A Constraint Programming Approach for Aircraft Disassembly Scheduling

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Abstract. The dismantling and recycling of aircrafts is one of the future challenges for the air transport industry in terms of sustainability. This problem is hard to solve and optimize as planning operations are highly constrained. Indeed, extracting each part requires technicians with the necessary qualifications and equipment. The parts to be extracted are constrained by precedence relations and the number of simultaneous technicians on specific zones is restricted. It is also essential to avoid unbalancing the aircraft during disassembly. Cost is a significant factor, influenced by the duration of ground mobilization and the choice of technicians for each operation. This paper presents a first constraint programming model for this problem using optional interval variables. This model is used to solve variations of a large instance involving up to 1500 tasks, based on real-life data provided by our industrial partner. The results show that the model can find feasible solutions for all variations of the instance and compares the solutions obtained to lower bounds.

Keywords: Aircraft Dismantling · Scheduling · RCPSP · Constraint Programming · Application · Industrial Problem

1 Introduction

As environmental concerns are more and more present, finding ways to reduce the impact of industries is pressing. In addition to carbon emissions, another sustainability concern in the air transport industry is the disposal of aircrafts retired from service [19]. During this process, parts and materials can be collected in order to be reused or recycled [1,10,25]. This limits the amount of material discarded but also indirectly decreases the impacts of the construction and maintenance of new aircrafts as less raw materials are needed. While the recycling process may yield parts and materials, it is costly in itself. Thus, finding ways to increase the amount and value of what is recouped and decrease the costs of the recycling is crucial in order to incentivize companies towards sustainable disposal of their aircrafts.

This research is done as part of the Planum project which consists in studying and developing technologies and tools in order to facilitate the recycling of end-of-life aircrafts. The problem studied in this paper concerns the scheduling of the operations taking part in the dismantling phase of the recycling process, from the reception of the plane to the sectional cutting and shredding of the carcass. These operations mostly consist in parts removal but also include inspection and pollutant disposal tasks. In addition to the scheduling aspect, workers and other resources must be assigned in order to complete the operations. In this paper, a CP approach is proposed to tackle this problem and evaluated on large-scale instances obtained from an industrial partner.

2 Problem

The problem consists in ordering the different tasks to perform from the reception of the plane to the sectional cutting of its carcass. Several considerations must be taken into account: Different operations may involve a different number of technicians and may require specific certification levels for some technicians. Some technicians may not be available during the whole planning horizon. There are precedences between some operations.

The different parts of the plane may have space restrictions that limit the number of technicians working at the same time there. Thus, the plane is divided into locations that each have an occupancy limit corresponding to the maximum number of technicians allowed to work there at the same time. Finally, the plane must be kept balanced during the whole disassembly process by ensuring that the difference of mass between its extremities does not overstep given thresholds.

The main objective is to minimize the total time taken by the whole extraction process. This is modelled with a *makespan* value that corresponds to the time step at which the last operation finishes. A secondary objective is to minimize the dismantling cost by limiting the use of more costly resources.

The problem is formally defined as such: The set of all operations to perform is denoted $\mathcal{O}$. With each operation $i \in \mathcal{O}$ is associated the duration needed to perform the operation d_i, a location l_i where the operation takes place, an occupancy τ_i, a mass removed m_i, a set of precedences $\mathcal{P}_i$ referencing operations that must be finished before the start of the operation and a set of requirements needed to perform the operation $\mathcal{Q}_i$. Each element $q \in \mathcal{Q}_i$ of this set is a tuple $(\mathcal{C}_{i,q}, n_{i,q})$ where $\mathcal{C}_{i,q}$ is a set of categories of the resource needed and $n_{i,q}$ indicates the amount of this resource needed.

All the available resources are part of the set $\mathcal{R}$. Each resource $j \in \mathcal{R}$ is associated with a category c_j, a set of unavailabilities $\mathcal{U}_j$ consisting of time windows when the resource is not available and a cost f_j which corresponds to the cost per time step to use this resource.

