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Optimal Selection of Manufacturing Configurations Using Object-Oriented and Mathematical Data Models

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Abstract. In this work, we optimize manufacturing configurations, i.e., the set of necessary assets, using the known capabilities and capacities of manufacturing equipment. In particular, the work provides an Object-Oriented data model and the translation of the Object-Oriented data model into a Mathematical data model for efficiently utilizing optimization algorithms. The main contribution is developing an optimization strategy for adapting to varying demand periods with the requested capability and capacity.

The proposed methodology is validated in optimizing the planning for small-box hinged product assemblies in aerospace manufacturing, which can be assembled in a reconfigurable environment with common pick and place, drilling, fastening, and inspection procedures.

Keywords. data models; object-oriented data models; manufacturing; resource planning; optimization

1. Introduction

Manufacturing data models represent manufacturing assets, such as processes, activities, and resources[1]. These models can be conceptual but are often utilised in manufacturing software applications, such as simulation tools, planning systems, and testing[2].

In this work we present data models for representing manufacturing assets, and a novel optimization strategy for demand satisfaction. The Object-Oriented data model facilitates the development of manufacturing software solutions due to the useful properties of Object-Oriented models such as abstraction, encapsulation, inheritance, and polymorphism. The Mathematical data model facilitates the utilization of state-of-the-art optimization algorithms.

The main contributions of this work are:

1. An Object-Oriented data model for efficient software implementations of manufacturing systems;

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2. A Mathematical data model for efficient implementation of optimization methods for optimal configuration selection of manufacturing resources;
3. An optimization strategy for adapting to demand periods with the requested capability and capacity;
4. Definition and formulation of the demand-satisfaction problem and new objective function with decision parameters.

The remainder of the work is organized as follows: In the Related Work section, we compare existing solutions in the literature and analyze their advantages and limitations. In the Object-Oriented Data Model section, we define the data model for representing manufacturing assets and their relations. The Mathematical Data Model section translates the Object-Oriented Data Model and mathematically formulates the demand satisfaction problem. The Use-Case section validates the proposed methodology using a real industrial scenario. The manuscript ends with a Conclusions section outlining future works in this research direction.

2. Related Work

Rapid market changes challenge manufacturing companies, requiring adaptation strategies explored by researchers via optimization and data modeling.

Optimization studies include Youssef et al. [3] showing minimization of reconfiguration effort while maintaining capacity. Goyal et al. [4] used NSGA II and TOPSIS algorithms for optimal configurations in reconfigurable manufacturing systems. Koren et al. [5] proposed a method for scalable manufacturing design to meet market demands effectively. Dou et al. [6] discussed integrated configuration design and scheduling with a mixed-integer programming model. Moghaddam et al. [7] addressed configuration design for scalable systems handling demand fluctuations.

Data modeling studies involve capability and skill models of manufacturing resources [8,9], knowledge-based ontology modeling [10], and object-oriented modeling [1,11]. Järvenpää et al. [8] presented an ontological capability model for rapid reconfiguration. Kocher et al. [9] proposed a formal capability and skill model for a knowledge graph of resources. Ahmad et al. [10] used ontology for information integration and knowledge generation. Torayev et al. [1] designed a hierarchical model for manufacturing equipment.

A gap exists between practical data models and theoretical optimization methods due to the distinct focus on either data modeling or optimization. This work aims to bridge this gap by developing object-oriented and mathematical data models for optimal configuration selection of manufacturing resources.

3. Object-oriented data model

Figure 1 depicts an Object-Oriented data model for manufacturing reconfiguration using UML class diagram rules. It consists of the following classes:

Asset. A manufacturing asset is a physical or logical object with either a perceived or actual value to a manufacturing company.

