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Co-Optimization of Supply Chain Reconfiguration and Assembly Process Planning for Factory-in-a-Box Manufacturing

Factory in a box (FiB) is an emerging technology that meets the dynamic and diverse market demand by carrying a factory module on vehicles to perform on-site production near customers' locations. It is suitable for meeting time-sensitive demands, such as the outbreak of disasters or epidemics/pandemics. Compared to traditional manufacturing, FiB poses a new challenge of frequently reconfiguring supply chain networks since the final production location changes as the vehicle carrying the factory travels. Supply chain network reconfiguration involves decisions regarding whether suppliers or manufacturers can be retained in the supply chain or replaced. Such a supply chain reconfiguration problem is coupled with manufacturing process planning, which assigns tasks to each manufacturer that impacts material flow in the supply chain network. Considering the supply chain reconfigurability, this article develops a new mathematical model based on nonlinear integer programming to optimize supply chain reconfiguration and assembly planning jointly. An evolutionary algorithm (EA) is developed and customized to the joint optimization of process planning and supplier/manufacturer selection. The performance of EA is verified with a nonlinear solver for a relaxed version of the problem. A case study on producing a medical product demonstrates the methodology in guiding supply chain reconfiguration and process planning as the final production site relocates in response to local demands. The methodology can be potentially generalized to supply chain and service process planning for a mobile hospital offering on-site medical services. [DOI: 10.1115/1.4054519]

Keywords: assembly, modeling and simulation, production system optimization, supply chain, mobile factory

1 Introduction

Factory in a box (FiB) or mobile factory is an emerging production method of manufacturing as-needed products near customers' locations over a certain period of time. Based on the FiB concept, production modules are loaded in containers that are transported by vehicles to be deployed in an area in need of highly desired products. When the production demand is met, vehicles can transport the factory again to another production location to meet respective demands.

The concept of FiB is motivated by time-sensitive production demands over a certain period due to natural disasters or epidemics/pandemics. For example, during a pandemic, a significant

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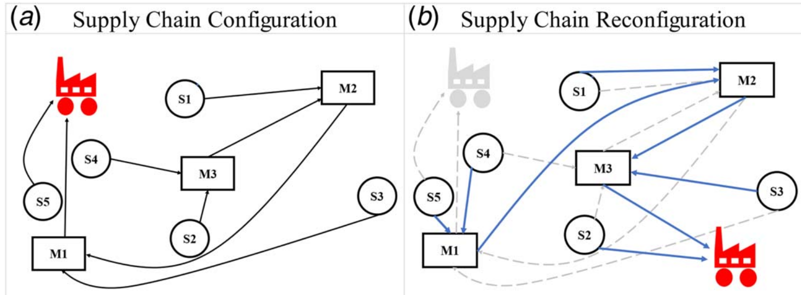

Fig. 1 Supply chain configuration as FiB travels from (*a*) to a new destination (*b*). The icon showing the factory over the wheels is the FiB, the rectangles represent the manufacturers producing semi-completed modules, and the circles are raw material suppliers. The connections among the circles and rectangles are material flows in the supply chain. It can be seen that as the vehicle changes the production location, the supply chain network is changed accordingly.

challenge is to produce personal protective equipment, ventilators, respirators, medicine, and vaccination for healthcare centers near the most vulnerable communities [1]. The FiB is also motivated by meeting mass personalization through distributed and on-site production of personalized products. The FiB is a promising manufacturing solution to meet demand diversification and timeliness constraints. Recent efforts of FiB in the industry are made by GE Healthcare to scale up the production of therapeutics through the development of modular facilities called KUBio to manufacture antibodies, vaccines, and viral vectors [2–4].

The FiB can be implemented for different production scales. At a small scale, the vehicle can travel through multiple suppliers to pick up necessary supplies before making final production near customers' locations, a philosophy similar to the contemporary food truck. Recent research investigated the vehicle routing problems for the small-scale FiB [5]. The FiB is not the same as food trucks at a large production scale since the factory deployed near the customers' site still requires continuous supplies of raw materials and semi-completed modules from suppliers and manufacturers, as outlined by a supply chain network (Fig. 1(*a*)). However, the research on the FiB at a large production scale is very scarce.

Unlike traditional manufacturing, in which factories are all stationary at fixed locations, the final production location of the FiB frequently changes. The location change can pose a new challenge to the configuration of supply chain networks and manufacturing process planning. The concept of the supply chain configuration [6] refers to a network of suppliers and manufacturers selected to complete different assembly tasks with material supply relationships among them to create a final product (Fig. 1(*a*)). As the FiB travels to the next location, it might be necessary to select/deselect certain suppliers or manufacturers considering the supply chain cost. On the one hand, selecting more localized suppliers may be preferred when the next production site is far from the previous one. Conversely, retaining more existing suppliers/manufacturers may reduce the reconfiguration cost for manufacturing but lead to a higher cost of transportation when the production location is very far. As such, the reconfiguration of a supply chain network cannot be formulated as a re-optimization problem since existing suppliers and manufacturers may help reduce reconfiguration costs.

The supply chain network reconfiguration problem is also affected by how manufacturing processes are planned to make the products, such as the assembly sequence and subassembly modules, called assembly hierarchy [7]. Appropriate planning of the assembly hierarchy can better fit the capabilities of new suppliers after reconfiguration. Due to limited time for decisions as the FiB travels, the decision scenario is different from traditional ways by which assembly planning and supply chain configuration are decided sequentially with updating. The conventional methods are usually iterative and cause a long lead time for product realization [6]. Production managers or engineers operating FiB should jointly consider the reconfiguration of supply chain networks coupled with manufacturing planning to reduce the lead time.

1.1 State of the Art. The review of the state of the art in this study is narrowed to the scope of decision-making problems motivated above relevant to the supply chain network configuration/reconfiguration coupled with product designs and assembly system development in response to demand changes.

Assembly system and supply chain configuration considering product designs. As product design changes, the resulting subassembly modules will lead to the reconfiguration of the supply chain network by adding/removing suppliers/manufacturers and modifying material flows. The relationship between product design and a supply chain network was discussed in depth by Refs. [8,9]. Strategic and tactical optimization were combined with a computer simulation model to study operations of a supply chain [10] by integrating manufacturing and product designs. The research was also conducted to create strategies that reconfigure/re-balance an assembly system with growing levels of the product design where reconfiguration occurred considering product design changes and generational product evolution [11,12]. Assembly system reconfiguration planning was studied for several generations of assembly systems given a product family aiming to minimize the life cycle cost [13]. In addition, the researchers developed a co-evolutionary algorithm (EA) [14] and integrated decision-making approaches for product design, manufacturing process planning, equipment selection, and supply chain configuration [15–18]. More recently, the co-reconfiguration of product family and supply chain was dealt with by game theory based on bi-level multiobjective optimization [19].

Supply chain reconfiguration dealing with disruptions or demand changes when product variety increases has been an area of concern in the recent decade. For dynamic reconfiguration in response to disruptions [20], the *bullwhip effect* is studied as a considerable variation of customer demand that can lead to orders that do not add up to inventory orders that vendors and suppliers make [21]. Deterministic and stochastic models with fuzzy control were created to estimate the total cost and performance of a system affected by the bullwhip effect on a supply chain [22]. Recent research proposed to estimate supply chain reconfiguration costs by comparing a graph similarity [9]. In addition, supply chain reconfiguration considers the cost of outsourcing tasks and supply chain risks [23] to determine the favorability of outsourced tasks. Most of the reconfiguration research was formulated as integer linear programming, bilinear goal programming [11], multiobjective decision-making based on discrete event simulation [12], or integrated decision tree learning and agent-based simulation to make adaptive decisions regarding operational units chain [24]. It is found that the joint decision on assembly planning and supply chain configuration is much

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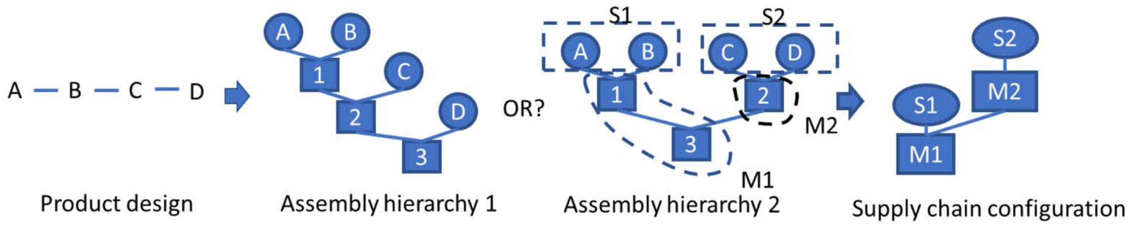

Fig. 2 Illustration of the decision-making problem for assembly hierarchy and supply chain configuration. A, B, C, D denote raw components to be assembled. Symbols S and M are material suppliers and manufacturers selected for each task, represented as numbers. The supply chain reconfiguration is the change of these supplier/manufacturer selections.