A set of locations $\mathcal{L}$ contains all the locations where operations can take place. Each location $l \in \mathcal{L}$ is associated to a capacity k_l that indicates the maximum number of technicians that can work simultaneously in this location and optionally a zone z_l which corresponds to one of the balance zones of the aircraft. There are four balance zones in total: `Aft` and `Fwd` which correspond to the rear and front of the aircraft and `Left` and `Right` which correspond to the wings.

A global planning horizon H is given. Two global parameters: B_{af} and B_{lr} indicate the maximum difference of mass allowed at any point in the planning between the `Aft` and `Fwd` zones and the `Left` and `Right` zones respectively.

The objective is to minimize first the makespan under the following constraints: (1) The makespan must be lower or equal to the global planning horizon H; (2) Precedences between tasks must be respected; (3) A resource cannot be allocated to different operations at the same time; (4) The difference of mass between the `Aft` and `Fwd` zones cannot overstep the balance parameter B_{af} at any time during the planning; (5) The difference of mass between the `Left` and `Right` zones cannot overstep the balance parameter B_{lr} at any time during the planning; (6) The capacity k_l of a location must not be overloaded at any time; (7) A resource may not be used during its unavailabilities; (8) All the resources needed for a task must be allocated during its whole duration.

Once the optimal makespan has been reached or after some limit, a secondary objective is to minimize the cost of the planning under the same constraints.

3 State of the Art

The Aircraft Dismantling Scheduling problem presented in the previous section is a variation of the Resource Constrained Project Scheduling Problem (RCPSP) [28,4] which consists in scheduling a series of tasks consuming several resources under precedence constraints. The objective is to find a feasible schedule that minimizes the makespan of the tasks. This problem is NP-complete [8]. Several variants of the problem exist [9]. The closest one to our current problem is probably the Multi-Skill Project Scheduling Problem (MCPSP) introduced in [2]. It consists in scheduling tasks and assigning workers with different skill levels to them. It is essentially a relaxed version of the Aircraft Disassembly Scheduling problem without the capacity and balance constraints. In [24], the authors use a CP model to solve several instances of the MSPSP with up to 60 tasks, 19 workers and 15 different skills.

Other publications are related to the problem studied in this paper: In [20], the authors propose a genetic algorithm to solve an aircraft assembly RCPSP. The authors of [17] propose an integer programming approach to schedule aircraft engine assembly lines which also involves workers with several skills on up to 100 tasks. In [18] the authors propose an approach to schedule technicians on short-term aviation maintenance processes (up to 48h). In [21,26,5,6] different approaches are studied to solve problems linked to aircraft disassembly by finding optimal sequences to access specific components based on spatial and geometrical data. Several CP approaches have also been proposed for problems linked to disassembly scheduling: In [16], a disassembly problem with capacity constraints is studied. The stochastic aspects of disassembly processes are studied in [3] and [22]. In [27,7,11] several MILP and CP models are proposed to solve disassembly problems but are only able to solve instances up to 150 tasks. To our knowledge, this work is the first one to propose a CP model able to solve large-scale RCPSP industrial instances with up to 1500 tasks.

4 Model

The CP model proposed relies on conditional time-intervals [13,15] implemented in CP Optimizer [14]. This modeling approach operates under a paradigm where each interval can be present or not. Resource constraints within this framework are represented as cumulative functions, which are applied over the time intervals that can be constrained within a predefined range. A detailed description of the complete model follows.

$$\text{minimize } \max_{a_i \in \mathcal{A}} (e_i) \tag{1}$$

$$\text{minimize } \sum_{r_{j,i,q} \in R} (x_{j,i,q} \times d_i \times f_j) \tag{2}$$

$$\text{subject to}$$

$$S_j = \mathit{sequence}(\{\omega_{j,i,q} \forall i \in \mathcal{O}, q \in \mathcal{Q}_i\} \cup \{\upsilon_{j,u} \forall u \in \mathcal{U}_j\}) \qquad \forall j \in \mathcal{R} \tag{3}$$