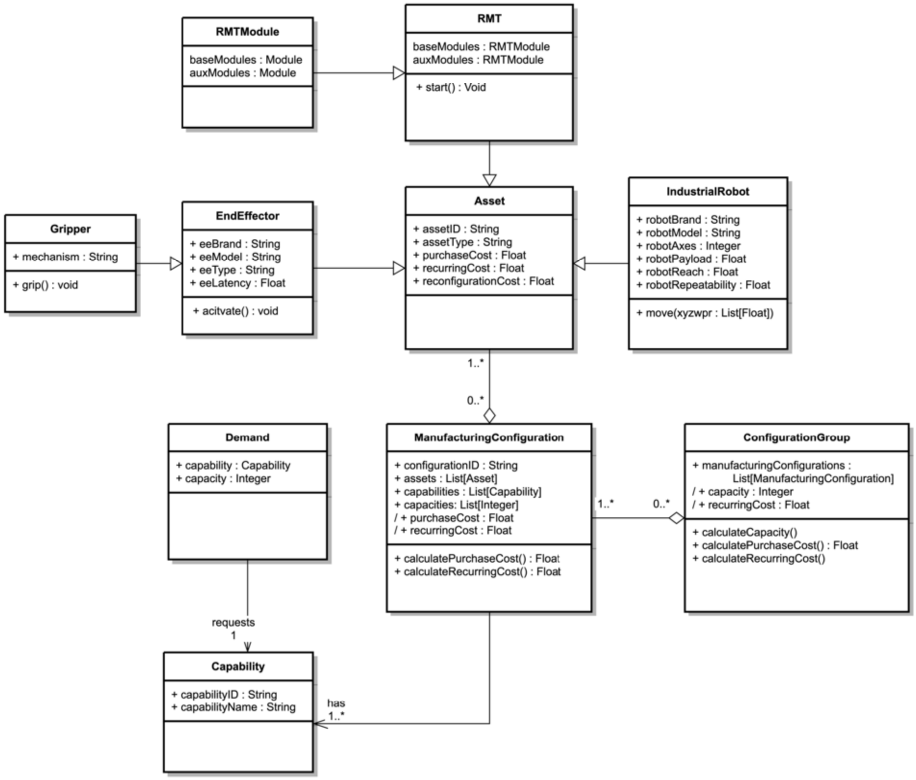

Figure 1. Object-oriented data model of manufacturing reconfiguration

The represented Asset class allows for defining different asset types using the Object-Oriented paradigm's inheritance property. Defining the Asset class in this Object-Oriented way facilitates the extension of the manufacturing data model with new types of assets as shown in Figure 1. Any asset has an asset type, such as a "base asset" or "auxiliary asset," and is distinguished within the same type of asset by its unique asset identifier. A base asset is an asset that is relatively big in dimensions and static compared to an auxiliary asset. Usually, auxiliary assets can be attached to base assets to give certain functionalities.

Manufacturing Configuration. A manufacturing configuration is a group of base and auxiliary assets that are physically and logically bound together with the capability of performing manufacturing operations. Each operational capability has the related capacity and associated cost of operating for a unit period (usually one hour of production). A manufacturing configuration has a purchase cost and recurring costs calculated based on the group's assets. Figure 1 represents the Manufacturing Configuration class using the aggregation association of the UML class diagram.

Configuration Group. A configuration group comprises identical or different manufacturing configurations with the same capability. For example, different manufacturing configurations can be grouped into a configuration group to match a demand capacity that any single manufacturing configuration cannot achieve alone. A configuration group does not necessarily contain identical manufacturing configurations. It can comprise complementing manufacturing configurations to match the required demand capacity. However, all manufacturing configurations in a configuration group have the same capability, possibly with different capacities. The total capacity of a configuration group is the sum of the capacities of manufacturing configurations comprising the group.

Capability. A manufacturing capability is the ability of a manufacturing configuration to execute a manufacturing operation such as drilling, welding, picking, or similar. In Figure 1, the Capability class is represented with simple attributes such as identification string and capability name.

Demand. A manufacturing demand consists of demanded capability and capacity. For example, demand might be 50 pick-and-place operations per 1 hour. In Figure 1, the Demand class has a uni-directional association with the Capability class. For modularity, the Demand class can request only one capability from the Capability class. Multiple capabilities and capacities can be represented by aggregating required capabilities.

4. Mathematical data model

In this section, we develop a Mathematical data model, a more general approach to data modeling in which data is represented as mathematical objects, and the relationships between data objects are represented as mathematical relationships between the objects. We mathematically formulate the demand satisfaction problem, relying on the Object-Oriented data model presented in the previous section.

