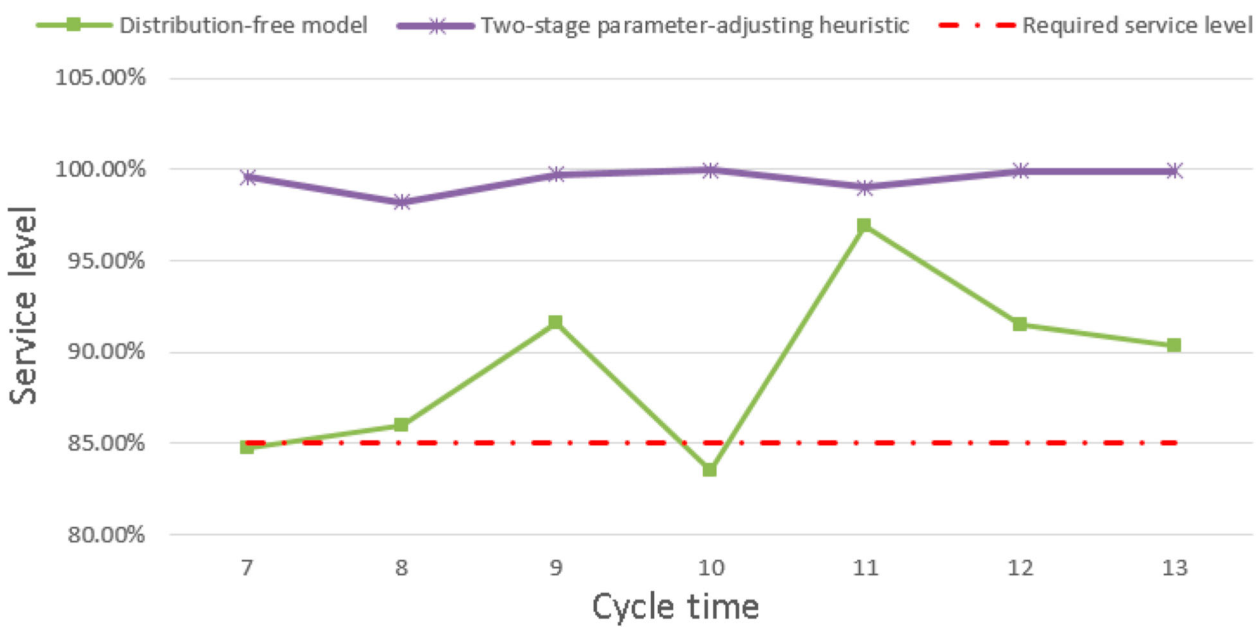

Figure 8. The impact of the cycle time on the service level.

(1) If there is a large positive correlation between the processing times of two tasks (i.e. their correlation coefficient is very close to 1), they may take large values at the same time, thus processing them on different workstations may improve the service level.
(2) Trade-off between the preset risk level α and the system cost is remarkably important in supporting the decision-making process. If the preset α is getting smaller, more workstations should be selected to satisfy the required joint probability (i.e. $1-\alpha$), and thus the system cost will increase.
(3) When the standard deviation σ_i of each task processing time increases, the processing time of task i may take a larger value, thus one workstation can operate less tasks within the cycle time. Therefore, to maintain the required service level, more workstations should be opened.
(4) The cycle time, which largely impacts the system cost (i.e. a multiplication of the cycle time and the unit cost for operating workstations and handling hazardous tasks), should be set reasonably, due to the trade-off between the cycle time and the number of opened workstations, i.e. the number of opened workstations decreases with the increase of cycle time.