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less studied. Such a joint decision problem using an AND/OR graph and dynamic programming was investigated in Ref. [6]. However, this research did not consider the reconfigurability issue associated with FiB manufacturing.

Supply chain configuration considering manufacturing complexity. The previous research also considered operational and manufacturing complexity induced by product variety from diverse customers' orders [25–28]. The complexity, modeled as an entropic effect, is related to the variants of components needed to assemble the product of interest and is considered to impact the configuration of supply chain and assembly systems.

1.2 Research Gaps and Proposed Work.

Very limited research has addressed decision-making problems associated with FiB. An initial attempt to design the supply chain configuration for FiB was discussed in Ref. [26]. The vehicle routing problem to procure materials for FiB when the production is implemented under a smaller scale (i.e., food truck mode [5]). The existing work did not jointly consider how assembly planning may impact the supply chain configuration and reconfiguration when the final production location constantly changes, as concerned by FiB. The following research gaps have been identified. There is a lack of

- Quantitative guidelines for FiB manufacturing to change or keep suppliers and manufacturers while considering the reconfiguration cost when the vehicle moves to a new production site.
- An effective estimation method to evaluate reconfiguration cost in assembly processes that is necessary for optimization, given limited data on process cost changes. The assembly process planning can be affected by supply chain configuration [6] when the FiB relocates. Existing research addressing the assembly system reconfiguration, such as [12], assumes that the cost change data are available, although such an assumption is not always realistic.
- Math models that characterize the interaction between the supply chain reconfiguration and the assembly planning to enable joint decision-making. As such, a methodology is needed to optimize the subassembly plan jointly and the supply chain network reconfiguration, given a supply chain configuration. The joint decision of assembly planning and supply chain reconfiguration is crucial for meeting the short decision time windows in the FiB.

To address the aforementioned gaps, this research establishes a methodology for jointly designing assembly planning and supply chain configuration, considering reconfigurability to support FiB. First, a binary nonlinear programming model is formulated for the concurrent optimization of the supply chain and assembly planning by characterizing the hierarchical relationship between subassembly modules. A novel similarity model is incorporated to deal with the challenge of estimating the reconfiguration effort in assembly planning with limited assembly cost data. This research also develops an EA customized to the nonlinear problem to identify the best-discovered solutions with computational feasibility. A case study is presented to showcase how the proposed EA can be used to jointly optimize supply chain reconfiguration and assembly hierarchy for the FiB manufacturing of real-world medicine. The effectiveness of EA is demonstrated by comparing it to a nonlinear optimization solver for a relaxed version of the problem of optimizing supply chain configuration for FiB.

The rest of this article is organized as follows: Sec. 2 formulates the joint optimization of supply chain configuration and assembly hierarchy planning for FiB. Section 3 develops an EA algorithm customized to the joint optimization problem. Section 4 conducts a case study for supply chain reconfiguration and assembly plan change in FiB manufacturing of medicine as the vehicle relocates. The experiments also verify the proposed EA using a nonlinear programming solver. Finally, this article is concluded in Sec. 5, including managerial insights.

2 Co-Optimization of Supply Chain Configuration and Assembly Planning for Factory in a Box

This section presents a mathematical model for co-optimizing supply chain networks and assembly planning, considering supply chain/assembly reconfigurability as the FiB relocates. The configuration of a supply chain network involves the selection of suppliers that provide raw materials and manufacturers that perform manufacturing tasks. It is affected by the assembly planning that determines assembly tasks and the hierarchical material flows among these tasks, called assembly hierarchy [7]. Figure 2 shows an example of a decision-making problem for assembly hierarchy selection and supply chain configuration given the product assembly as represented by a liaison graph. The decisions are changed for supply chain configuration and assembly hierarchy when the FiB relocates to a different production location.

In this formulation, the inputs are the product designs presented by liaison graphs reflecting product designs, suppliers/manufacturers' information, and/or initial supply chain network design (if available). This article proposes a mathematical formulation to jointly achieve the (1) determination of assembly hierarchies, (2) selection of suppliers and manufacturers for assembly tasks, and (3) precedence between manufacturers and suppliers to determine the supply chain network. The details of the mathematical model are presented below:

Sets:

- S = set of suppliers that provide raw materials, components, or resources.
- $M = \{m_1 \ldots m_n,\ m^v\}$, set of n manufacturers and m^v is the "factory in a box."
- R = set of resources, raw materials, or components needed to create a product.
- T = set of tasks needed to complete a product.
- $C = \{c,\ c'\}$set of tasks t in candidate assembly hierarchy.
- Ω = set of common components in hierarchy c or c'.

Parameters:

- d^1_{sm}, the distance between chosen supplier s and manufacturer m (or vehicle m^v).

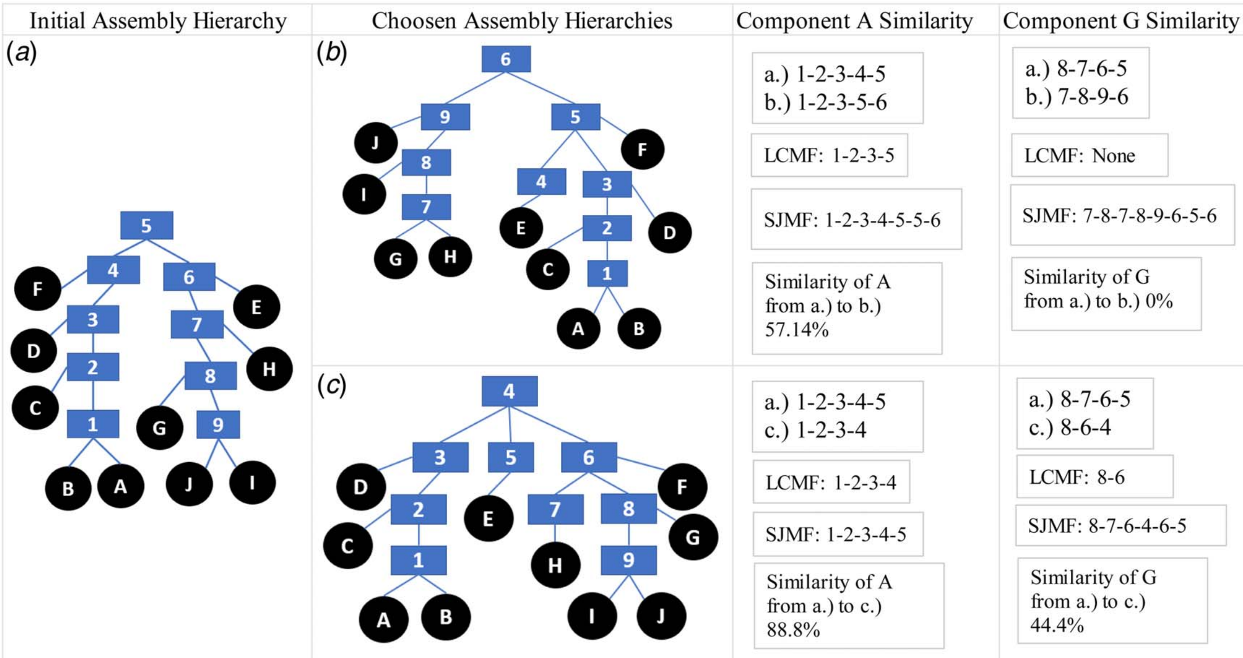

Fig. 3 The similarity of material flows of varying assembly hierarchies: (*a*) initial assembly hierarchy, (*b*) and (c) comparative assembly hierarchy with calculated similarity values

- $d^2_{mm'}$, the distance between manufacturer m and the next manufacturer m' (or final manufacturer, the FiB vehicle, m^v).
- c^a_{rs}, the cost for supplier s charged for providing resource r.
- c^b_{tm}, the cost for manufacturer m to perform task t or assembly service.
- $s_{rt} = 1$ if resource r is needed for task t to be complete, if not it is $= 0$.
- w_r, the weight of resource r.
- c^{trans}, the cost of transportation per unit weight per unit distance.
- c_{add}, the cost of adding a supply chain relationship.
- n^p, the total number of products needed.
- n, the number of tasks needed to create the assembly.
- z^0_{m1m2}, an initial supply chain between different manufacturers. It is equal to 1 if there is a relationship between m_1 and m_2 and equal to 0 otherwise.