4.1. Mathematical model

The below notations and definitions are translated to a Mathematical data model from the Object-Oriented data model:

- Demand periods with required capability and capacity requirements for each period:

$$\mathscr{D} = [(B_1, P_1), \ldots, (B_t, P_t), \ldots, (B_T, P_T)] \tag{1}$$

  where $P_t \in \mathbb{Z}^+$ is a required capacity for a capability $B_t \in \mathscr{B}$ at demand period t.
- The set of available capabilities:

$$\mathscr{B} = \{B_1, \ldots, B_{N_{\mathscr{B}}}\}. \tag{2}$$

- The set of available assets:

$$\mathscr{A} = \{A_1, \ldots, A_{N_{\mathscr{A}}}\} \tag{3}$$

  where A_i is i-th manufacturing asset.
- The set of manufacturing configurations:

$$\mathscr{F} = \{F_1, \ldots, F_{N_{\mathscr{F}}}\} \tag{4}$$

  where $F_i = \{A_{i,1}, \ldots, A_{i,N_{F_i}}\}$ is i-th manufacturing configuration and $A_{i,j}$ is the j-th asset of i-th manufacturing configuration.

- A configuration-to-assets matching function that matches a manufacturing configuration to a set of assets:

$$g : \mathscr{F} \rightarrow 2^{\mathscr{A}} \tag{5}$$

  where $2^{\mathscr{A}}$ is a power set of assets (i.e., the set of all subsets of $\mathscr{A}$).
- A capability-to-configurations matching function that matches a capability to a set of manufacturing configurations:

$$f : \mathscr{B} \rightarrow 2^{\mathscr{F}} \tag{6}$$

- A capacity function that matches a manufacturing configuration and a capability to a capacity per unit time:

$$h : \mathscr{B} \times \mathscr{F} \rightarrow \mathbb{Z}^{+} \tag{7}$$

- A recurring cost function that matches a manufacturing configuration to a recurring cost per unit time:

$$r : \mathscr{F} \rightarrow \mathbb{R} \tag{8}$$

  Function r is usually calculated by summing up a recurring cost of each asset in a manufacturing configuration F.

4.2. Demand satisfaction problem

After translating the Object-oriented data model into a mathematical language, we can formally define the demand satisfaction problem.

Let there be two or more demand periods with differing capabilities and capacities. For example, in the first period, there is a demand for 10 ops/hour drilling capability; in the second demand period, the demand is 12 ops/hour welding capability, and so on:

$$\mathscr{D} = \{(B_1, P_1), (B_2, P_2), \ldots, (B_T, P_T)\} \tag{9}$$

Let $R(x_t)$ be a recurring cost for the demand period t and defined as:

$$R(x_t) = \sum_{i=1}^{|f(B_t)|} r(f(B_t)_i) \cdot x_{t,i} \tag{10}$$

and let

$$Q(x_{t-1}, x_t) \tag{11}$$

be a reconfiguration effort function that returns the cost required to switch from manufacturing configuration at demand period $t-1$ to a manufacturing configuration at demand period t.

The reconfiguration effort function Q depends on a use case and company requirements. For example, it can be the number of assets needed to remove and install, the cost of software reconfiguration, and the change in the number of hours and staff. In literature, there are several definitions of reconfiguration functions with names such as "Reconfiguration Smoothness"[12], "Responsiveness Index"[13], "Robustness Index"[14], "Similarity Coefficient"[15], "Reconfiguration Effort"[16], "Effort Index"[17]. For this reason, we leave the definition of the Q function open.

Following the definitions of the recurring cost and reconfiguration cost, the demand satisfaction problem is defined as below:

$$\min_{x} \sum_{t=1}^{T} \alpha R(x_t) + \beta Q(x_{t-1}, x_t) \tag{12}$$

such that

$$\sum_{i=1}^{|f(B_t)|} h(B_t, f(B_t)_i) \cdot x_{t,i} \geq P_t \ \forall t \in [1, \ldots, T] \tag{13}$$

and

$$x_{t,i} \in \mathbb{Z}^{+} \ \forall t \in [1, \ldots T] \tag{14}$$

Equation (13) is a demand-satisfaction constraint, and Equation (14) is an integrality constraint.