6. Extension to multi-product multi-attribute-workstation DLBP

Most related literature considers the single-product situation, due to the complexity of the DLBP (Özceylan et al. 2018). In the real-world disassembly system, however, the EOL products to be disassembled are usually heterogeneous and can be categorised into different types (Ilgin and Gupta 2010), and products of different types require different operations. In addition, a disassembly system possesses multi-attribute equipments or workstations. There is a common assumption in most existing studies that assigning multi-attribute workstations to product types and the disassembly line balancing are separated. However, due to their interrelationship, integrating the assignment and disassembly line balancing may provide advantages, such as the system cost reduction and the performance improvement. Therefore, in this part, we extend the problem to a more general situation, i.e. considering the multiple types of products and multi-attribute workstations.

The problem is described as follows:

(1) There is a set L of product types, and $L = \{1, 2, \ldots, |L|\}$. For each product type $l \in L$, there is a set T_l of disassembly tasks and a set S_l of disassembly nodes, and $T = \cup_{l \in L} T_l$ and $S = \cup_{l \in L} S_l$. For each disassembly node $k \in S_l$ of product type $l \in L$, there is a set P_{kl} of preceding tasks and a set Q_{kl} of successor tasks.

(2) There is a set J of workstations with ordered sequence, and $J = \{1, 2, \ldots, |J|\}$. For each workstation $j \in J$, a binary attribute parameter δ_{jl} is used to describe whether workstation j is capable to disassemble product of type $l \in L$.

(3) Disassembly task processing times are assumed to be stochastic, and only partial distributional information (i.e. the mean and covariance matrix) is given. The risk level of violating the cycle time constraint should be controlled.

(4) For each product type $l \in L$, the precedence constraints of tasks should be satisfied, and only one disassembly process is selected.

The problem is to determine (i) the assignment of multi-attribute workstations to product types, (ii) the opened workstations, (iii) the disassembly process of each product type and (iv) the task-to-workstation assignment, such that the system cost is minimised.

6.1. Model extension

In this part, we first describe new parameters and new decision variables, and then present a distributionally robust chance-constrained formulation [**P4**] for the extension problem.

New parameters:

- L: Set of product types indexed by l, and $L = \{1, 2, \ldots, |L|\}$.
- T_l: Set of tasks, indexed by i, to disassembly a product of type $l \in L$, and $\cup_{l \in L} T_l = T$.
- S_l: Set of subassembly nodes (statuses), indexed by k, of a product of type $l \in L$, i.e. $S_l = \{0, 1, \ldots, |S_l|\}$ and $\cup_{l \in L} S_l = S$, where 0 denotes the beginning status of an EOL product, and $|S_l|$ denotes the status with all required separated components disassembled.
- P_{kl}: Set of preceding tasks of subassembly node $k \in S_l$ and $l \in L$.
- Q_{kl}: Set of successor tasks of subassembly node $k \in S_l$ and $l \in L$.
- c_{jl}: Cost for assigning workstation j to product type $l \in L$.
- δ_{jl}: Binary parameter, which is equal to 1 if workstation j is capable to disassemble products of type $l \in L$, and 0 otherwise.
- $\mathcal{M}$: A large enough number.

Decision variables:

- η_{jl}: Binary variable, equal to 1 if workstation $j \in J$ is assigned to product type $l \in L$, 0 otherwise.
- y_{jl}: Binary variable, equal to 1 if workstation $j \in J$ is opened to disassemble products of type $l \in L$, 0 otherwise.
- λ_{jl}: Binary variable, equal to 1 if workstation j is the last opened workstation for product type $l \in L$, and 0 otherwise.

$$[\mathbf{P4}]: \ \min \quad \left\{ \sum_{l \in L} \sum_{j \in J} c_{jl} \eta_{jl} + C \left(\sum_{l \in L} \sum_{j \in J} C_f y_{jl} + C_h \sum_{j \in J} z_j \right) \right\} \tag{15}$$

s.t. Constraint (1),

$$\sum_{l \in L} \eta_{jl} = 1, \quad \forall j \in J, \tag{16}$$

$$\eta_{jl} \le \delta_{jl}, \quad \forall j \in J, \ l \in L, \tag{17}$$

$$\sum_{i \in Q_{kl}} \sum_{j \in J} x_{ij} = 1, \quad \forall k = 0, \ l \in L, \tag{18}$$

