



# Optimized skill configuration for the seru production system under an uncertain demand

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## Abstract

Owing to its high efficiency and flexibility, the seru production system (SPS), which originated in Japan, has attracted greater attention in management and academic studies. This research focuses on optimizing the configuration for implementing the SPS under an uncertain demand. The study is aimed at formulating a robust production system capable of effectively responding to stochastic demands. The primary issues are determining the amount of skill training required and matching workers with their corresponding skills. A stochastic optimization model is developed to minimize the total expected cost of the system, while considering the costs associated with training, staff shortage, and staff surplus. A heuristic algorithm is developed to solve this problem. Experimental results indicate that, compared to the full-skilled training strategy, appropriate partial skill training (such as the long chain skill training strategy) can yield greater benefits. The total cost and amount of skill training increase with growing differences in the product mix compositions, demand fluctuations, and number of product types. Moreover, the skill level of workers increases with a decrease in training cost and an increase in staff shortage and surplus costs.

**Keywords** Japanese cellular manufacturing · Seru production system · Worker skill configuration · Stochastic optimization

## 1 Introduction

The seru production system (SPS), a Japanese cellular manufacturing technique, has gained popularity in Japanese manufacturing companies owing to its high efficiency and flexibil-

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ity (Miyake 2006; Stecke et al. 2012; Roth et al. 2016). The SPS involves converting from an assembly line with several workers to one with few workers who can assemble a component/product from start to finish. A few Japanese newspapers have also represented seru as dismantling of a conveyor belt (Shinohara 1995). When implementing the SPS, workers who originally worked on an assembly line are cross-trained and assigned to several serus. Research on machine-centered production systems has consistently focused on allocating tasks to machines (Alhadi et al. 2020; Quinton et al. 2020). However, for a human-centered production system, grouping workers into different serus is an important issue in the SPS (Kaku et al. 2009; Yu et al. 2014, 2017; Wang and Tang 2018). In this study, we aim to optimize the skill configuration of workers for implementing the SPS through an assembly line under an uncertain demand.

Currently, increasing diversification, smaller volumes, and shortened lifecycles appear to be prominent characteristics of customer demands. Owing to these new requirements, manufacturers face challenges pertaining to quick responses to dynamic and uncertain demands as well as the increased costs required to maintain a profitable production system due to increasing labor costs, material costs, etc. (Yin et al. 2017, 2018). Existing assembly lines are subject to costly conveyor belts and inefficient management of frequent product changes. However, in the SPS, simple self-made tools that offer the same functionality are employed, instead of expensive equipment. Meanwhile, the SPS involves a U-shaped work station, which reduces space consumption. Apart from these financial benefits, employing multi-skilled workers enables a more efficient and flexible assembly line suitable for a wide variety of products with short life cycles. Thus far, several manufacturing companies have adopted the SPS, particularly electronic industries such as Sony and Canon (Yin et al., 2008, 2017); these companies have achieved considerable benefits in terms of cost reduction and market responsiveness to the new demand conditions. For instance, Canon implemented the SPS in 54 plants in 23 countries from 1998 to 2003; during this period, 20,000 m of assembly conveyor belts were dismantled and 720,000m<sup>2</sup> of shop-floor space was saved (Yin et al. 2008). Consequently, manufacturing firms can benefit significantly by converging their original assembly lines to the SPS.

Although many Japanese newspapers and magazines have reported on the SPS (Stecke et al. 2012), theoretical research in this area is still in its nascent stages (Yu et al. 2017). Moreover, very few studies on the implementation of the SPS have focused on the skill levels in the seru. Most of these studies focus on implementing the SPS using an assembly line, while assuming that all the serus in the SPS are capable of assembling all types of products (Kaku et al. 2009; Liu et al. 2012; Yu et al. 2013). However, this assumption is not always economic or practical, as it necessitates large-scale training and equipment duplications. In particular, when the tasks are highly complex and varied, it can be difficult to obtain full-skilled workers because of the limited learning capacity and high training costs (Slomp and Molleman 2002; Molleman 1998). Besides, Liu et al. (2013) and Ying et al. (2017) proposed models for implementing the SPS through the training and assignment of cross-trained workers. They focused on balancing the workers in each seru, under a simple assumption that each seru can only produce one type of product; this reduced the flexibility of the system. In addition, the objective functions considered in previous studies are measures related to time (Kaku et al. 2009; Liu et al. 2012; Yu et al. 2012), training and balancing costs (Liu et al. 2013; Ying et al. 2017; Yilmaz 2020; Wang and Tang 2018), or sustainable objectives (Liu et al. 2015). Thus, greater attention should be devoted toward staff utilization. Furthermore, even if the SPS offers several advantages under a dynamic demand, its impacts under an uncertain demand have not been adequately documented. Liu et al. (2013) and Ying et al. (2017) simply assumed that each seru in this system serves a single type of product