$$\mathit{noOverlap}(S_j) \qquad \forall j \in \mathcal{R} \tag{4}$$

$$\begin{aligned} b_{af} = \mathit{step}(0, B_{af}) + &\sum_{a_i \in \mathcal{A} | z_{l_i} = \texttt{Aft}} \mathit{stepAtStart}(a_i, m_i) + \\ &\sum_{a_i \in \mathcal{A} | z_{l_i} = \texttt{Fwd}} \mathit{stepAtStart}(a_i, -m_i) \end{aligned} \tag{5}$$

$$\begin{aligned} b_{lr} = \mathit{step}(0, B_{lr}) + &\sum_{a_i \in \mathcal{A} | z_{l_i} = \texttt{Left}} \mathit{stepAtStart}(a_i, m_i) + \\ &\sum_{a_i \in \mathcal{A} | z_{l_i} = \texttt{Right}} \mathit{stepAtStart}(a_i, -m_i) \end{aligned} \tag{6}$$

$$0 \leq b_{af} \leq B_{af} \times 2 \tag{7}$$

$$0 \leq b_{lr} \leq B_{lr} \times 2 \tag{8}$$

$$o_l = \sum_{a_i \in \mathcal{A} | l_i = l} \mathit{pulse}(a_i, \tau_i) \qquad \forall l \in \mathcal{L} \tag{9}$$

$$0 \leq o_l \leq k_l \qquad \forall l \in \mathcal{L} \tag{10}$$

$$\mathit{alternative}(a_i, \{\omega_{j,i,q} \forall j \in \mathcal{R} | c_j \in \mathcal{C}_{i,q}\}, n_{i,q}) \qquad \forall i \in \mathcal{O}, q \in \mathcal{Q}_i \tag{11}$$

$$e_p \leq s_i \qquad \forall i \in \mathcal{O}, p \in \mathcal{P}_i \tag{12}$$

Variables Interval variables represent the operations to perform. Each operation $i \in \mathcal{O}$ is thus modelled with an interval variable $a_i \in \mathcal{A}$ characterized by a start s_i and an end e_i initialized to $[0, H - d_i]$ and $[d_i, H]$ respectively. These interval variables are always present and their duration is fixed to the duration of the corresponding operation: d_i. The assignment of resources to operations is also represented by interval variables. For each requirement $q \in \mathcal{Q}_i$ of each operation $i \in \mathcal{O}$, all the compatible required resources $(j \in \mathcal{R} | c_j \in \mathcal{C}_{i,q})$ are associated to a corresponding optional interval variable $\omega_{j,i,q} \in \Omega$ which presence $x_{j,i,q}$ indicates whether the resource is assigned to the operation. The initial domain of the interval variables corresponds to the whole planning horizon $([0, H])$. Operation variables are always set to present while assignment variables are optional.

The unavailabilities of the resources are also modelled as interval variables $\upsilon_{j,u}$ which are set to the time windows corresponding to the unavailabilities. All the optional assignment and unavailability interval variables of a same resource are added to a sequence variable S_j (3).

Constraints Each sequence variable is subject to a *noOverlap* constraint (4). This constraint ensures that a resource is never assigned to more than one operation simultaneously and is not assigned when unavailable.

Balance and occupancy constraints are modelled using cumulative functions. There are two cumulative functions used for the balance constraints: The cumulative function b_{af} (5) represents the difference of mass between the `Aft` and `Fwd` zones of the aircraft. The cumulative function b_{lr} (6) does the same for the `Left` and `Right` zones. When weight is removed in a balance zone as part of an operation, it is either added to or subtracted from the relevant cumulative function. For example, if an operation removes a weight of 50 in the tail of the aircraft, this amount will be added to the cumulative function b_{af} while an operation that removes weight in the cockpit will have this weight subtracted from the b_{af} function. In order to avoid having to deal with negative cumulative functions, these are shifted by the amount of tolerated mass difference (B_{af} or B_{lr}). Thus, the cumulative function starts at the tolerated mass difference and must at all time be comprised between 0 and twice this amount (7, 8).