Binary decision variables:

- $x_{rsm} = 1$ if resource r is given by supplier s and sent to manufacturer m (vehicle m^v) or $= 0$ otherwise.
- $y_{tm} = 1$ if task t is assigned to manufacturer m (vehicle m^v) or $=$ 0 otherwise.
- $z_{m1m2} = 1$ if m_1 precedes m_2 (if subassembly leaves m_1 and is sent to m_2) or $= 0$ otherwise.

Auxiliary decision variables:

- $u_{rm} = 1$ if resource is located at manufacturer m (or m^v); 0 otherwise.
- $w_{tt'} = 1$ if task t precedes task t' or $= 0$ otherwise.

Similarity model notations:

- $\theta_p =$ cost of production.
- RC = estimated cost of reconfiguration.
- $\theta_{rc} =$ overall cost of reconfiguration.
- LCMF = longest common material flow.
- SJMF = shortest joint material flow.
- $SS_t =$ subassembly plan similarity is 1 if task t in assembly hierarchy c creates the same subassembly module as task t in assembly hierarchy c' and $= 0$ otherwise.
- $SS_{cc'} =$ the similarity of assembly planning, evaluated by the average number of tasks that generate the same subassembly in assembly hierarchy c to hierarchy c'.
- $SCh_{cc'r} =$ the similarity of material flow for raw material r from assembly hierarchy c to hierarchy c'.
- $SC_{c,c'} =$ overall similarity of material flow for all raw materials.
- $\dim(\varphi) =$ total number of common tasks in assembly hierarchies c and c'.

2.1 Objective Function.

2.1 Objective Function. The objective is to minimize the cost of production and reconfiguration effort, i.e.,

$$min\ \Theta = (\theta_p * n^p + \theta_{rc}) \tag{1}$$

where the cost of production θ_p is expressed as follows:

$$\theta_p = \sum_{r\in R}\sum_{s\in S}\sum_{m\in M} x_{rsm}(c^a_{rs} + c^{trans}\ d^1_{sm}\ w_r) + \sum_{m\in M}\sum_{t\in T} c^b_{tm} y_{tm} + \sum_{r\in R}\sum_{m\in M}\sum_{m'\in M} c^{trans} u_{rm} z_{mm'} d^2_{mm'} w_r \tag{2}$$

Equation (2) contains three arguments that describe the cost of production. The first term estimates the expenses of raw material r (i.e., resource or component) and their corresponding transportation cost between supplier s and manufacturer m. The second term is the cost of assembly operations in manufacturing, and the third term covers the transportation cost of the subassemblies among manufacturer m and m'.

Estimation of reconfiguration cost θ_{rc}. Reconfiguration concerns the changes in assembly processes and supply chain networks. As the FiB travels to a new production site, a new optimal assembly hierarchy may be selected to fit updated supply chains better. If the supplier/manufacturer's replacement cost c_{rep}, including addition or removal of a supplier/manufacturer, is known, the supply chain reconfiguration cost in θ_{rc} can be estimated by

$$RC = c_{rep} \sum_{m\in M}\sum_{m'\in M} (z_{mm'} - z^0_{mm'}) \tag{3}$$

Another part is the reconfiguration cost for the assembly processes. Due to the limited amount of data available for estimating the assembly cost changes [27], this article proposes a method of

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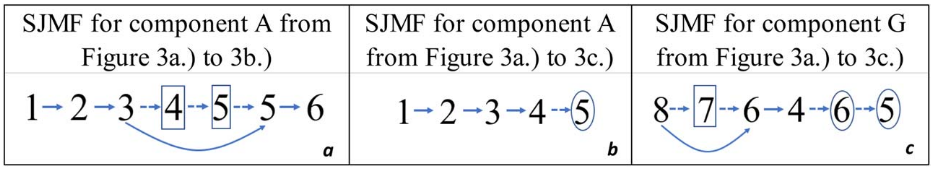

Fig. 4 Shortest joint material flow for components A and G from Fig. 3(*a*) to Fig. 3(*b*) or Fig. 3(*c*).

comparing the assembly hierarchies considering the material flow to evaluate the potential reconfiguration effort.

Figure 3 illustrates an example of comparing the similarity between different assembly hierarchies showing the initial assembly hierarchy. Figures 3(*b*) and 3(*c*) are two alternative assembly hierarchies to be compared with Fig. 3(*a*). As the assembly plan changes from Fig. 3(*a*) to either Fig. 3(*b*) or Fig. 3(*c*), it is necessary to readjust/add/reduce machines and operations. These efforts are highly affected by the *similarity* of the assembly plans before and after the changes, which can be defined as the percentage of tasks that create the same subassemblies between two assembly hierarchies. Such similarity of assembly planning $SS_{cc'}$ can be estimated by

$$SS_{c,c'} = \frac{\sum_{t\in\varphi} SS_t}{\dim(\varphi)} \tag{4}$$

where $\dim(\varphi)$ is the total number of common tasks in assembly hierarchies c and c' and SS_t is equal to 1 if the subassembly module created after task t in assembly hierarchy c is the same subassembly module that is created after task t in assembly hierarchy c'. It is equal to 0 otherwise.

The reconfiguration cost is also affected by the change in material flow of raw material r, denoted as $SCh_{cc'r}$, which can be indirectly evaluated by such a similarity, i.e.,

$$\mathrm{SCh}_{c,c',r} = \frac{2 * \mathrm{NOTL}_{c,c',r}}{2 * \mathrm{NOTL}_{c,c',r} + 3 * \mathrm{NOBT}_{c,c',r} + \mathrm{NOIT}_{c,c',r}} \tag{5}$$

where $\mathrm{NOTL}_{c,c',r}$ is the number of assembly tasks in the LCMF for component r, $\mathrm{NOBT}_{c,c',r}$ is the number of bypassing moves of component r using LCMF and the SJMF, and $\mathrm{NOIT}_{c,c',r}$ is the number of end idle tasks of component r using LCMF and SJMF. $\mathrm{SCh}_{c,c',r}$ examines how the individual component flows in the production process in different assembly hierarchies. The order in which a subassembly module is produced will change as new assembly hierarchies are implemented. These concepts were introduced by Ref. [27] and are briefly reviewed by examples using Fig. 4 as follows.

- *Example 1* (Fig. 4(*a*))*:* Consider component A in the assembly hierarchies in Figs. 3(*a*) and 3(*b*). In Fig. 3(*a*), component A flows through tasks 12345, and in Fig. 3(*b*), it flows through tasks 12356. Task 4 is bypassed, and Task 6 is included. The LCMF is 1235, and the SJMF is shown in Fig. 4(*a*) can be 1234556, which is not unique. As such, the number of tasks in LCMF (i.e., NOTL) is 4, and there are two bypassing tasks (i.e., tasks 4 and 5, each enclosed by a square) and zero end idle tasks. By Eq. (5), the total similarity of component A (i.e., material flow) between the assembly hierarchies in Figs. 3(*a*) and 3(*b*) can be calculated as 0.5714.
- *Example 2* (Fig. 4(*b*))*:* Consider component A in assembly hierarchies a and c in Fig. 3. In Fig. 3(*a*), A flows through tasks 12345; however, in Fig. 3(*c*), it flows through one fewer task compared with the initial assembly hierarchy (i.e., 1234). Figure 4(*b*) shows that the SJMF can be 12345 as the material flow between tasks 4 and 5 exists in Fig. 3(*a*) but does not exist in Fig. 3(*c*), represented by a dashed arrow. Hence, NOTL is 4, NOBT is 0, and NOIT (i.e., task 5 denoted by a circle) is 1. The total similarity of component A between the hierarchies in Figs. 3(*a*) and 3(*c*) is 0.888.
- *Example 3* (Fig. 4(*c*))*:* Consider component G as it flows in Figs. 3(*a*) and 3(*c*). The SJMF can be 876465 illustrated in Fig. 4, which shows task 7 is bypassed (curved arrow), and tasks 6 and 5 are idled (dashed arrow) in the assembly hierarchy d. NOTL = 2, NOBT = 1, and NOIT = 2, making the overall material flow similarity for component G, 0.444 or 44.4%.