The parameters $\alpha \geq 0$ and $\beta \geq 0$ in Equation (12) control weights of recurring and reconfiguration costs in the optimization objective. As shown in the Use-case section, alpha and beta parameters play an important role in selecting the manufacturing configurations for the demand satisfaction problem.

5. Use-case

In this section, we validate the applicability of the proposed Object-Oriented data model, Mathematical data model, and optimization strategy for a small-box hinged product assembly in aerospace manufacturing.

5.1. Assembly process

The small-box hinged product is a product family that consists of rudders and elevators in an aerospace context. They are similar in size and build philosophy so they can be assembled with common capabilities. A reconfigurable assembly system can accommodate for variations in build volume and key datum requirements between different aircraft and product types. A hinged product's assembly also includes its assembly fixture configuration. The assembly processes are presented in Figure 2.

As illustrated in Figure 2(a), the assembly starts with an empty jig frame, where adjustable interfaces are available for mounting the assembly tooling. In Figure 2(b), the next stage's configuration is presented. Upper beam, lower beam, and two skin locations are loaded into the jig frame (Op 1-4) by robotic pick and place capability. After manually

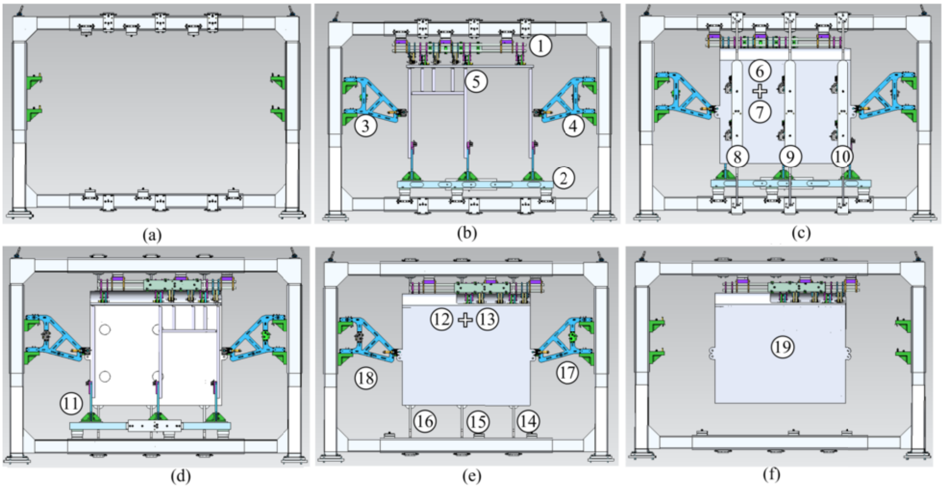

Figure 2. Hinged product build sequence: (a) Empty jig frame (b) Upper beam, lower beam and two skin locations are loaded, with hingeline, ribs and spars assembled and measured (Op 1-5), (c) Upper skin assembled with three profile board supports (Op 6-10), (d) Back view of (c) and lower beam to be removed (Op 11), (e) Lower skin assembled, three profile boards and two skin locations are to be removed (Op 12-18), (f) Final inspection (Op 19)

locating the hinge line datum, ribs and spars, automated inspection (Op 5) is carried out where steps and gaps are measured. In Figure 2(c), upper skin is picked and placed into the jig (Op 6), drilled and fastened (Op7). After that, three profile boards are loaded providing support to the assembled product (Op 8-10). Figure2(d) shows the jig frame from the back, where lower beam is to be removed (Op11). In Figure 2(e), lower skin is loaded, drilled and fastened (Op 12-13). At this point, the product is assembled. To release the product from its assembly fixture, three profile boards and two skin locations are to be removed (Op 14-18). Finally, the product is inspected (Op19) for its profile tolerance in Figure 2(f).

5.2. *Special-case*

In this use-case, we analyze a special case with a demand for "Pick-and-place" and "Drilling" capabilities with different capacities in each demand period.

Given the anticipated demand periods as below:

$$\mathscr{D} = [(B_1, 50), (B_2, 50), (B_3, 100), (B_3, 100)] \tag{15}$$

where $B_1 = B_3 =$ "Pick and place" and $B_2 = B_4 =$ "Drilling", the goal is to find an optimal manufacturing configuration for "Pick-and-place" and "Drilling" capabilities with the requested capacity for multiple demand periods.