Occupancy constraints also use cumulative functions: For each location in the airplane $l \in \mathcal{L}$, a cumulative function o_l models the number of technicians working in this location. This cumulative function is linked to the operation activities taking place at this location and must not overstep the capacity of the location k_l (10).

An *Alternative* constraint is used to link the operation activity $a_i \in \mathcal{A}$ with the optional assignment activities $\{\omega_{j,i,q} \forall j \in \mathcal{R} | c_j \in \mathcal{C}_{i,q}\}$ for each requirement $q \in \mathcal{Q}_i$ of each operation $i \in \mathcal{O}$ (11). Note that its third parameter is its cardinality which is set to the amount of the resource required $n_{i,q}$ so that the constraint selects exactly the required number of resources among the optional activities. Finally, precedence constraints ensure that preceding activities are finished when an activity starts (12).

Objectives The main objective of the problem is to minimize the makespan which is modelled as the maximum of the ends of the operation activities (1). The secondary objective is the total operating cost which corresponds to the sum of the costs of each assignment. For each assignment activity $\omega_{j,i,q}$, its cost is computed as the duration of the activity multiplied by the cost of the corresponding resource. This cost is then multiplied by the boolean attribute corresponding to the presence of the assignment activity $x_{j,i,q}$ (the attribute *presenceOf* of an interval variable in CP Optimizer is considered as a value of 1 if true and 0 otherwise in an expression). Thus, only present activities contribute towards the global cost. The cost objective is the sum of all these costs (2).

The two objectives of the problem are solved using a lexicographical search: First, the makespan objective is solved to optimality or until a given limit is reached. Second, the cost objective is minimized subject to an additional constraint that prevents the makespan objective to regress.

5 Experiments

Data The instances used in the experiments are based on data provided by an industrial partner from the Planum research project. It was collected during the full dismantling of a Boeing 737-600 aircraft. It consists in a list of 1459 operations that are performed as part of the aircraft disassembly. Each operation details the section of the plane where the task takes place; the estimated time and the man power needed to perform the task. Note that this data is not enough to make complete instances of the problem as several items are currently missing and in the process of being collected by the industrial partner. The following data had to be completed with arbitrary values: the level of certification needed for each operation as well as the mass removed; all the data relative to the technicians and some of the precedences between operations.

The instances used in the experiments were created based on this dataset. Each instance uses the same set of technicians with 21 technicians available. Some unavailability periods are randomly assigned to some of the technicians. Four different certification categories are considered: uncertified (11 technicians), B1 (6), B2 (2) and B1 and B2 (2). A subset of operations chosen randomly requires either a B1 or a B2 certification. The cost of each technician is expressed as a value per time period that varies between 750 and 1250 depending on the certification level of the technician. A mass value between 0 and 50 is assigned to operations of the four balance zones. The maximum difference of mass allowed is 100 on the aft - forward axis and 50 on the left - right axis. The instance B737-600-Full corresponds to the whole set of operations. All the other instances are subsets of this instance where some of the operations were randomly removed. An anonymized version of these instances is made available at https://github.com/cftmthomas/AircraftDisassemblyScheduling as well as the model and results.

Experimental Protocol The model is implemented in the java API of CP Optimizer 22.1.1 [14]. Experiments were run on a laptop with a 2.6 GHz Intel i5 processor and a memory of 16GB. The model was run on each instance with a lexicographical search of 1 hour with 40 min allocated to the first objective (makespan) and 20 min allocated to the secondary objective (cost). If an optimal solution is reached for the first objective before the end of its allocated time, the remaining time is added to the allowed search time for the secondary objective. The automatic search of CP Optimizer was used. It consists in an adaptive large neighbourhood search [12] that automatically switches to a failure directed search [23] if stagnation is detected in order to improve the lower bound of the objective and prove the solution optimal.