$$\sum_{j \in J} x_{ij} \le 1, \quad \forall i \in T, \tag{19}$$

$$x_{ij} \le \eta_{jl}, \quad \forall\, i \in T_l,\ j \in J, \tag{20}$$

$$y_{jl} \ge x_{ij}, \quad \forall j \in J,\ i \in T_l,\ l \in L, \tag{21}$$

$$\sum_{i \in Q_{kl}} \sum_{j \in J} x_{ij} = \sum_{i \in P_{kl}} \sum_{j \in J} x_{ij}, \quad \forall l \in L,\ k \in S^l \backslash \{0, |S^l|\}, \tag{22}$$

$$\sum_{i \in Q_{kl}} x_{iv} \le \sum_{i \in P_{kl}} \sum_{j=1}^{v} x_{ij}, \quad \forall v \in J,\ k \in S^l \backslash \{0, |S^l|\},\ l \in L, \tag{23}$$

$$\sum_{j \in J} \lambda_{jl} = 1, \quad \forall\, l \in L, \tag{24}$$

$$\lambda_{jl} \le y_{jl}, \quad \forall\, j \in J,\ l \in L, \tag{25}$$

$$\sum_{j \in J} j x_{ij} \le \sum_{j \in J} j \lambda_{jl}, \quad \forall\, i \in T_l,\ l \in L, \tag{26}$$

$$\sum_{r \in J} y_{rl} \ge \sum_{r=1}^{j} \eta_{jl} - \mathcal{M}(1 - \lambda_{jl}), \quad \forall\, j \in J,\ l \in L, \tag{27}$$

$$\sum_{r \in J} y_{rl} \le \sum_{r=1}^{j} \eta_{jl} + \mathcal{M}(1 - \lambda_{jl}), \quad \forall\, j \in J,\ l \in L, \tag{28}$$

$$z_j \ge x_{ij}, \quad \forall\, i \in H,\ j \in J, \tag{29}$$

$$x_{ij}, y_{jl}, z_j, \eta_{jl}, \gamma_{jl} \in \{0, 1\}, \quad \forall\, l \in L,\ j \in J,\ i \in T_l. \tag{30}$$

The objective function is to minimise the total cost, including the assigning cost (i.e. $\sum_{l \in L} \sum_{j \in J} c_{jl} \eta_{jl}$), the workstation operating cost (i.e. $\sum_{l \in L} C_f \sum_{j \in J} y_{jl}$), and the cost for handling hazardous tasks (i.e. $C_h \sum_{j \in J} z_j$).

Joint chance constraint (1) ensures the probability of jointly satisfying all cycle time constraints is no less than $1 - \alpha$. Constraint (16) ensures that a workstation should be assigned to exactly one product type. Constraint (17) denotes that workstation j can only be assigned to product types within its capability. Constraint (18) ensures that for a product of type $l \in L$, there is only one disassembly process selected. Constraint (19) ensures that each disassembly task can be assigned to at most one workstation. Constraint (20) ensures that for product type $l \in L$, each disassembly task $i \in T_l$ can only be operated by a workstation which is assigned to type $l \in L$. Constraint (21) defines the opened workstations for each product type $l \in L$. Constraint (22) serves as the flow conservation. Constraint (23) respects the precedence restrictions. Constraint (24) implies that for each product of type $l \in L$, there exists one workstation being the last opened workstation. Constraint (25) denotes a workstation j must be assigned to disassembly products of type $l \in L$ if workstation j is the last opened workstation for product type $l \in L$. Constraints (26)–(28) respect the given sequence of workstations, in which for each product type $l \in L$, if workstation j is last opened (i.e. $\lambda_{jl} = 1$), the opened workstations must be the workstations with indexes smaller than j and the number of opened workstations is equal to the number of workstations with indexes smaller than j assigned to disassembly products of type $l \in L$. Constraint (29) defines the workstation handling hazardous tasks. Domains of decision variables are given by Constraint (30).