**Table 1** Matrix of product type and skill

Product type	BS	SS1	SS2	SS3	SS4
1	✓	✓			
2	✓		✓		
3	✓			✓	
4	✓				✓

**Table 2** Example of skill configuration for six workers

Worker	BS	SS1	SS2	SS3	SS4
1	*	*			*
2	*		*		
3	*				*
4	*		*	*	
5	*	*			
6	*			*	

type under a stable demand. Yu et al. (2012, 2014) considered the uncertainties in product mixes, batch sequences, and variable batch volumes. However, all the batches in these studies were generated based on probability distributions prior to implementing the SPS, without considering the arrival times. Thus, these SPSs in previous research were implemented under a known demand. Therefore, it is necessary to more clearly define the implementation of the SPS under an uncertain demand, from a practical perspective.

In this study, to supplement previous research on implementing the SPS, we focus on optimizing skill configurations of the seru under an uncertain demand. It should be noted that, in this study, skills represent the basic and specific skills required for assembling products, rather than the operations at different stations of an assembly line. Thus, it is reasonable to assume that, even if different products are assembled on the same assembly line, the tools and techniques can vary with respect to the stations. As an example, we consider 4 product types with one basic skill and four specific skills, as listed in Table 1. Let BS be the basic skill for all product types and SS1 be the specific skill for product type 1, SS2 for product type 2, and so on. Each worker possesses the basic skill and at least one specific skill. An example of a feasible skill configuration for six workers is presented in Table 2, where workers 2, 3, 5, and 6 possess one specific skill, while workers 1 and 4 serve two product types.

The assignment problem can be categorized based on several aspects, such as call center staffing problems (Atlason et al. 2004; Bhulai et al. 2012), machine-product scheduling problems (Mtze 2014), and project management problems (Huchzermeier and Loch 2001). These problems primarily focus on allocating appropriate tasks to each agent; this is also the problem addressed in this study. However, in this study, additional factors need to be considered due to the aspects such as high training costs for multi-skilled workers and decreased enthusiasm due to an underutilized workforce. Additionally, the assignment problem as well as the skill configuration problem are addressed in this study. For appropriately incorporating skill training, we explore manufacturing flexibility. Jordan and Graves (1995) demonstrated that limited flexibility with an appropriate configuration can offer most of the benefits of complete flexibility. In such a configuration, each plant serves only two product types, and each product type can be served by only two plants. Moreover, a long chain connects each plant and product type. Several studies have extended this idea and applied it to different

applications. For instance, Wallace and Whitt (2005) explored agent flexibility in call centers based on skill-based routing, Tomlin (2006) focused on agent flexibility in supply chain risk management; Huchzermeier and Loch (2001) studied agent flexibility in project management, and Bassamboo et al. (2010) investigated agent flexibility in newsvendor networks. Furthermore, Deng and Shen (2015) proposed additional flexibility design guidelines for unbalanced networks where the number of products exceeds the number of plants. Henao et al. (2016) extended this research to unbalanced networks where the number of plants exceeds the number of products. Moreover, Jordan and Graves (1995) developed an analytical method for the appropriate addition of skills; although this method selects product types that provide the greatest flexibility, it does not indicate the plants that would benefit from these additional skills. Consequently, adding a skill arc between individual products and workers is an important problem.

In this study, we also aim to offer managerial insights for the implementation of the SPS and address the following queries: (1) Can partially multi-skilled workers obtain greater benefits as compared to full-skilled workers? (2) What are the necessary changes in the performance and skill configuration of the SPS under varying demand fluctuations? (3) What is the optimal skill configuration of the SPS for different cost-related conditions?

In this study, we focus on designing the skill configuration for the implementation of the SPS, which enables manufacturers to realize improved responsiveness and reduced costs. A stochastic optimization model is proposed to determine the optimal benefits and skill configuration for this system. To achieve the optimal skill configuration of the SPS, we propose a heuristic algorithm to appropriately incorporate specific skill training. Owing to difficulties in the analytical calculations and the large-scale scenarios, scenario aggregation is employed to address the uncertain demand. To efficiently solve the massive realizations obtained via scenario aggregation, we introduce Cplex 12.6. In addition, a series of numerical experiments is designed to analyze the variations in cost and skill configuration with respect to the different uncertainties in demand (such as those in the composition of product mix (CPM), demand fluctuation, and number of product types (NPT)) and cost-related parameters (such as training cost, staff shortage cost, and staff surplus cost).

The remainder of this paper is organized as follows. The proposed mathematical model is discussed in Sect. 2. Section 3 introduces the method of solving this problem. Subsequently, the numerical experiments are presented in Sect. 4. Finally, the conclusions of this study and the scope of future research are highlighted in Sect. 5.