We assume that, initially, there is no manufacturing configuration, and the aim is to find a set of manufacturing configurations that provides optimal recurring costs within the demand periods and optimal reconfiguration costs between demand periods.

5.3. Reconfiguration effort Q-function

In Equation (12), we left the definition of the reconfiguration effort function Q open. For this use-case, we define the Q function as the number of manufacturing configurations needed to add and remove between the demand periods:

$$Q(x_{t-1}, x_t) = \sum_{F \in f(B_{t-1}) \cup f(B_t)} \Big| \mathbb{I}(F, t-1) - \mathbb{I}(F, t) \Big| \tag{16}$$

where

$$\mathbb{I}(F, t) = \begin{cases} x_{t,i} & \text{if } \exists i \text{ s.t. } F_{t,i} = F \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

5.4. Results and Analysis

We looked at 3 different optimization scenarios:

1. Optimization only with the recurring costs
2. Optimization only with the reconfiguration costs
3. Optimization with balanced costs

The results with different α and β parameters are shown in Tables 1, 2, and 3.

Table 1. Optimization results: $\alpha = 1$, $\beta = 0$

t	Configurations	$R(x_t)$	$Q(x_{t-1}, x_t)$
1	mcfg2 (x2) mcfg3 (x1)	263.0	3.0
2	mcfg4 (x5)	145.0	8.0
3	mcfg3 (x1) mcfg5 (x4)	447.0	10.0
4	mcfg4 (x9)	261.0	14.0
-	-	**Total: 1116.0**	**Total: 35.0**

Table 1 shows the scenario where only recurring costs are considered for the optimization, i.e., $\alpha = 1$ and $\beta = 0$. The manufacturing configurations selected by the optimization algorithm are heterogeneous. For example, the optimization algorithm suggests choosing 2 units of "mcfg2" configuration and 1 unit of "mcfg3" configuration for the first demand period. Since the reconfiguration cost is neglected during optimization, the optimization algorithm suggests discarding all the existing configurations and replacing them with 5 units of "mcfg4" configuration in the second demand period. In essence, the optimization suggests new configurations in each demand period.

Table 2 shows the scenario where only reconfiguration costs are considered for the optimization, i.e., $\alpha = 0$ and $\beta = 1$. The manufacturing configurations selected by the optimization algorithm are homogeneous. In this case, the optimization algorithm disregards the recurring costs and suggests selecting the manufacturing configuration with the most capabilities, the manufacturing configuration "mcfg5", for all demand periods.

Table 3 shows the scenario where both recurring and reconfiguration costs are considered for the optimization with different weights, i.e., $\alpha = 0.05$ and $\beta = 0.95$. In this

Table 2. Optimization results: $\alpha = 0$, $\beta = 1$

t	Configurations	$R(x_t)$	$Q(x_{t-1}, x_t)$
1	mcfg5 (x3)	270.0	3.0
2	mcfg5 (x5)	450.0	2.0
3	mcfg5 (x5)	450.0	0.0
4	mcfg5 (x5)	450.0	0.0
-	-	**Total: 1620.0**	**Total: 5.0**

Table 3. Optimization results: $\alpha = 0.05$, $\beta = 0.95$

t	Configurations	$R(x_t)$	$Q(x_{t-1}, x_t)$
1	mcfg2 (x3)	264.0	3.0
2	mcfg2 (x3)	264.0	0.0
3	mcfg2 (x3) mcfg5 (x2)	444.0	2.0
4	mcfg2 (x3) mcfg5 (x2)	444.0	0.0
-	-	**Total: 1416.0**	**Total: 5.0**

case, the optimization algorithm balances the recurring and reconfiguration costs. The optimization algorithm suggests selecting the manufacturing configuration "mcfg2" for the first two demand periods. It suggests adding the necessary configuration "mcfg5" only when necessary.

As can be seen from the tables, the α and β parameters in Equation (12) act as decision parameters for controlling the effect of different costs, in this case, recurring and reconfiguration effort cost functions. Changing α and β parameters allows for choosing different optimization scenarios.