The similarity of material flow for each component among the assembly hierarchies are summed up and multiplied by its weight to calculate the overall similarity of material flow defined in Eq. (6), i.e.,

$$SC_{c,c'} = \sum_{r\in\Omega} SCh_{c,c',r}\omega_r \forall c,\ c' \in C \tag{6}$$

where ω_r is the weight of component r.

By combining the supply chain reconfiguration cost, the similarity in assembly plan, and material flow, the reconfiguration cost can be reflected by

$$\theta_{rc} = RC + \sum_{c\in C}\sum_{c'\in C} \alpha(1 - SC_{c,c'}) + \beta(1 - SS_{c,c'}) \tag{7}$$

where α is the influence of material flow changes and β reflects the influence of the subassembly plan changes on the reconfiguration cost. This formulation can change the emphasis on material flow and assembly planning by setting different values for α and β. The similarity in Eq. (7) reflects the re-utilization of equipment and the same task recurrence for reconfiguration. The similarities $SC_{c,c'}$ and $SS_{c,c'}$ are affected by decision variables via assembly hierarchy.

When the vehicle relocates, it is likely that assembly planning, such as different assembly sequences and subassembly modules, can change to be adaptive to new suppliers and manufacturers. As such, this problem formulation is a joint decision of supplier/manufacturer selection and assembly planning (the selection of assembly hierarchy).

2.2 Constraints. New constraints are developed to reflect the interaction between the assembly hierarchy and material flow in the supply chain, thereby enabling a formulation of joint decision-making. The detailed formulation is as follows.

$$u_{rm} = \sum_{m'\in M} u_{rm'} z_{m'm} + \sum_{s\in S} x_{rsm} \forall r \in R,\ m \in M \tag{8}$$

$$y_{t^*m^*} = 1 \forall t^* \in T,\ m^* \in M \tag{9}$$

$$\sum_{m\in M, s\in S} x_{rsm} = 1 \forall r \in R \tag{10}$$

$$u_{r,m^v} = 1 \forall r \in R \tag{11}$$

$$s_{rt} y_{tm} \le u_{rm} \forall m \in M,\ r \in R,\ t \in T \tag{12}$$

$$z_{mm'} + z_{m'm} \le 1 \forall m \in M,\ m' \in M \tag{13}$$

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$$\sum_{m \in M-\{m^v\}, m' \in M} z_{mm'} = n - 1 \; m \in M, m' \in M \tag{14}$$

$$z_{m^v,m} = 0 \forall m \in M - \{m^v\} \tag{15}$$

$$\sum_{t \in T} s_{rt} \cdot y_{tm} \geq \sum_{s \in S} x_{rsm} \forall r \in R, m \in M \tag{16}$$

$$\sum_{t \in T} y_{tm} = 1 \forall m \in M \tag{17}$$

$$\sum_{m' \in M} z_{mm'} \leq 1 \forall m \in M - \{m^v\} \tag{18}$$

Equation (8) stipulates under which circumstance a raw material/component exists at a particular manufacturer. The raw material or resource r can be sent to the manufacturer from a supplier or from a manufacturer upstream in the supply chain. All subassemblies and resources assigned to a manufacturer must be received from the upstream manufacturer or supplier. By Eq. (9), specific tasks can only be assigned to a particular manufacturer or the final vehicle, denoted as m^*, considering manufacturers'/suppliers' capabilities (if known). Equation (10) describes how r is sent to a manufacturer through one supplier. Equation (11) requires all resources to reach the final manufacturer (i.e., the vehicle). Inequality (12) states that a task can be performed only if the required r for that task is located at the assigned manufacturer. A manufacturer cannot perform a task unless the required material is present. Two manufacturers do not provide subassemblies to each other as ensured by (13). Equation (14) estimates the total number of supply relationships given the number of tasks (n). Equation (15) prevents the vehicle (final manufacturer) from sending a subassembly to any upstream manufacturers/suppliers. Inequality (16) enforces that if r is assigned to manufacturer m provided by any supplier s, the associated assembly task must be performed at m. This constraint also allows a manufacturer to perform an assembly task of only joining subassemblies, but no raw materials are supplied to the manufacturer.

This article develops constraints (17) and (18) to deal with the challenge in math modeling of the joint decision-making for assembly hierarchy and supply chain configuration. Equation (17) makes a simplified assumption that each manufacturer can deal with only one assembly task, while inequality (18) requires each manufacturer to send no more than one subassembly to a single manufacturer except for the final manufacturer. It should be noted that these assumptions are made only to reflect the impact of assembly hierarchy on the supply chain configuration and facilitate the joint decision-making on assembly and supply chain configuration. In reality, it is possible that each manufacturer can process multiple tasks and send its semi-finished products to multiple manufacturers downstream in the supply chain network. Similarly, a supplier can send the same raw material to multiple manufacturers. This article proposes the concept of the virtual manufacturer and differentiated component so that the formulation can still hold:

- A concept of virtual manufacturer can be introduced to consider this reality by using the constraint (17). If a manufacturer has the potential to deal with p candidate tasks, p virtual manufacturers can be assumed to co-exist at the same location. For example, a manufacturer M1 can potentially process tasks T1, T2, and T3. Then three virtual manufacturers are introduced, such as manufacturer M1A for task T1, M1B for T2, and M1C for T3. The distance between the virtual manufacturers is zero, corresponding to the transportation cost of zero. Given the concept of virtual manufacturers, constraint (17) can be generalized.
- If a component or subassembly is reused in different assembly tasks, it should be differentiated for constraints (10) and (18). Consider an example of assembling AG-B-C-AG, where subassembly AG is involved in two assembly tasks. To make constraint (18) applicable, AG can be differentiated as A_1G_1 and A_2G_2 when assembled with B or C, respectively. Each task is handled by a manufacturer or a virtual manufacturer (if applicable).

It is optional to have each task assigned to only one manufacturer as follows:

$$\sum_{m \in M} y_{tm} = 1 \forall t \in T \tag{19}$$

3 Solution Procedure for the Joint Decision Problem for Factory in a Box

The objective function involving reconfiguration in Eq. (7) is nonlinear since it is a set of coding logics to identify similarity. The similarity model is not polynomial and is therefore challenging to linearize. Hence, the traditional mathematical programming solvers would be ineffective in solving the problem nor for problems with large-size instances. Thus, this article proposes an EA method customized to the FiB problem to efficiently explore the search space and find good solutions within computational feasibility.

The input information for the EA includes (1) the locations of suppliers and manufacturers, (2) the costs of raw materials from the suppliers, (3) the costs of performing a manufacturing task, (4) the weight of the raw materials, (5) the existing assembly plan and supply chain configuration, and (6) the raw materials needed for each manufacturing task (i.e., liaison graph). Table 1 outlines the logic flow used within the proposed EA for chromosome initialization, parent selection, crossover, mutation, and chromosome repair before stopping. All the major EA procedures are detailed below.