## 2 Model formulation

### 2.1 Assumptions and notations

A seru is essentially a converged assembly line. There are three types of serus: divisional seru, rotating seru, and yatai. Workers in divisional serus are cross-trained and are responsible for one or more operations. In this seru, workers cooperate to complete the product assembly, similar to a shortened assembly line. In a rotating seru, several workers assemble products from start to finish; they chase one by one like rabbit chasing and do not disturb any other workers in the same seru. Similarly, yatai is a single-worker version of the rotating seru. Yatai is used for representing the ideal form of seru (Yin et al. 2008). Details of these three types of serus are presented in Fig. 1.

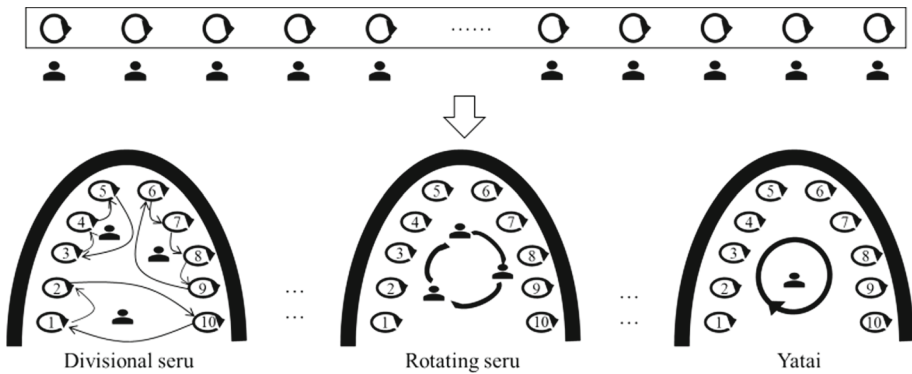


Fig. 1 Three types of seru

With regard to the SPS skill configuration problem, we consider that  $J$  workers are initially working on an assembly line. Owing to the uncertain product types and fluctuating volumes, manufacturers need to improve their responsiveness through the implementation of the SPS. In other words, an assembly line can be converged and converted into an SPS where all  $J$  workers are cross-trained with appropriate skill sets. In this study, we only focus on rotating seru; this implies that all the workers are capable of assembling products from start to finish, without any assistance.

First, the skill configuration of all the workers can vary over a wide range. In a rotating SPS, each worker should be trained with at least one specific skill. Under a deterministic demand, the training strategy involves simply assigning an appropriate number of workers to each product type. However, using specialists under an uncertain demand is not sufficiently flexible. For example, let us consider 3 product types with demands of 8, 10, and 12, along with 3 workers each with a capacity of 10. Provided all workers are single-skilled specialists for a single product, the expected sales will be 28. Evidently, if the first worker can serve both product types 1 and 3, the expected sales will increase to 30. It should be noted that the expected sales will not increase through the addition of any other skills. Although training all the workers in all specific skills is the simplest configuration for uncertain demands, we need to restrict the amount of skill training in order to control the training cost. Considering all specific skills as a set, as shown in Table 1,  $\{SS1 SS2 SS3 SS4\}$  is a specific skill set for this product mix. All the workers can be trained in any subset of the specific skill set, while converging the assembly line to the SPS. By counting the number of subsets of the specific skill set, the number of possible skill configurations for each worker is  $2^K + 1$ , where  $K$  is the total number of product types. Similarly, the total number of possible skill configurations is  $(2^K + 1)^J$ , where  $J$  is the number of workers.

Furthermore, the uncertain demand needs to be well defined. Although it is difficult to determine the accurate demand for each day, the distribution of demand should be estimated in advance based on historical production data. We assume that there are  $K$  product types, where the demand of product type  $k$  follows the distribution  $d_k \sim N(\mu_k, \sigma_k)$  for a certain period. This period can be 1 h, one day, or several days. The demand of a certain product type can only be served by workers who possess all the skills required for this product type. As this study focuses on the planning aspects, where the primary issue is skill configuration rather than scheduling, we explore balancing the demand and capacity. Staff shortage costs

are incurred when demand cannot be met under a particular skill configuration. Meanwhile, staff surplus costs are incurred when the workers are underutilized.