6. Conclusion

This work presented the Object-Oriented data model, Mathematical data model, and optimization strategy for the demand satisfaction problem. The work shows the translation of an Object-Oriented data model into a Mathematical data model for the real industrial scenario of small-box hinged product assembly. The demand satisfaction problem was formulated, and a new optimization objective function was derived with decision variables.

The work practically validated the proposed data models and optimization strategies in optimal manufacturing configuration selection of real manufacturing assets for assembly of the small-box hinged product in aerospace manufacturing.

It would be interesting to investigate the effect of other costs beyond recurring costs in future works. Since the cost of transitioning from one manufacturing configuration to another manufacturing configuration depends on the application and the resources of a company, in future works, we will investigate more general and modular reconfiguration effort functions.

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References

[1] Torayev A, Martínez-Arellano G, Chaplin JC, Sanderson D, Ratchev S. Towards Modular and Plug-and-Produce Manufacturing Apps. Procedia CIRP. 2022;107:1257-62.

[2] Rehman HU, Chaplin JC, Zarzycki L, Mo F, Jones M, Ratchev S. Service Based Approach to Asset Administration Shell for Controlling Testing Processes in Manufacturing. IFAC-PapersOnLine. 2022;55(10):1852-7.

[3] Youssef A, ElMaraghy HA. Optimal configuration selection for reconfigurable manufacturing systems. International Journal of Flexible Manufacturing Systems. 2007;19(2):67-106.

[4] Goyal KK, Jain P, Jain M. Optimal configuration selection for reconfigurable manufacturing system using NSGA II and TOPSIS. International Journal of Production Research. 2012;50(15):4175-91.

[5] Koren Y, Wang W, Gu X. Value creation through design for scalability of reconfigurable manufacturing systems. International Journal of Production Research. 2017;55(5):1227-42.

[6] Dou J, Su C, Zhao X. Mixed integer programming models for concurrent configuration design and scheduling in a reconfigurable manufacturing system. Concurrent Engineering. 2020;28(1):32-46.

[7] Moghaddam SK, Houshmand M, Saitou K, Fatahi Valilai O. Configuration design of scalable reconfigurable manufacturing systems for part family. International Journal of Production Research. 2020;58(10):2974-96.

[8] Järvenpää E, Siltala N, Lanz M. Formal resource and capability descriptions supporting rapid reconfiguration of assembly systems. In: 2016 IEEE International symposium on assembly and manufacturing (ISAM). IEEE; 2016. p. 120-5.

[9] Köcher A, Hildebrandt C, da Silva LMV, Fay A. A formal capability and skill model for use in plug and produce scenarios. In: 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA). vol. 1. IEEE; 2020. p. 1663-70.

[10] Ahmad M, Ferrer BR, Ahmad B, Vera D, Lastra JLM, Harrison R. Knowledge-based PPR modelling for assembly automation. CIRP Journal of Manufacturing Science and Technology. 2018;21:33-46.

[11] Sormaz D, Khoshnevis B. Process planning knowledge representation using an object-oriented data model. International Journal of Computer Integrated Manufacturing. 1997;10(1-4):92-104.

[12] Youssef A, ElMaraghy HA. Assessment of manufacturing systems reconfiguration smoothness. The International Journal of Advanced Manufacturing Technology. 2006;30(1):174-93.

[13] Goyal KK, Jain PK, Jain M. A novel methodology to measure the responsiveness of RMTs in reconfigurable manufacturing system. Journal of Manufacturing Systems. 2013;32(4):724-30.

[14] Benderbal HH, Dahane M, Benyoucef L. A new robustness index formachines selection in reconfigurable manufacturing system. In: 2015 International Conference on Industrial Engineering and Systems Management (IESM). IEEE; 2015. p. 1019-26.

[15] Huang S, Wang G, Yan Y, Hao J. Similarity coefficient of RMS part family grouping considering reconfiguration efforts. IEEE Access. 2018;6:71871-83.

[16] Maganha I, Silva C, Ferreira L, Thurer M, Frazzon EM, Silvestri M. Proposal of a reconfigurability index using analytic network process. In: 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM). IEEE; 2019. p. 1310-3.

[17] Ameer M, Dahane M. Reconfiguration effort based optimization for design problem of Reconfigurable Manufacturing System. Procedia Computer Science. 2022;200:1264-73.