Chromosome representation: The chromosome illustrated in Fig. 5 consists of three segments: (1) the first segment provides the information regarding the task sequence; (2) the second segment identifies the manufacturer that is assigned with a specific task; and (3) the third segment identifies which supplier will provide the needed raw materials (resources). Candidate values for the chromosomes, including task sequence and associated components, are

Table 1 EA pseudo-code

Input: Cost data of suppliers and manufacturers, product assembly design, and distances
Output:
- selection of subassembly hierarchy (including subassemblies/assembly tasks),
- assignment of tasks to manufacturers,
- assignment of raw materials to suppliers

Initialization
Generate feasible populations randomly
Chromosome repair to prevent infeasible solutions
- avoid repetitive task assignment
- avoid repetitive manufacturer assignment

while **not** stopping criteria are met
  do
  //Crossover
Generate a random number between 0 and 1
If rand (0,1) < Crossover Rate
  Use Roulette Wheel to select parents from the population
  Apply 2-point crossover operator
//mutation
Apply floating-point mutation based on Mutation Rate
If the Offspring chromosome needs repair?
  Apply *chromosome repair* to prevent infeasible solutions
Else
  Determine the fitness of offspring
end while

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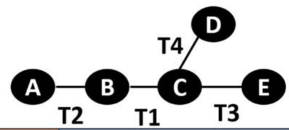

	Task Sequence				Task Manufacturer Assignment				Resource Suppler Assignment				
Locus	1st Task	2nd Task	3rd Task	4th Task	Task 1	Task 2	Task 3	Task 4	3	2	1	5	4
Gene	1	2	3	4	M2	M5	M6	Mv	S8	S1	S6	S2	S9

Fig. 5 An example chromosome representing solutions based on a liaison graph

Crossover Operator

Task Sequence				Task Manufacturer Assignment				Resource Suppler Assignment				
1st Task	2nd Task	3rd Task	4th Task	Task 1	Task 2	Task 3	Task 4	3	2	1	4	5
1	2	4	3	M5	M2	M8	Mv	S8	S1	S6	S2	S9
1	2	4	3	M18	M1	M20	Mv	S5	S14	S3	S12	S20

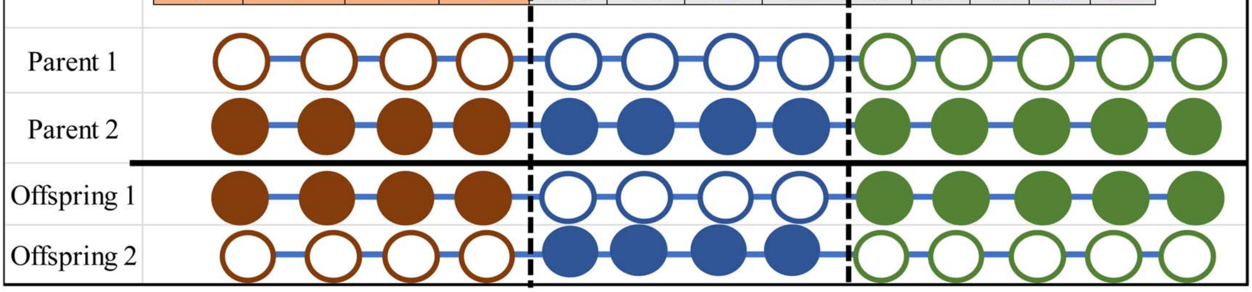

Fig. 6 Illustration of the two-point crossover operator for the example chromosome

affected by the assembly hierarchy generated from the assembly design (liaison graph) [7]. For example, the chromosome in Fig. 5 is interpreted as follows: (1) the assembly sequence is tasks $1 \rightarrow 2 \rightarrow 3 \rightarrow 4$, (2) the first task (task 1) is assigned to manufacturer M2, the second task (task 2) is assigned to M5, the third task (task 3) is assigned to M6, and the fourth task (task 4) is performed at the manufacturing vehicle M_v, and (3) raw material components are supplied by suppliers S8 (component C denoted as $r=3$), S1 (B, $r=2$), S6 (A, $r=1$), S2 (E, $r=5$), and S9 (D, $r=4$) as indicated in liaison graph mentioned earlier. Each locus within the chromosome is defined as the location of a particular gene of interest, while the allele refers to the actual value associated with the gene [28].

The chromosome representation can determine the binary decision variables x_{rsm}, y_{tm}, $z_{mm'}$, and auxiliary variable u_{rm}. The decision variables are decoded from the chromosome as follows:

- x_{rsm} is derived from all three segments of the chromosome and the liaison graph. The first segment of the chromosome, the assembly hierarchy among tasks, in addition to the liaison graph, elucidates the raw material r needed for each task t and the order in which they are required. It is also possible that no raw material is used for a particular task when this task only combines two subassemblies. The second segment of the chromosome illustrates which manufacturer m is assigned to a task, thus mapping the raw material used by each task to the assigned manufacturer in the supply chain. The third segment of the chromosome indicates the supplier s that provides for the raw materials r needed in the corresponding task in the second segment. For example, in Fig. 5, the first and second components, C ($r=3$) and B ($r=2$), needed in the corresponding task 1 (determined by the liaison graph) are provided by suppliers *S8* and *S1*, respectively. Task 1 is sent to the second manufacturer (*M2*), making decision variables $x_{382}=1$ and $x_{212}=1$. Similarly, other nonzero decision variables for this example are x_{165}, x_{523}, x_{49v} (=1).
- y_{tm} is derived directly from the second segment of the chromosome, where each locus of a gene defines the order in which the manufacturers will be assigned to the tasks located in the genes of segment 1. The allele of a gene in segment 2 indicates the manufacturer that will perform the task. (e.g., "*M2*," "*M5*," and "M6"). For the example chromosome, the nonzero decision variables are y_{12}, y_{25}, y_{36}, and y_{4v} (=1).
- $z_{mm'}$ is defined using the information in segments 1 and 2 of the chromosome given earlier. Depending on a given task sequence and a product's liaison graph, operations can be performed sequentially or in parallel in the assembly hierarchy. In the example chromosome, the nonzero decision variables are z_{25}, z_{56}, and z_{6v} (=1).
- u_{rm} is the auxiliary variable and can be determined by decision variables y_{tm} and x_{rsm} following Eq. (8) and inequality (12), respectively. It is equal to 1 when a resource r is located at manufacturer m as a resource or as a subassembly for task t. The chromosome in the example has the following nonzero decision variables u_{32}, u_{22}, u_{15}, u_{56}, and u_{4v} (=1).

Population initialization: The population is initialized via a stochastic operator that randomly assigns feasible values for (1) the task sequence, (2) the task manufacturer assignment, and (3) the raw material supplier assignment. The fitness of the population is estimated by Eqs. (1)–(7).

EA crossover operator: A two-point crossover was applied to the three-segment chromosome to generate new solutions in the next EA iteration. The first cutting point of the proposed two-point crossover is placed between the first segment (task sequence) and the middle segment (task manufacturer assignment). The second cutting point is between the task manufacturer segment and the resource supplier assignment, as illustrated in Fig. 6. The infill patterns and colors/gray scales of the loci aim to distinguish different gene segments in the offspring.

EA mutation operator: To further exploit the search space without creating an infeasible solution, a floating-point mutation operator was only applied to the task manufacturer and resource supplier segments (i.e., segments 2 and 3) of the chromosome. For example, in Fig. 7, the mutated offspring gene has the initial manufacturer/supplier values of M5-M2-M8-M3-S8-S1-S6-S2-S9.

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	Task Sequence				Task Manufacturer Assignment				Resource Suppler Assignment				
	1st Task	2nd Task	3rd Task	4th Task	Task 1	Task 2	Task 3	Task 4	3	2	1	4	5
Mutated Offspring	1	2	4	3	M5	M2	M8	Mv	S8	S1	S6	S2	S9
Offspring	1	2	4	3	M12	M7	M20	Mv	S3	S19	S5	S10	S26

Fig. 7 Illustration of proposed floating-point mutation for the example chromosome

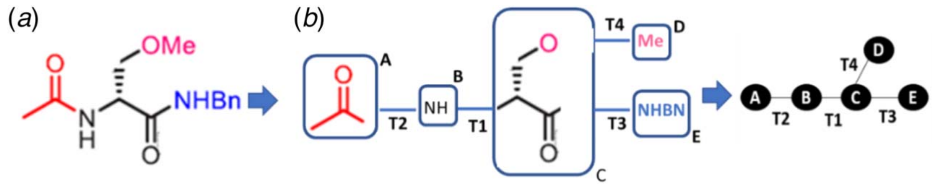

Fig. 8 An equivalent assembly process for producing the medicine, R-1: (*a*) R-1 formula and (*b*) equivalent liaison graph with assembly tasks

After a floating-point mutation, the offspring for the second and third segments have M12-M7-M5-M3 and S3-S19-S5-S10-S16, respectively.

Chromosome repair: Sometimes, an evolutionary operation (e.g., floating-point mutation) can lead to an invalid solution and should be repaired. For example, given the task sequence in the first segment generated by random permutation, the feasibility of the second segment deciding the task manufacturer assignment can be inspected by a chromosome repair logic/code. Suppose any manufacturer assignment is found to violate the model constraints. The chromosome in the second segment will be changed to a different value by a random number generator to ensure solution feasibility during evolution.

4 Case Study

In this section, the proposed EA is first verified with a nonlinear programming solver for a relaxed version of the original problem without considering reconfiguration based on the input data. Then, the results are presented, including two scenarios that show how the reconfiguration cost and vehicle relocation impact the reconfiguration of the supply chain and assembly process planning in FiB.