In summary, the primary challenge faced by a manager is determining the appropriate skill set for each worker. This study intends to formulate a model for minimizing the cost of the SPS subjected to an uncertain demand by determining the amount and type of skills that a worker should possess. Consequently, the decision variables in this research are the skill sets for each worker. Let  $Y_{jk}$ , with a value of 1, denote that the specific skill  $k$  can be handled by worker  $j$ . All parameters and variables are denoted as follows:

Notations:

- $k$ : index of product type and specific skills ( $k = 1, 2, \dots, K$ );
- $j$ : index of workers ( $j = 1, 2, \dots, J$ );
- $A$ : capacity of a worker;
- $d_k$ : demand of product type  $k$ ;
- $C$ : training cost for a worker with any specific skill;
- $\alpha_c$ : coefficient of staff shortage cost for one worker;
- $\alpha$ : coefficient of penalty cost for lost sales,  $\alpha = \alpha_c/A$ ;
- $\beta_c$ : coefficient of staff surplus cost for one worker;
- $\beta$ : coefficient of penalty cost for idle capacity,  $\beta = \beta_c/A$ .

Decision variables:

$x_{jk}(\omega)$ : the number of product type  $k$  assembled by worker  $j$  in scenario  $\omega$ .

$$Y_{jk} = \begin{cases} 1, & \text{if worker } j \text{ is trained with specific skill } k \\ 0, & \text{otherwise} \end{cases}$$

## 2.2 Stochastic optimization model for SPS skill configuration

As the SPS in this study is composed of rotating serus,  $J$  workers from the original assembly line need to be trained in operations of the different stations on the conveyer belt; this is to ensure that they are capable of handling at least one product type from start to finish. Although different product types need to be served within a single station depending on the formal production design, these operations could vary. We assume that, for each worker at a station, the processing time and the training cost of a specific skill are identical. Consequently, we calculate the training cost of each worker based solely on the training of specific skills. The training cost of worker  $j$  can be expressed as  $\sum_{k=1}^K Y_{jk}C$ , where  $C$  is the training cost for a worker with a single specific skill. For instance, the training cost of a worker is  $2C$  when the worker is trained in specific skills 1 and 2.

To evaluate the performance of a certain skill configuration, staff shortage or surplus in this system need to be considered. For a certain skill configuration, the primary issue pertains to demand allocation, which determines the appropriate demand allocation for each worker required to maximize expected sales. Hence, we define  $x_{jk}$  as the number of assembled items of product type  $k$  by worker  $j$ . Staff shortage cost occurs when the demand of product type  $k$  cannot be met; it is expressed as  $(d_k - \sum_{j=1}^J x_{jk})^+ \times C \times \alpha$ , where  $(d_k - \sum_{j=1}^J x_{jk})^+ = \max\{0, (d_k - \sum_{j=1}^J x_{jk})\}$ , and  $\alpha$  is the coefficient of the penalty cost for lost sales (staff shortage cost). Contrarily, staff surplus cost arises when the capacity of worker  $j$  is underutilized; it can be expressed as  $(A - \sum_{k=1}^K x_{jk})^+ \times C \times \beta$ , where  $(A - \sum_{k=1}^K x_{jk})^+ = \max\{0, (A - \sum_{k=1}^K x_{jk})\}$ , and  $\beta$  is the coefficient of penalty cost for idle capacity (staff surplus cost). For convenient exposition, we set the training cost of one specific skill for a single worker as  $C = 1, \forall j, k$ . To summarize, under a deterministic

**Table 3** Skill configuration and demand allocation for scenario 1

Worker index	Product type 1	Product type 2	Product type 3	Specific skill set
1	30			{1}
2	10	20		{1, 2}
3		30		{2}
4			30	{3}
5			30	{3}

condition, where demand  $d_k$  is known before making training and allocation decisions, the problem can be expressed as

*P1*

$$\min \left[ \sum_{j=1}^J \sum_{k=1}^K Y_{jk} + \sum_{k=1}^K \left( d_k - \sum_{j=1}^J x_{jk} \right)^+ \times \alpha + \sum_{j=1}^J \left( A - \sum_{k=1}^K x_{jk} \right)^+ \times \beta \right] \tag{1}$$

s.t.

$$0 \leq x_{jk} \leq Y_{jk} \times A, \quad \forall j, k \tag{2}$$

$$\sum_{k=1}^K x_{jk} \leq Y_{jk} \times A, \quad \forall j \tag{3}$$

$$\sum_{j=1}^J x_{jk} \leq d_k, \quad \forall k \tag{4}$$

$$1 \leq \sum_{k=1}^K Y_{jk} \leq K, \quad \forall j \tag{5}$$

$$1 \leq \sum_{j=1}^J Y_{jk} \leq J, \quad \forall k \tag{6}$$

Equation (1) expresses the objective of minimizing the total cost (TC). The first term denotes the training cost for all workers, and the second and third terms refer to the staff shortage cost and the staff surplus cost, respectively. Constraint (2) ensures that the assembly of a certain product type is only allocated to workers who are capable of serving it. Constraint (3) ensures that the demand allocated to a worker does not exceed the worker’s capacity. Constraint (4) ensures that production does not exceed the demand of any product type. Constraint (5) implies that each worker can assemble one product type at the least and all product types at the most. Constraint (6) implies that each product type can be served by one worker at the least and all workers at the most.