6.2. An illustrative example

Solution approaches for the extension problem also focus on tackling the joint chance constraint (1) in model **[P4]**. For our proposed two-stage parameter-adjusting heuristic, it solves formulation **[P4]**, in which Constraint (1) is replaced by Constraints (14), (11) and (12), during each iteration. The ways to handle Constraint (1) by the SAA method and the deterministic approach for the extension problem are shown in Appendices 2 and 3. Similarly, for the distribution-free model and the solution method based on normal distribution assumption, we employ their approximation methods for the joint chance constraint (1) as well.

In the following, we present an illustrative example, to evaluate the two-stage parameter-adjusting heuristic for the extension problem. The illustrative example is based on the hand light instance (Bentaha, Battaïa, and Dolgui 2015a), by adding 3 disassembly processes with the same task precedence constraints (i.e. which are considered as the tasks of the second product type). The numbers of disassembly processes, disassembly tasks and disassembly nodes are doubled, thus the number of workstations is twice as much as that of the original hand light instance. That is, there are 10 workstations and

Table 11. Task-to-workstation assignments for the extension problem example.

		Deterministic approach										
Type	Task	Workstation assignment	1	2	3	4	5	6	7	8	9	10
1	1	2,3,6,7,8,10										
	2			1								
	3											
	4			1								
	5											
	6				1							
	7				1							
	8											
	9			1								
	10			1								
2	11	1,4,5,9										
	12		1									
	13											
	14		1									
	15											
	16					1						
	17					1						
	18											
	19		1									
	20		1									
Objective (Cost)		1090										
Coverage level		90.15%										
Service level		35.71%										
Time (s)		2.4										

		The SAA										
Type	Task	Workstation assignment	1	2	3	4	5	6	7	8	9	10
1	1	2,3,6,7,8,10										
	2			1								
	3											
	4											
	5					1						
	6											
	7							1				
	8							1				
	9								1			
	10								1			
2	11	1,4,5,9										
	12		1									
	13											
	14											
	15		1									
	16											
	17					1						
	18					1						
	19						1					
	20						1					
Objective (Cost)		1900										
Coverage level		99.98%										
Service level		99.83%										
Time (s)		10.9										

		Distribution-free model										
Type	Task	Workstation assignment	1	2	3	4	5	6	7	8	9	10
1	1	2,3,5,6,7,8,10										
	2			1								
	3											
	4				1							
	5											
	6							1				
	7			1								
	8											
	9				1							
	10				1							
2	11	1,4,9	1									
	12											
	13					1						
	14											
	15											
	16						1				1	
	17						1					
	18											
	19		1									
	20					1						
Objective (Cost)		1810										
Coverage level		96.06%										
Service level		71.23%										
Time (s)		13.5										

		Normal distribution assumption										
Type	Task	Workstation assignment	1	2	3	4	5	6	7	8	9	10
1	1	2,3,6,7,8,10										
	2			1								
	3											
	4			1								
	5											
	6							1				
	7				1							
	8											
	9				1							
	10				1							
2	11	1,4,5,9										
	12		1									
	13											
	14		1									
	15											
	16						1					
	17					1						
	18											
	19					1						
	20					1						
Objective (Cost)		1630										
Coverage level		99.32%										
Service level		94.75%										
Time (s)		5.6										

		Two-stage parameter-adjusting heuristic										
Type	Task	Workstation assignment	1	2	3	4	5	6	7	8	9	10
1	1	2,3,6,7,8,9,10										
	2			1								
	3											
	4			1								
	5											
	6							1				
	7			1								
	8											
	9				1							
	10				1							
2	11	1,4,5										
	12		1									
	13											
	14											
	15		1									
	16											
	17						1					
	18					1						
	19					1						
	20						1					
Objective (Cost)		1630										
Coverage level		99.83%										
Service level		98.54%										
Time (s)		9.9										