Table 1. Lexicographical search results

Instance	# ops.	Makespan				Cost			
		1st sol.		best sol.		obj. switch		best sol.	
		gap	time	gap	time	gap	time	gap	time
01	16	0	0.02	0	0.02	0.38	0.23	0	0.26
02	29	3.61	0.07	0	0.07	0.08	0.49	0.01	1.48
03	41	0.53	0.14	0	0.15	0.15	0.81	0.01	19.59
04	54	0.34	0.43	0	0.45	0.22	1.51	0.02	153.99
05	63	0.38	0.46	0	0.51	0.16	1.08	0.02	67.18
06	105	0.73	0.55	0	1.05	0.20	42.37	0.11	1739.50
07	104	0.78	0.66	0	1.38	0.16	1.94	0.11	25.54
08	111	0.32	0.56	0	1.08	0.17	2.86	0.07	16.58
09	145	0.59	0.62	0.05	7.85	0.17	2401.06	0.15	2428.92
10	126	1.28	0.57	0.04	2.60	0.19	2401.04	0.12	2424.98
20	294	2.03	1.48	0.05	21.67	0.18	2401.99	0.08	2543.88
30	442	0.16	1.61	0.04	113.61	0.15	2402.62	0.10	2875.37
40	588	1.83	5.49	0.03	547.91	0.16	2402.96	0.10	3362.61
50	729	1.38	7.42	0.09	104.45	0.13	2401.92	0.10	3118.61
60	890	0.54	25.16	0.10	477.57	0.16	2403.34	0.11	3544.60
70	1028	0.62	30.61	0.19	711.38	0.16	2403.42	0.15	3583.29
80	1166	0.13	92.13	0.11	258.47	0.15	2403.65	0.13	3538.19
90	1310	0.17	97.57	0.16	739.67	0.17	2404.26	0.14	3521.01
Full	1459	0.20	178.82	0.17	2317.62	0.16	2403.99	0.15	3593.69

Search results Table 1 reports the experiment results for the makespan and the cost objective, which are reported as gap values, computed as $(obj - LB)/LB$ where LB is the lower bound found by the solver at the end of the search.

We can see that on large instances (> 800 tasks), even finding the first solution can take a lot of time which indicates that it is in itself a difficult problem. Interestingly, the quality of the first solutions found is already quite good as their objectives are relatively close to the best solutions obtained at the end of the search. The model is able to prove the optimality of the best solution found only on smaller instances ($<$120 tasks). For the other instances, the gap of the best solution obtained goes up to 17% of the lower bound. In subsequent experiments where the balance, capacity and certifications constraints were relaxed, the model was not able to find better solutions for most instances despite being noticeably faster to find a first solution and during the search. This might indicate that the solutions obtained by the full model are optimal.

Comparison of objectives In order to compare the impact of both objectives, the results presented above for the full instance are compared to a lexicographical search where the objectives are inverted: The cost is the primary objective and the makespan the secondary objective. Figure 1 shows the evolution of the two considered objectives during the search for both approaches.

The solid curves correspond to the lexicographical search on the makespan objective first. The dashed curves correspond to the inverted lexicographical search on the cost objective first. Blue curves correspond to the makespan objective while orange curves correspond to the cost objective. The vertical dotted

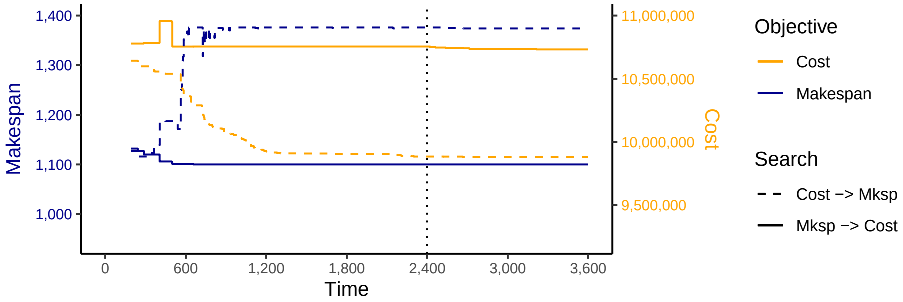

Fig. 1. Comparison of the objectives during a lexicographical search.

line indicates the moment when the objective is changed at 40 min. For both graphs, the y value at the bottom corresponds to the lower bound computed for the objective (943 and 9206000 respectively).