4.1 Problem Description.

FiB is suitable for the on-site production of medical devices or medicines assisting disaster recovery. This case study simulates a scenario of employing FiB to produce a real-world medicine, R-1, with its chemical formula [29], as shown in Fig. 8(*a*). The manufacturing processes are modeled as an equivalent assembly process with five feasible assembly hierarchies without considering reconfiguration based on the input data.

Although the connections among molecules are chemical bonds achieved by chemical processes, these bonds are analogous to mechanical joining/bonding under process constraints such as an assembly sequence. Thus, an equivalent assembly task can be defined as the chemical process needed to create a new chemical bond. It is envisioned that the proposed method of assembly planning and supply chain network design is applicable as long as the chemical process constraints, such as precedence or zoning constraints, are satisfied.

The chemical formula was first used to generate a liaison graph that illustrates the tasks required to combine the molecular components, as shown in Fig. 8(*b*). A liaison graph [7] consists of nodes representing the respective product component and arcs representing the tasks required to join two components together. The identification of components in the equivalent assembly process is restricted by chemical process mechanisms and functional groups. There are five components held by four chemical bonds and the feasible assembly processes. The *equivalent assembly process* can be described as follows. Through chemical processes, (1) task T1 equivalently connects NH, (2) T2 connects functional group A, (3) T3 connects functional group C to NHBn, and (4) task T4 connects O and Me. The assembly hierarchy or precedence relations for the R-1 formula are considered for the optimization. There are multiple ways of connecting these components to create the final R-1 discussed in detail in Ref. [29]. Figure 9 shows three candidate processes with different assembly sequences as constrained by chemical production, and Fig. 10 shows an example of the detailed assembly procedure for the assembly process P3.

Note: The equivalent assembly only reflects an equivalent concept of incrementally building the chemical formula structure. In reality, each equivalent assembly task involves reactions among different compounds to generate the structure instead of traditional welding, bolting, fastening, or wiring in mechanical assembly. Mechanical assemblies may also be chosen to demonstrate the FiB manufacturing of medical devices such as respirators or ventilators.

Model inputs: The inputs to the optimization model include:

- *A liaison graph* to present product assembly design as shown in Fig. 8(*b*).
- *Assembly hierarchies that determine all assembly tasks* as illustrated in Figs. 9 and 10.
- *The information on the suppliers and manufacturers*. Similar to Refs. [27,30], the input data are simulated from a random

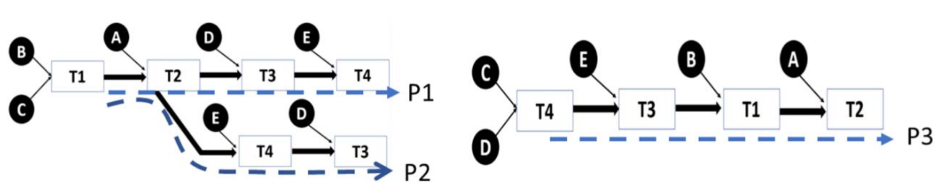

Fig. 9 Three equivalent assembly processes P1–P3

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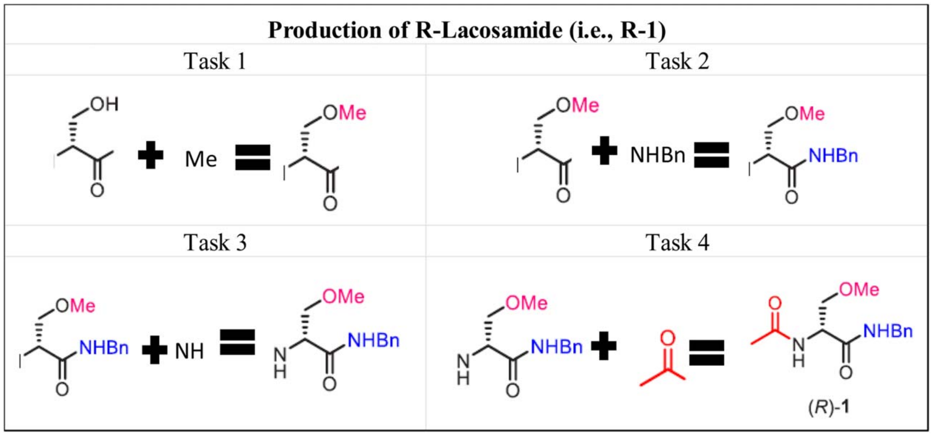

Fig. 10 Production process P3

number generator to generate small, medium, and large distances; weights; and costs to supply a resource/raw material and perform an assembly sequence. This information includes

(1) The cost to provide raw materials and perform assembly tasks. Table 2 presents the manufacturing cost of supplying resources from up to 24 candidate suppliers. The rows in Table 2 represent the raw material components needed to create the product of interest. The columns are the supplier information that can be potentially included in the supply chain. These values are normalized between 0 and 1, representing the cost of supplying a certain component of a final product. Similarly, Table 3 presents the normalized cost of performing tasks by up to 24 candidate manufacturers. The rows in Table 3 represent the tasks needed to create the final product of interest. The columns represent the potential manufacturers included in the supply chain.
(2) The normalized distance between suppliers and manufacturers that impacts the transportation cost and the cost of reconfiguration (Tables 4 and 5). The rows in Table 4 represent the potential suppliers, and the columns represent the manufacturers. Table 5 lists manufacturers in the rows and the columns, and the values represent the distance between potential preceding manufacturers. Zeros are along the diagonal because the distance between a chosen manufacturer and itself is zero.
(3) The weight (e.g., grams) of the components (Table 6) can be estimated from the molar mass (e.g., grams per mole (g/mol)) of the reactants that yield the quantity of the

Table 2 Cost of resources from different suppliers

	S1	S2	S3	S4	S5	S6	…	S24
A	0.1994	0.5872	0.7689	0.6975	0.6678	0.1246	…	0.1842
B	0.8348	0.124	0.5841	0.577	0.7818	0.1669	…	0.9959
C	0.0809	0.2819	0.6519	0.4954	0.3532	0.1341	…	0.8609
D	0.9798	0.63	0.1768	0.2857	0.2664	0.0846	…	0.7228
E	0.8489	0.1503	0.7373	0.2099	0.0713	0.246	…	0.7536

Table 3 Cost of assembly tasks at different manufacturers

	M1	M2	M3	M4	M5	M6	…	M24
T1	0.9403	0.1758	0.869	0.3869	0.4872	0.6327	…	0.0311
T2	0.6795	0.3	0.2828	0.7364	0.7574	0.0393	…	0.2545
T3	0.2953	0.8543	0.8616	0.9231	0.2419	0.6759	…	0.5531
T4	0.8646	0.0373	0.2741	0.3956	0.1642	0.8928	…	0.1254

Table 4 Distance between suppliers and manufacturers

	M1	M2	M3	M4	M5	M6	…	M24
S1	0.8147	0.1576	0.6557	0.706	0.4387	0.276	…	0.2344
S2	0.9058	0.9706	0.0357	0.9318	0.3816	0.6797	…	0.4397
S3	0.127	0.9572	0.8491	0.0069	0.7655	0.6551	…	0.5786
S4	0.9134	0.4854	0.934	0.9462	0.7952	0.1626	…	0.3442
S5	0.6324	0.8003	0.6787	0.9071	0.1869	0.2761	…	0.7302
S6	0.0975	0.1419	0.7577	0.8835	0.9301	0.4984	…	0.2151
…	…	…	…	…	…	…		…
S24	0.9418	0.6352	0.8252	0.7268	0.775	0.2892	…	0.5933

Table 5 Distance between manufacturers

	M1	M2	M3	M4	M5	M6	…	M24
M1	0	0.3786	0.8116	0.5328	0.3507	0.939	…	0.8023
M2	0.3786	0	0.4709	0.2305	0.6443	0.9948	…	0.0278
M3	0.8116	0.4709	0	0.1848	0.9849	0.9797	…	0.9174
M4	0.5328	0.2305	0.1848	0	0.2217	0.2301	…	0.6944
M5	0.3507	0.8443	0.9049	0.2217	0	0.343	…	0.62
M6	0.939	0.1948	0.9797	0.1174	0.2303	0	…	0.677
…	…	…	…	…	…	…		…
M24	0.8023	0.0278	0.9174	0.6944	0.32	0.997	…	0

Table 6 Weight of equivalent components

	A	B	C	D	E
Weight	0.9678	0.6201	0.156	0.3984	0.8825

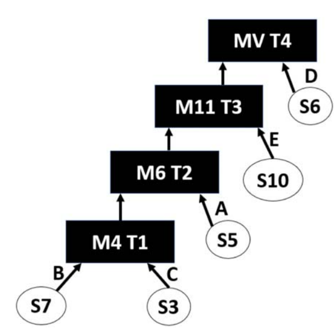

Fig. 11 Initial supply chain configuration

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product/component (e.g., moles (mol)) [29]. The transportation cost is directly proportional to the weight and the distance traveled.