20 disassembly tasks, and other input data are shown in Table 1. Besides, the mean values and the standard deviations of the first 10 tasks (i.e. tasks of the first product type) and the last 10 tasks (i.e. tasks of the second product type) are the same, and the correlations between the first 10 tasks and the last 10 tasks are the same, the values are shown in Table 2. Moreover, we assume that workstations 2, 3, 5, 6, 7, 8, 9, 10 are capable to disassembly products of type 1, and workstations 1, 3, 4, 5, 9 are capable for products of type 2, and the cost c_{jl} for assigning workstation j to a product type l is set to be 1.

Table 11 reports the computational results obtained by the deterministic approach, the SAA, the distribution-free model, the solution approach based on normal distribution assumption and our proposed two-stage parameter-adjusting heuristic. We can observe from Table 11 that the objective value, i.e. the system cost, obtained by the deterministic approach is the smallest, while the coverage level and the service level are also smallest. Besides, the coverage level and the service level obtained by the SAA method are 99.98% and 99.83%, which are higher than those obtained by other approaches. However, the objective value yielded by the SAA is 1900, which is also larger than those of other approaches. The objective values obtained by the distribution-free model is 1810, about 11.04% larger than those of the solution method based on normal distribution assumption and the two-stage parameter-adjusting heuristic. The coverage level and the service level obtained by the distribution-free model are lower than the solution method based on normal distribution assumption and the two-stage parameter-adjusting heuristic. Moreover, the objective values obtained by the solution method based on normal distribution assumption and the two-stage parameter-adjusting heuristic are the same, and our proposed two-stage parameter-adjusting heuristic are 99.83% and 98.54%, which are about 0.51% and 4% higher than those of solution method based on normal distribution assumption.

Concluding, for the illustrative extension problem example, we can observe from Table 11 that the two-stage parameter-adjusting can also obtain high-quality solutions, in terms of the coverage level and the service level, within a reasonable time.

7. Conclusion

This paper considers a stochastic disassembly line design problem, incorporating with the correlation between uncertain task processing times. Only partial information is known beforehand, i.e. the mean and covariance matrix of task processing times. For the problem, a new distributionally robust model with joint chance constraint is proposed. In order to solve the problem efficiently, an approximated mixed integer second-order cone programming (MI-SOCP) formulation is constructed, and a two-stage parameter-adjusting heuristic is then developed. Then numerical experiments on instances with difference scales are conducted, to compare the two-stage parameter-adjusting heuristic with existing solution approaches in the literature. We observe that the existing approaches usually fail to meet the required service level. The two-stage parameter-adjusting heuristic outperforms the existing approaches, in terms of the service level, with a cost sacrifice. In addition, sensitivity analyses have been conducted, to test the impacts of input parameters, including the preset risk level α, the standard deviation, the correlation coefficients of tasks with precedence relation and the cycle time. We also make some proposals for the practitioners and managers. Moreover, we also investigate the extension problem, by considering the multiple product types and integrating the workstation-to-product-type assignment with the original disassembly line balancing. An illustrative example is studied, and the computational results show that the two-stage parameter-adjusting heuristic can also provide computational efficiency, i.e. obtaining high-quality solutions within a reasonable time.

The heuristic proposed in this work is based on the conservative approximation technology, thus it usually obtains high service level with a cost sacrifice. Besides, the computational time of the proposed heuristic is larger than those of the existing methods. In addition, the considered problem only focuses on the disassembly process, which is actually one part of reverse flow in closed-loop supply chain (Habibi et al. 2017a). Therefore, in future research, we may consider the following issues: (i) designing approaches to obtain the approximation to the distributionally robust formulation with high quality, (ii) developing more efficient approaches to address the problem, and (iii) integrating other practical parts of reverse flow in closed-loop supply chain, such as the collection-disassembly problem (Habibi et al. 2017b). Moreover, a comprehensive theoretical analysis on the correlation between uncertain parameters is also an interesting research issue.