We can see that both objectives are in conflict. Indeed, trying to improve one of them prevents the other to be improved or even degrades it. Furthermore, in both cases, once the switch of objective occurs, the secondary objective can only be marginally improved as the main one is constrained and limits the solution space.

6 Conclusion

This paper presents an aircraft disassembly scheduling problem. While it shares similarities with the Resource-Constrained Project Scheduling Problem (RCPSP), it incorporates several unique constraints specific to aircraft dismantling, such as capacity and balance limitations, as well as the need for specific certification levels of technicians to carry out certain tasks. We propose a Constraint Programming (CP) model that employs interval variables, sequence variables, and cumulative functions. The model is assessed using a set of scenarios comprising up to 1500 tasks, which are derived from real data provided by an industrial partner. Our experiments demonstrate that the model can effectively identify feasible solutions for all instances. However, proving optimality is only feasible for instances with a smaller scale.

Future Work Several research opportunities remain open based on this work. One potential avenue is to compare the performance of the CP model with other optimization approaches. Another direction for research involves enhancing the performance of the current model, either by implementing more effective pruning techniques or by developing custom search heuristics. Additionally, considering the extensive number of tasks and the time horizon involved, investigating a rolling horizon search strategy for this problem could also prove worthwhile.

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References

1. Asmatulu, E., Overcash, M., Twomey, J.: Recycling of Aircraft: State of the Art in 2011. Journal of Industrial Engineering (2013)
2. Bellenguez, O., Néron, E.: Lower bounds for the multi-skill project scheduling problem with hierarchical levels of skills. In: International conference on the practice and theory of automated timetabling. pp. 229–243. Springer (2004)
3. Bentaha, M.L., Battaïa, O., Dolgui, A.: Chance constrained programming model for stochastic profit–oriented disassembly line balancing in the presence of hazardous parts. In: Advances in Production Management Systems. Sustainable Production and Service Supply Chains: IFIP WG 5.7 International Conference, APMS 2013, State College, PA, USA, September 9-12, 2013, Proceedings, Part I. pp. 103–110. Springer (2013)
4. Brucker, P., Drexl, A., Möhring, R., Neumann, K., Pesch, E.: Resource-constrained project scheduling: Notation, classification, models, and methods. European Journal of Operational Research **112**(1), 3–41 (1999). https://doi.org/10.1016/S0377-2217(98)00204-5
5. Camelot, A., Baptiste, P., Mascle, C.: Decision support tool for the disassembly of reusable parts on an end-of-life aircraft. In: Proceedings of 2013 International Conference on Industrial Engineering and Systems Management (IESM). pp. 1–8. IEEE (2013)
6. Dayi, O., Afsharzadeh, A., Mascle, C.: A lean based process planning for aircraft disassembly. IFAC-PapersOnLine **49**(2), 54–59 (2016)
7. Edis, E.B.: Constraint programming approaches to disassembly line balancing problem with sequencing decisions. Computers & Operations Research **126**, 105111 (2021)
8. Garey, M.R., Johnson, D.S.: Complexity results for multiprocessor scheduling under resource constraints. SIAM journal on Computing **4**(4), 397–411 (1975)
9. Hartmann, S., Briskorn, D.: An updated survey of variants and extensions of the resource-constrained project scheduling problem. European Journal of Operational Research **297**(1), 1–14 (2022). https://doi.org/10.1016/j.ejor.2021.05.004
10. Khan, W., Soltani, S., Asmatulu, E., Asmatulu, R.: Aircraft recycling: A review of current issues and perspectives. International SAMPE Technical Conference (01 2013)
11. Kizilay, D.: A novel constraint programming and simulated annealing for disassembly line balancing problem with and/or precedence and sequence dependent setup times. Computers & Operations Research **146**, 105915 (2022)
12. Laborie, P., Godard, D.: Self-adapting large neighborhood search: Application to single-mode scheduling problems. Proceedings MISTA-07, Paris **8** (2007)
13. Laborie, P., Rogerie, J.: Reasoning with conditional time-intervals. In: FLAIRS conference. pp. 555–560 (2008)