Due to the uncertainty in demand, it is difficult to determine the appropriate demand allocation for each worker beforehand. Although demand allocation can be adjusted in response to every change in the demand, the skill training of workers cannot be adjusted immediately. Consider 5 workers each with a capacity of 30 and 4 demand scenarios involving 3 product types: {40,50,60}; {40,70,40}; {50,70,30}; {50,60,40}. Under scenario 1, the optimal solution can be achieved by P1, as shown in Table 3. However, considering the capacity shortage of product type 2, the demand cannot be satisfied using this skill configuration under sce-

narios 2 and 4. To incorporate the uncertain demand, we consider a two-stage model that is based on the two-stage stochastic optimization model proposed by Long et al. (2012). The first stage involves the determination of the skill configuration of the SPS, whereas the second stage pertains to demand allocation, where the precise demand is unknown in the first stage. Let  $\omega \in \Omega$  denote the realization of the demand that follows a probability distribution and is unknown during the decisions of stage 1, where  $\Omega$  denotes the set of all scenarios. It is evident that  $P2$  is identical to  $P1$  under a certain scenario. The two-stage stochastic optimization problem can be formulated as follows:

*P2-Stage 1:*

$$\min \left\{ \sum_{j=1}^J \sum_{k=1}^K Y_{jk} + E[Q(Y_{jk}, \xi(\omega))] \right\} \tag{7}$$

s.t.

$$(5)(6)$$

*P2-Stage 2:* in scenario  $\omega$

$$Q(Y_{jk}, \xi(\omega)) = \min \left[ \sum_{k=1}^K \left( d_k(\omega) - \sum_{j=1}^J x_{jk}(\omega) \right)^+ \times \alpha + \sum_{j=1}^J \left( A - \sum_{k=1}^K x_{jk}(\omega) \right)^+ \times \beta \right] \tag{8}$$

s.t.

$$0 \leq x_{jk}(\omega) \leq Y_{jk} \times A, \quad \forall j, k \tag{9}$$

$$\sum_{k=1}^K x_{jk}(\omega) \leq A, \quad \forall j \tag{10}$$

$$\sum_{j=1}^J x_{jk}(\omega) \leq d_k(\omega), \quad \forall k \tag{11}$$

The objective function of stage 1 is to minimize cost from the perspective of implementing the SPS. Furthermore, the objective function of stage 2 is to minimize the staff shortage and staff surplus costs under a realized scenario  $\omega$ . Constraints (9)–(11) are scenario-based constraints extended from constraints (2)–(4) of the deterministic problem.

### 3 Solving methodology

#### 3.1 Scenario aggregation

The SPS implementation model formulated in this study is used for a stochastic optimization problem in which the demand is uncertain. Apart from the extreme cases of single-skilled SPS and full-skilled SPS, it is difficult to specify the objective function with an exact mathematical expression, e.g. an integral formula. To address this uncertainty, we describe the problem using a scenario-based expectation equation, i.e., (7). However, according to the



practical situation, the number of possible scenarios in  $\Omega$  is so large that enumeration is almost impossible. Therefore, we introduce the scenario aggregation method in this paper. Scenario aggregation was first proposed by Rockafellar and Wets (1991) for solving multi-stage stochastic programming problems. This method mainly involves obtaining an overall solution by aggregating the solutions of a sufficiently large number of  $N$  sample scenarios to reach an approximate solution. In particular, stochastic variables are sampled from the given distributions to represent each scenario, while the expected objective of the stochastic programming is approximated by averaging the objectives of a large number of scenarios. This method is now widely applied in solving stochastic programming problems such as the airline fleet composition problem (Listes and Dekker 2005), empty container repositioning problem (Long et al. 2012), and stochastic unit commitment problem (Schulze et al. 2017).

Using scenario aggregation, (7) can be rewritten from the scenario-based perspective as follows:

$$\min \left\{ \sum_{j=1}^J \sum_{k=1}^K Y_{jk} + \frac{1}{N} \sum_{n=1}^N \left[ \sum_{k=1}^K \left( d_k(\omega^n) - \sum_{j=1}^J x_{jk}(\omega^n) \right)^+ \times \alpha + \sum_{j=1}^J \left( A - \sum_{k=1}^K x_{jk}(\omega^n) \right)^+ \times \beta \right] \right\} \tag{12}$$

s.t.

$$0 \leq x_{jk}(\omega^n) \leq Y_{jk} \times A, \quad \forall j, k, n \tag{13}$$

$$\sum_{k=1}^K x_{jk}(\omega^n) \leq A, \quad \forall j, n \tag{14}$$

$$\sum_{j=1}^J x_{jk}(\omega^n) \leq d_k(\omega^n), \quad \forall k, n \tag{15}$$