Acknowledgments

The authors would like to thank the anonymous referees for their constructive comments.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China (NSFC) under grants 71531011, 71771048, 71832001 and 71571134. This work was also supported by the Fundamental Research Funds for the Central Universities.

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Appendix 1

Preliminary analyses are conducted to adjust the input parameter Δ_1 (i.e. the difference for calculating the individual risk levels as arithmetic procession) in the two-stage parameter-adjusting heuristic. By arithmetic procession with identical difference Δ_1, we mean that if the first stage of the heuristic selects $|J'|$ workstations, their risk levels are estimated as $\alpha_1, \alpha_2 = \alpha_1 + (2-1)\cdot\Delta_1, \ldots, \alpha_{|J'|} = \alpha_1 + (|J'|-1)\cdot\Delta_1$. Note that the summation of the individual risk levels of the first $|J'|$ workstations equals $|J'|\cdot\alpha_1 + \frac{|J'|\cdot(|J'|-1)}{2}\cdot\Delta_1 = \alpha$. We test 10 different values of Δ_1, i.e. $\Delta_0, \frac{\Delta_0}{1.5}, \ldots, \frac{\Delta_0}{3}, -\frac{\Delta_0}{3}, -\frac{\Delta_0}{2.5}, \ldots, -\Delta_0$. Note that Δ_0 is a difference value such that $\sum_{j\in\{1,2,\ldots,|J'|\}}\alpha_j = \alpha$ and $\alpha_j \geq 0,\ \forall j \in \{1,2,\ldots,|J'|\}$. In this work, we set $\Delta_0 = (\alpha - |J'|\cdot\frac{\alpha}{|J|})\cdot\frac{2}{|J'|\cdot(|J'|-1)}$ (i.e. when the individual risk level α_1 equals $\frac{\alpha}{|J|}$).

The analysis is based on the benchmark instance L99a, where there are 30 tasks, 9 workstations and 20 disassembly nodes. Four workstations are assumed to be selected in the first stage, and computational results are shown in Table 11, in which columns 6–9 report the task-to-workstation assignments. For example, under $\Delta_1 = \Delta_0$ in the first row, disassembly tasks 1, 3 and 30 are assigned to workstation 1, and '∅' denotes that the workstation is not opened. We can observe from Table 11 that the task-to-workstation assignments are different under different Δ_1. Besides, it can be obtained from Table 11 that under $\Delta_1 = -\Delta_0$, the obtained objective value is 450, which is 18.18% smaller than those obtained under other values of Δ_1, and the service level is 96.66%, which is only 2.95% lower than the best value. Therefore, during the computational experiments, we set $\Delta_1 = -\Delta_0$.

We also examine the impact of swapping individual risk levels of different workstations, and the computational results are reported in Table A1. Each row in Table 2 reports the obtained task-to-workstation assignment, objective value, coverage level and service level

Table A1. The impact of identical difference Δ_1 for calculating the individual risk levels as arithmetic procession.