(4) The initial supply chain configuration, including (1) the task sequence (i.e., tasks T1-T2-T3-T4) as shown in Fig. 11 and (2) the initial assembly plan (i.e., manufacturers 4-6-11-M_v and suppliers 7-3-5-10-6).

4.2 Verification of Evolutionary Algorithm. It is a grand challenge to quantify the logic involved in the similarity model that evaluates reconfiguration effort (Eq. (7) for θ_{rc}) [26] as equations or inequalities for optimization packages. Thus, this study ignores the reconfiguration based on similarity so that a nonlinear programming solver, COUENNE (Convex Over and Under ENvelopes for Nonlinear Estimation), can be employed as a benchmark to verify the computational performance of the proposed chromosome representation and operators used in EA. A total of seven problem instances with three repetitions were solved with increasing problem sizes, and the results were averaged over the replications and reported in Table 7. It can be seen that the number of manufacturers and suppliers ranging from 10 to 24 significantly impacted the computing time required to find a solution.

Table 7 Comparison of EA and COUENNE solver for FiB optimization

Case study I results			Fitness value		CPU times (s)	
Problem instance	Manufactures	Suppliers	COUENNE-FiB	EA-FiB	COUENNE-FiB	EA-FiB
1	10	10	319.441	320.0223	29.55	133.0987
2	12	12	404.867	405.532	22.39	154.0258
3	14	14	548.774	549.723	36.72	159.9387
4	16	16	712.393	713.625	164.57	192.0851
5	18	18	877.724	878.8547	243.895	242.9403
6	20	20	1086.66	1090.801	877.05	270.763
7	24	24	1557.38	1559.376	1178.753	295.3524

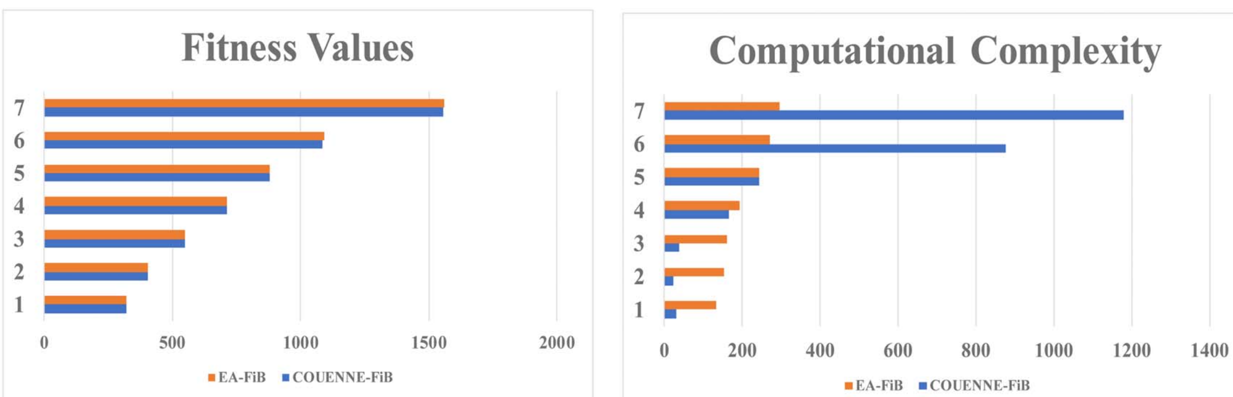

Fig. 12 EA versus COUNNE comparison: fitness values and computational complexity

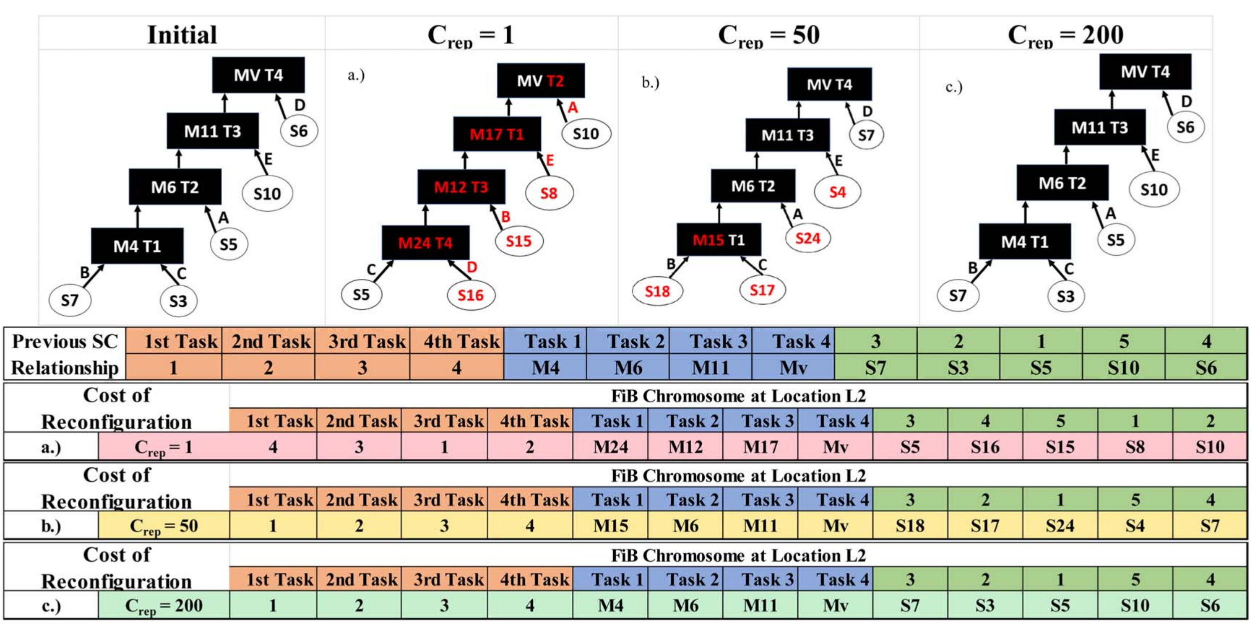

Fig. 13 The impact of different costs given a fixed location on supply chain network design

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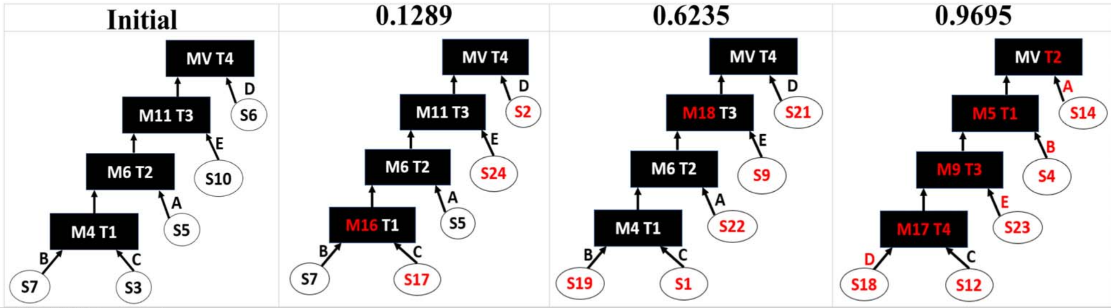

Normalized Distance from initial SC		FiB Chromosome at Location L2												
		1st Task	2nd Task	3rd Task	4th Task	Task 1	Task 2	Task 3	Task 4	3	2	1	5	4
a.)	0.1289	1	2	3	4	M16	M6	M11	Mv	S7	S17	S5	S24	S2
Normalized Distance from initial SC		FiB Chromosome at Location L2												
		1st Task	2nd Task	3rd Task	4th Task	Task 1	Task 2	Task 3	Task 4	3	2	1	5	4
b.)	0.6235	1	2	3	4	M4	M6	M18	Mv	S19	S1	S22	S9	S21
Normalized Distance from initial SC		FiB Chromosome at Location L2												
		1st Task	2nd Task	3rd Task	4th Task	Task 1	Task 2	Task 3	Task 4	3	4	5	1	2
c.)	0.9695	4	3	1	2	M17	M9	M5	Mv	S18	S12	S23	S4	S14

Fig. 14 Supply chain reconfiguration as FiB moves to different locations

The results of the numerical cases show that the EA performs very close to the COUENNE solver in terms of the obtained fitness values with a maximum percent difference of 0.38%. The computational time for the mathematical model increased significantly as the problem sizes increased (Fig. 12). The EA could find reasonable solutions in a fraction of the time required by the exact optimization solver for larger problem sizes. Thus, the numerical experiment results verify the EA's effectiveness in optimizing the assembly planning and supply chain configuration.