(5)(6)

### 3.2 Heuristic algorithm for adding skills to serus

The key problem is deciding which skill sets should be assigned to each seru. For a certain scenario, with the constraints (10) and (11), Eq. (8) can be written as  $Q(Y_{jk}, \xi(\omega)) = \min[(\sum_{k=1}^K d_k(\omega) - \sum_{k=1}^K \sum_{j=1}^J x_{jk}(\omega)) \times \alpha + (AJ - \sum_{k=1}^K \sum_{j=1}^J x_{jk}(\omega)) \times \beta]$ . Clearly, the value of  $Q(Y_{jk}, \xi(\omega))$  decreases with an increment in the best sales for scenario  $\omega$ . Hence, the problem in stage 2 can be transformed to maximize the best sales  $\sum_{k=1}^K \sum_{j=1}^J x_{jk}(\omega)$  of the scenario, which is the demand that can be met by SPS. Jordan and Graves (1995) proposed the flexibility manufacturing problem and developed a measure to search for suitable limited flexibility configurations. This measure has been extended to different applications, as mentioned in Sect. 1, and has been proven to be effective. Due to the different numbers of workers and product types, the problem analyzed in this study is similar to but more complex than the flexibility manufacturing problem. Therefore, we develop a heuristic algorithm based on the measure proposed by Jordan and Graves (1995) and Deng and Shen (2015).

We set up the system with the assumption that all the workers are well-trained and have the basic skill set, and we make decisions regarding how to impart specific skills to each

worker. First, we divide all the workers into  $K$  groups according to the mean of the different product demands in the initial condition. Therefore, all the workers are trained with at least one specific skill, and there is at least one worker for each product type even if the mean of demand is less than the capacity of one worker. Second, to handle the skill training problem, we introduce the flexibility adding method proposed by Jordan and Graves (1995) and the flexibility design guidelines for unbalanced networks proposed by Deng and Shen (2015). According to Jordan and Graves (1995), we can also transform the problem in terms of minimizing the demand shortfall that cannot be satisfied by SPS equivalently. There are multiple subsets in a demand for  $K$  product types. The problem of minimizing the demand shortfall under limited skill training is  $\max_L \{\sum_{k \in L} d_k - \sum_{j \in P(L)} A\}$ , where  $L$  includes all the subsets of the index set  $\{1, 2, \dots, k\}$ , including the empty set. We define  $p1$  as the probability of the shortfall for a certain subset of products, and  $p2$  as the probability of the shortfall for a full-skilled system. The main reason for adding skill sets appropriately is to ultimately reduce the probability that  $p1$  exceeds  $p2$ . For a given product subset  $L$ ,  $P(L)$  is the subset of groups that can produce at least one of the products in  $L$ . The probability that the shortfall for the given subset of products  $L$  exceeds the shortfall for full skill training is expressed as  $\Pi(L) = \Pr\{\sum_{k \in L} d_k - \sum_{j \in P(L)} A > (\sum_{k=1}^K d_k - \sum_{j=1}^J A)^+\}$ . Jordan and Graves (1995) demonstrated that the probability  $\Pi(L)$  can be calculated by  $\Pi(L) = [1 - \Phi(z_1)]\Phi(z_2)$ , where  $z_1 = -E[a]/\sigma[a]$ ,  $z_2 = -E[b]/\sigma[b]$ ,  $a = \sum_{k \in L} d_k - \sum_{j \in P(L)} A$  and  $b = \sum_{k=1}^K d_k - \sum_{j=1}^J A - a$ , where the demands for all product types follow normal distribution. The detail of the calculation of  $\Pi(L)$  can be found in Jordan and Graves (1995). A large value of  $\Pi(L)$  indicates a significant probability that the shortfall of this subset can exceed the full-skilled SPS, which means that more capacity should be assigned to the product types in this subset  $L$ . Therefore, we find the product type by finding the maximum  $\Pi(L^*)$  from all the subsets. On the other hand, a decision is made regarding which worker should be trained to acquire the selected specific skill  $k^*$ . According to the additional flexibility design guidelines for unbalanced networks Deng and Shen (2015), the additional flexibility should be adding evenly to the plants circle and connecting the same pair of plants to more than one product is ultimately avoided. Therefore, we tentatively add training for specific skill  $k^*$  for a worker from every group except group  $k^*$ , and select the group of workers  $g^*$  with the minimum  $\Pi^*$  thereafter. There are some rules for adding specific skill training: (1) First, we choose the group without specific skill  $k^*$ ; (2) If there is more than one worker in a group, we impart specific skill to the worker who has the smallest specific skill set; (3) If there is more than one group with the minimum  $\Pi^*$ , we choose the group that can help build the long chain circle. The details of the algorithm are shown below.