						Task-to-workstation assignment						
	Δ_1	α_1 (%)	α_2 (%)	α_3 (%)	α_4 (%)	1	2	3	4	Obj	Coverage level (%)	Service level (%)
1	Δ_0	1.67	3.06	4.44	5.83	[1,3,30]	[6,10,16]	[23,27,29]	∅	550	99.90	99.36
2	$\frac{\Delta_0}{1.5}$	2.36	3.29	4.21	5.14	[1,3,30]	[6,10,16]	[23,27,29]	∅	550	99.90	99.36
3	$\frac{\Delta_0}{2}$	2.71	3.40	4.10	4.79	[2,4,30]	[6,10,16]	[23,27,29]	∅	550	99.88	99.34
4	$\frac{\Delta_0}{2.5}$	2.92	3.47	4.03	4.58	[1,3,30]	[6,10,16]	[23,27,29]	∅	550	99.90	99.36
5	$\frac{\Delta_0}{3}$	3.06	3.52	3.98	4.44	[2,5,8]	[13,22]	[26,28,29,30]	∅	550	99.94	99.60
6	$-\frac{\Delta_0}{3}$	4.44	3.98	3.52	3.06	[1,3,30]	[6,10,16]	[23,27,29]	∅	550	99.90	99.36
7	$-\frac{\Delta_0}{2.5}$	4.58	4.03	3.47	2.92	[2,4,6]	[10,16,30]	[23,27,29]	∅	550	99.73	97.85
8	$-\frac{\Delta_0}{2}$	4.79	4.10	3.40	2.71	[2,5,7]	[10,16,30]	[23,27,29]	∅	550	99.67	97.84
9	$-\frac{\Delta_0}{1.5}$	5.14	4.21	3.29	2.36	[1,3,30]	[6,10,16]	[23,27,29]	∅	550	99.90	99.36
10	$-\Delta_0$	5.83	4.44	3.06	1.67	[1,3,6,30]	[11,18]	[23,27,29]	∅	450	99.60	96.66

under each swap. It can be observed from Table A1 that under all tested combinations of individual risk levels, the minimum objective value is 450, which is equal to that under the 10th combination of individual risk levels without such swap. Besides, under the swap of the values of α_1 and α_2 in the combinations 7, 8, 9 and 10, the obtained service level is 97.40%, which is 0.77% higher than that the 10th combination without swap. That is, for the tested instance, swapping individual risk levels of different workstations may improve the solutions in terms of 0.77% increase of the service level. However, swapping individual risk levels of different workstations may also increase the computational time sixfold, for the tested instance. Therefore, swapping individual risk levels of different workstations has not been considered in the two-stage parameter-adjusting heuristic.

Appendix 2

We adapt the SAA method (Bentaha et al. 2014c) for our problem (Pagnoncelli, Ahmed, and Shapiro 2009). We replace the partial known distribution $\mathbb{P}$ by an empirical one that satisfies the given conditions, corresponding to a finite set Ω of randomly generated scenarios. Note that in each scenario $\omega \in \Omega$, task processing times are randomly generated following a Lognormal distribution, satisfying the given mean and covariance matrix. Following the expected-penalty-based SAA models, the objective function is transformed into the weighted sum of the total cost and the average estimate of the amount of time exceeding the cycle time. Note that a recourse variable $\pi_j(\omega)$, $\forall j \in J, \omega \in \Omega$, is introduced, denoting the amount of time exceeding the given cycle time C of workstation j under scenario $\omega \in \Omega$ (Bentaha, Battaïa, and Dolgui 2014b). For the original considered problem, a stochastic mixed integer programming (MIP) formulation [**P5**] is proposed (Table A2):

$$[\mathbf{P5}]: \ \min \quad \Big\{ C \cdot C_f \cdot \sum_{j \in J} y_j + C \cdot C_h \cdot \sum_{j \in J} z_j + \frac{\theta}{|\Omega|} \cdot \Big(\sum_{\omega \in \Omega} \sum_{j \in J} \pi_j(\omega) \Big) \Big\}$$

$$\text{s.t.} \quad (2)\text{–}(8),$$

$$\sum_{i \in T} t_i(\omega) \cdot x_{ij} - \pi_j(\omega) \le (1 - \alpha_j) \cdot C, \quad \forall j \in J, \ \omega \in \Omega, \tag{A1}$$

$$x_{ij}, y_j, z_j, \in \{0, 1\}, \pi_j(\omega) \ge \ 0, \quad \forall i \in T, \ j \in J, \ \omega \in \Omega. \tag{A2}$$