4.3 Results. The optimization was implemented under two different scenarios:

Scenario I (fixed location with varying cost of reconfiguration)

The values of c_{rep} in Eq. (3) were set to three unitless levels (1, 50, and 200) adopted from [21] to show the impact of reconfiguration cost on supplier selection and assembly planning. Using the initial supply chain represented by the "Previous SC Relationship" in Fig. 13, it can be seen that when the reconfiguration cost is low (i.e., $c_{rep} = 1$), there is a significant difference between the newly selected supply chain configuration compared to the initial configuration (i.e., {M24, M12, M17} and {S16, S15, S8}). As the reconfiguration cost increases to a moderate value (i.e., $c_{rep} = 50$), there are few deviations from the initial supply chain (i.e., M15 S18-S17-S24-S4). However, the selected supply chain does not change at all from the initial supply chain when the reconfiguration cost is high (i.e., $c_{rep} = 200$).

Scenario II (fixed cost of reconfiguration with varying locations for final production)

As the FiB travels to different locations, the selection/deselection of suppliers and manufacturers is necessary. Further experimentation was conducted to evaluate the impact of the FiB relocation on assembly planning and supply chain reconfiguration. The reconfiguration cost (c_{rep}) was set to 20, while the normalized distance from the initial production location (i.e., vehicle's location) increased to 0.1289, 0.6235, and 0.9695. These normalized values

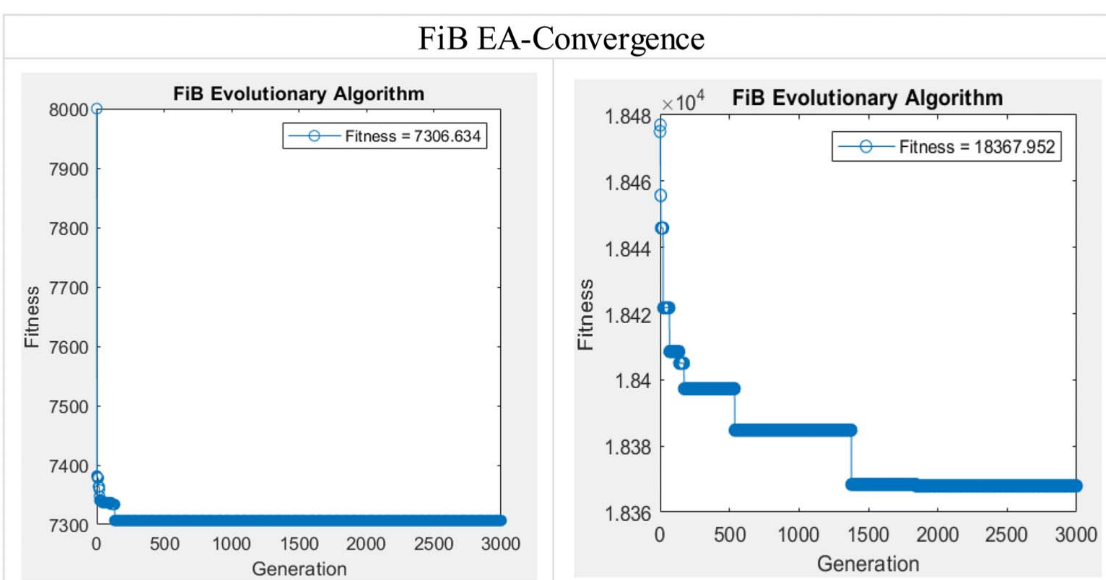

Fig. 15 Example of EA-FiB convergence for two problem instances: Left: 15 suppliers and 15 manufacturers. Right: 24 suppliers and 24 manufacturers.

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may reflect the scenarios where the vehicle travels between cities from Florida to Georgia, Florida to Texas, and Florida to Arizona, respectively.

It was found, in Fig. 14, that when the distance from the initial supply chain is low (0.1289), the selected supply chain is similar to the initial one with four members {M6, M11, S7, S5} performing the same assembly tasks {T1-T2-T3-T4}. However, as the factory moves to a normalized distance of 0.6235 from the initial location, only two members {M4, M6} are retained in the supply chain performing the same assembly tasks. Finally, when the factory moves to a normalized distance of 0.9695, not only are there no members of the initial supply chain retained but also a different process could be selected {T4-T3-T1-T2} to best match the suppliers/manufacturers' capability. Therefore, this study provides a quantitative tool for production managers to determine reconfiguration strategies of supply chain networks when the vehicle moves to different locations.

EA convergence

For each numerical experiment, the EA was run to ensure the proper exploration of the solution space and convergence to a good-quality solution occurs. Figure 15 shows convergence charts with 3000 generations for two problem instances: 15 suppliers + 15 manufacturers (left) and 24 suppliers + 24 manufacturers (right). For both instances, the best possible values were found with at least 1000 generations to spare. It can be observed that setting the convergence criterion to 3000 generations is sufficient (i.e., increasing the number of generations beyond 3000 generations no longer improves the quality of obtained solutions).

5 Conclusion

FiB manufacturing is an emerging manufacturing approach to on-site production near customers' locations, meeting time-sensitive demands with short delivery time and a high degree of flexibility. The FiB presents a significant challenge to the manufacturing process planning and the supply chain network reconfiguration due to constant changes in production location. In addition, the reconfiguration is closely coupled with manufacturing process planning (i.e., assembly hierarchy that determines assembly tasks, sequence, and subassembly modules). Also, limited data can be available to estimate the manufacturing reconfiguration cost.

An optimization model based on nonlinear integer programming was developed to jointly determine subassembly selection and assignment of assembly tasks to suppliers/manufacturers. The proposed new formulation captures the relationship between the assembly hierarchy and material flow in the supply chain, thereby enabling joint decision-making for assembly planning and supply chain configuration. The results could jointly determine the assembly hierarchy for process planning and supply chain configuration, including the logic arrangement of suppliers/manufacturers with material flow among them. The research also incorporated a novel similarity model to address the challenge of assessing the efforts of assembly process reconfiguration involved in the optimization, and an EA was developed and customized to solve the problem. A case study demonstrated the production of a medicine product in the FiB application. First, the study solved a relaxed version of the problem without considering reconfiguration so that a nonlinear programming solver (COUENNE) could be employed as a benchmark. The results verified the EA's performance with a maximum percent difference of 0.38% from COUENNE with reduced computational time when the problem size grows larger. Then, two numerical experiments showed the capability of the algorithm in quantitatively determining the selection/deselection of suppliers or manufacturers as the vehicle constantly relocates to different production sites.

The results imply managerial insights into supply chain reconfiguration and assembly planning. When the FiB vehicle travels to a new location not far from the previous one, the initial supply chain configuration and process planning are preferred. When the vehicle travels further away, the supply chain is configured by more local suppliers, and process planning might be changed accordingly. This research sheds light on the relationship between supply chain reconfiguration and assembly process planning for the development of FiB manufacturing. It also establishes quantitative guidelines for supply chain network design considering the assembly plan and reconfiguration. The outcome of this research can potentially benefit the production facilities to cope with time-sensitive demands, such as personal protection gear and medical supplies for a pandemic or natural disaster. The methodology can be potentially generalized to the supply chain and service process planning involved in mobile hospitals, which offer on-site medical services near patients' homes. Future work will incorporate the uncertainty in supply chain resilience to develop robust solutions, given limited information on disruptions. Stochastic programming or multistage optimization approaches will be explored to deal with the uncertainty.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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