*Algorithm:*

Phase 1: Start

Step 1: Assign workers to  $G$  skill groups according to the mean demand for  $K$  product types,  $G = K$ .

a. Ensure that there is at least one worker in each skill group.

b. All the workers are assigned to skill groups.

Phase 2: Determine the product type  $k^*$  that requires capacity addition the most.

Step 2: Let  $L$  be all the subsets of  $K$  product types, including the empty set.

Step 3: Determine the subset  $L^*$  with the maximum  $\Pi(L^*)$  from  $L$ .

Step 4: If there is more than one product type in subset  $L^*$ , update  $L = L^*$  and repeat Steps 2–4; else, update  $k^* = k'$ .

Phase 3: Determine the skill group  $g^*$  for training specific skill  $k^*$ .

Step 5: Let set  $S_{k^*}$  represent the set of skill groups that cannot handle specific skill  $k^*$ .

- a. If there is only one skill group  $g'$  in  $S_{k^*}$ , update  $g^* = g'$  and go to Step 6.
- b. If  $S_{k^*}$  is an empty set, update  $S_{k^*}$  as the skill groups where workers without specific skill  $k^*$  are included; then, go to d.
- c. If there is more than one skill group in  $S_{k^*}$ , go to d.
- d. Tentatively add training for specific skill  $k^*$  for all the skill groups in  $S_{k^*}$  and determine the minimum  $\Pi^*$  of all groups in  $S_{k^*}$ . Update  $S'_{k^*} = \{g \in S_{k^*}, \Pi_g = \Pi^*\}$ ,  $S_{k^*} = S'_{k^*}$ . If  $k^* < \max\{S_{k^*}\}$ , update  $g^*$  as the first  $g' > k^*$ ; otherwise, update  $g^* = \min\{S_{k^*}\}$ . Go to Step 6.

Phase 4: Add specific skill training for worker  $j^*$  in group  $g^*$ .

Step 6: Let set  $S_g$  represent the set of workers in group  $g^*$  that cannot handle specific skill  $k^*$ . If there is only one worker  $j'$  in set  $S_g$ , update  $j^* = j'$ ; otherwise, update  $j^*$  as the worker with smallest specific skill set.

Step 7: Repeat Steps 2–6 until there is no improvement in expected sales.

## 4 Numerical experiments and discussion

The experiments are designed based on the real production data of a Chinese company, which is referred to herein as M. M is a high-end medical device manufacturer that offers various types of products, follows a complex assembly process, and manufactures products in small and medium batches. According to production data for six months, the demand for each product approximately follows a normal distribution. To analyze the characteristics of the proposed model more accurately, we design simple basic experiments and adjust the relevant parameters to determine the optimal skill level configuration and the impact of the relevant parameters. All tests were performed on a PC with the following configuration: Intel(R) Core (TM) i5-4210U processor with a clock speed of 2.40 GHz; Windows 7 operating system; 4 GB of RAM. The algorithm was implemented in MATLAB. The following subsections present three aspects of the experiments. The first subsection describes the basic experiments on the implementation of the proposed model in a real-world application. In the second part, we analyze the impact of demand-related parameters, such as the CPM, coefficient of demand fluctuation (CoF), and NPT. In the third subsection, we evaluate the changes in the TC and skill configuration with different cost parameters.

### 4.1 Basic experiment

To illustrate the application of the proposed model and method, the basic experiment are described in this subsection. We consider a line-seru conversion problem with 20 workers on the original conveyer belts. In addition to the initial training for the basic skill set, all the workers are trained to acquire at least one specific skill so that they can assemble at least one type of product from the beginning to the end. Meanwhile, all the workers have the same capacity  $A$  of 50 pieces of type-independent products.

Consider an uncertain demand for  $K = 10$  product types. For a more effective analysis, we consider a simple demand condition in which the demands for all the products follow the same normal distribution with a mean of 100 and a variance of 50. We set the coefficient of penalty cost for lost sales (staff shortage cost) as  $\alpha = 20/50 = 0.4$ , and the coefficient of penalty cost for idle capacity (staff surplus cost) as  $\beta = 10/50 = 0.2$ . To achieve a balance between result accuracy and computation time,  $N = 500$  scenarios are considered in scenario aggregation. The details of the parameters are listed in Table 4.