14. Laborie, P., Rogerie, J., Shaw, P., Vilím, P.: Ibm ilog cp optimizer for scheduling: 20+ years of scheduling with constraints at ibm/ilog. Constraints **23**, 210–250 (2018)
15. Laborie, P., Rogerie, J., Shaw, P., Vilím, P., Katai, F.: Interval-based language for modeling scheduling problems: An extension to constraint programming. Algebraic Modeling Systems: Modeling and Solving Real World Optimization Problems pp. 111–143 (2012)
16. Lee, D.H., Xirouchakis, P., Zust, R.: Disassembly scheduling with capacity constraints. CIRP Annals **51**(1), 387–390 (2002)
17. da Matta Oliveira Borsato Pinhão, J., Ignacio, A.A.V., Coelho, O.: An integer programming mathematical model with line balancing and scheduling for standard work optimization: A realistic application to aircraft engines assembly lines. Computers & Industrial Engineering **173**, 108652 (2022). https://doi.org/10.1016/j.cie.2022.108652
18. Niu, B., Xue, B., Zhong, H., Qiu, H., Zhou, T.: Short-term aviation maintenance technician scheduling based on dynamic task disassembly mechanism. Information Sciences **629**, 816–835 (2023). https://doi.org/10.1016/j.ins.2023.01.137
19. Ribeiro, J.S., Gomes, J.d.O.: Proposed Framework for End-of-life Aircraft Recycling. Procedia CIRP **26**, 311–316 (Jan 2015). https://doi.org/10.1016/j.procir.2014.07.048
20. Shan, S., Hu, Z., Liu, Z., Shi, J., Wang, L., Bi, Z.: An adaptive genetic algorithm for demand-driven and resource-constrained project scheduling in aircraft assembly. Information Technology and Management **18**, 41–53 (2017)
21. Srinivasan, H., Gadh, R.: Selective disassembly of components with geometric constraints. In: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. vol. 19746, pp. 571–579. American Society of Mechanical Engineers (1999)
22. Tian, G., Zhou, M., Chu, J.: A chance constrained programming approach to determine the optimal disassembly sequence. IEEE Transactions on Automation Science and Engineering **10**(4), 1004–1013 (2013)
23. Vilím, P., Laborie, P., Shaw, P.: Failure-directed search for constraint-based scheduling. In: Michel, L. (ed.) Integration of AI and OR Techniques in Constraint Programming. pp. 437–453. Springer International Publishing, Cham (2015)
24. Young, K.D., Feydy, T., Schutt, A.: Constraint programming applied to the multi-skill project scheduling problem. In: Principles and Practice of Constraint Programming: 23rd International Conference, CP 2017, Melbourne, VIC, Australia, August 28–September 1, 2017, Proceedings 23. pp. 308–317. Springer (2017)
25. Zhao, D., Guo, Z., Xue, J.: Research on scrap recycling of retired civil aircraft. IOP Conference Series: Earth and Environmental Science **657**(1), 012062 (feb 2021). https://doi.org/10.1088/1755-1315/657/1/012062
26. Zhong, L., Youchao, S., Ekene Gabriel, O., Haiqiao, W.: Disassembly sequence planning for maintenance based on metaheuristic method. Aircraft Engineering and Aerospace Technology **83**(3), 138–145 (2011)
27. Zwingmann, X., Ait-Kadi, D., Coulibaly, A., Mutel, B.: Optimal disassembly sequencing strategy using constraint programming approach. Journal of Quality in Maintenance Engineering **14**(1), 46–58 (2008)
28. Özdamar, L., Ulusoy, G.: A survey on the resource-constrained project scheduling problem. IIE Transactions **27**(5), 574–586 (1995). https://doi.org/10.1080/07408179508936773