For the extension problem, we develop the SAA-based model [**P6**] as follows:

$$[\mathbf{P6}]: \ \min \quad \left\{ \sum_{l \in L} \sum_{j \in J} c_{jl} \eta_{jl} + C \left(\sum_{l \in L} \sum_{j \in J} C_f y_{jl} + C_h \sum_{j \in J} z_j \right) + \frac{\theta}{|\Omega|} \Big(\sum_{\omega \in \Omega} \sum_{j \in J} \pi_j(\omega) \Big) \right\}$$

$$\text{s.t.} \quad (16)\text{–}(29), (A1)\text{–}(A2)$$

Appendix 3

A deterministic method is adapted for our problem, which is to ensure the cycle time constraints by restricting the cycle time greater than or equal to the sum of mean processing times of tasks assigned to a workstation multiplying the individual confidence level, i.e. $\sum_{i \in T} x_{ij} \cdot \mu_i \le (1 - \alpha_j) \cdot C$, where μ_i denotes the mean processing time of task $i \in T$.

Table A2. The impact of swapping of individual risk levels of different workstations.

	Swap of the values of α_1 and α_2							Swap of the values of α_1 and α_3						
	Task-to-workstation assignment							Task-to-workstation assignment						
	1	2	3	4	Obj	Coverage level (%)	Service level (%)	1	2	3	4	Obj	Coverage level (%)	Service level (%)
1	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
2	[2, 4, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.88	99.34	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
3	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
4	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
5	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
6	[2, 5, 7]	[10, 16, 30]	[23, 27, 29]	∅	550	99.67	97.84	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
7	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[2, 4, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.88	99.34
8	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[2, 4, 6]	[10, 16, 30]	[23, 27, 29]	∅	550	99.73	97.85
9	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[1, 3, 6]	[10, 16, 30]	[23, 27, 29]	∅	550	99.74	97.85
10	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36

	Swap of the values of α_1 and α_4							Swap of the values of α_2 and α_3						
	Task-to-workstation							Task-to-workstation						
	1	2	3	4	Obj	Coverage level (%)	Service level (%)	1	2	3	4	Obj	Coverage level (%)	Service level (%)
1	[1, 3, 6, 30]	[11, 18]	[23, 27, 29]	∅	450	99.60	96.66	[1, 3, 6, 30]	[11, 18]	[23, 27, 29]	∅	450	99.60	96.66
2	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
3	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
4	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
5	[2, 4, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.88	99.34	[2, 4, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.88	99.34
6	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
7	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
8	[1, 3, 6]	[10, 16, 30]	[23, 27, 29]	∅	550	99.74	97.85	[1, 3, 6]	[10, 16, 30]	[23, 27, 29]	∅	550	99.74	97.85
9	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
10	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36

	Swap of the values of α_2 and α_4							Swap of the values of α_3 and α_4						
	Task-to-workstation							Task-to-workstation						
	1	2	3	4	Obj	Coverage level (%)	Service level (%)	1	2	3	4	Obj	Coverage level (%)	Service level (%)
1	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[2, 5]	[8, 13, 30]	[22, 26, 28, 29]	∅	550	9.63	96.74
1	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
3	[1, 3, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.68	97.40	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
4	[2, 4, 30]	[6, 11, 18]	[23, 27, 29]	∅	450	99.66	97.39	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
5	[2, 4, 30]	[6, 10, 16]	[23, 27, 29]	∅	450	99.88	99.34	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60
6	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 6]	[10, 16, 30]	[23, 27, 29]	∅	550	99.74	97.85
7	[2, 5, 8]	[13, 22]	[26, 28, 29, 30]	∅	550	99.94	99.60	[2, 4, 6]	[10, 16, 30]	[23, 27, 29]	∅	550	99.73	97.85
8	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36
9	[1, 3, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.90	99.36	[2, 4, 30]	[6, 10, 16]	[23, 27, 29]	∅	550	99.88	99.34
10	[1, 3, 6, 30]	[11, 18]	[23, 27, 29]	∅	450	99.60	99.66	[1, 3, 6, 30]	[11, 18]	[23, 27, 29]	∅	450	99.60	96.66