**Table 4** Parameters of basic experiment

Parameters	Value
$K$	10
$d_k$	$N$ (100, 50)
$J$	20
$A$	50
$\alpha$	0.4
$\beta$	0.2
$N$	500

Using the heuristic algorithm described in Sect. 3.2, we first divide the workers into 10 groups according to the mean demand for the 10 product types. Second, the product type  $k^* = 1$  that requires capacity addition the most is determined by finding the maximum  $\Pi(L^*) = 0.25$  from among all the subsets of the 10 product types, including the empty set. Third, we determine the skill groups that cannot handle specific skill  $k^*$  or have the lowest capacity for product type  $k^*$ , which is  $\{2,3,4,5,6,7,8,9,10\}$ . To tentatively add training for specific skill  $k^*$  for all the skill groups and to obtain the minimum  $\Pi^*$ , we determine  $g^* = 2$  as the first instance of  $g' > k^*$ . Fourth, we add training for specific skill  $k^* = 1$  for worker  $j^* = 3$  because this is the first worker who cannot handle product type 1 and has with the smallest specific skill set. These steps are repeated until there is no improvement in expected sales. The search path in the basic experiment is shown in Table 5; a row in the table indicates that one more specific skill is imparted to a worker. For example, row 5 in Table 4 represents 24 times of specific skill are trained, and the 24th one is training worker 9 with specific skill 4. The expected value of sales, shortage, surplus, and TC after the addition of this skill are 834.322, 172.668, 165.678, and 126.2028, respectively. Therefore, the optimal point is the 21st line in the table, which represents a solution that involves training for 40 specific skills in this system, with a minimum TC of 81.3412. By performing a simulation with this demand, the TC for the full-skilled training strategy (in which all the workers are trained with all specific skills) is determined to be 103.8314 which is higher than that in the proposed strategy. Moreover, the improvement in expected sales when switching from the obtained strategy (935.758) to the full-skilled training strategy (940.804) is minimal.

Figure 2 depicts the trends of both expected sales and TC with an increasing number of specific skill training (NSST). The expected sales increase until the 55th addition of a specific skill training to the system. Despite the general trend, inflection points clearly exist when NSST is 30 and 40. With the increment in NSST from 20 to 30, the expected sales increase drastically from 804.666 to 888.206 while the TC declines from 139.9964 to 99.8724. However, both the increment in expected sales and the decline in TC become slower between NSST values of 30 and 40. Interestingly, even though the expected sales still increase, TC bottoms out slightly after an NSST of 40.

As shown in Fig. 3, where NSST is 40, the dotted lines that connect products and workers constitute a closed long chain. Jordan and Graves Jordan and Graves (1995) argued that the long chain connecting production system can offer high flexibility, almost as much as the total flexibility, and that the improvement of flexibility is negligible upon adding more flexibility when the value of  $\Pi$  is less than 0.05. Table 3 shows that the  $\Pi$  value for the optimal cost is 0.0081, which is less than 0.05. Therefore, with the implementation of SPS and manufacturing flexibility, similar results are obtained. However, the results of our experiments are related to

**Table 5** Procedures of finding optimal costs

Index	Number of specific skill training	Worker index	Specific skill index	Sales	Shortage	Surplus	Cost	$\Pi$
1	20			804,666	202.324	195.334	139,9964	0.25
2	21	3	1	810,018	196.972	189,982	137,7852	0.25
3	22	5	2	816,536	190,454	183,464	134,8744	0.25
4	23	7	3	825,284	181,706	174,716	130,6256	0.25
5	24	9	4	834,322	172,668	165,678	126,2028	0.25
6	25	11	5	842,35	164,64	157,65	122,386	0.25
7	26	13	6	849,364	157,626	150,636	119,1776	0.25
8	27	15	7	857,768	149,222	142,232	115,1352	0.25
9	28	17	8	866,552	140,438	133,448	110,8648	0.25
10	29	19	9	874,812	132,178	125,188	106,9088	0.25
11	30	1	10	888,206	118,784	111,794	99,8724	0.1072
12	31	6	1	891,034	115,956	108,966	99,1756	0.1072
13	32	8	2	894,082	112,908	105,918	98,3468	0.1072
14	33	10	3	898,814	108,176	101,186	96,5076	0.1072
15	34	12	4	903,81	103,18	96,19	94,51	0.1072

Table 5 continued

Index	Number of specific skill training	Worker index	Specific skill index	Sales	Shortage	Surplus	Cost	$\Pi$
16	35	14	5	907,594	99,396	92,406	93,2396	0.1072
17	36	16	6	912,366	94,624	87,634	91,3764	0.1072
18	37	18	7	917,704	89,286	82,296	89,1736	0.1072
19	38	20	8	923,324	83,666	76,676	86,8016	0.1072
20	39	2	9	931,148	75,842	68,852	83,1072	0.0586
21	40	4	10	935,758	71,232	64,242	81,3412	0.0081
22	41	7	1	935,924	71,066	64,076	82,2416	0.0081
23	42	9	2	936,576	70,414	63,424	82,8504	0.0081
24	43	11	3	937,318	69,672	62,682	83,4052	0.0081
25	44	13	4	937,834	69,156	62,166	84,0956	0.0081
26	45	15	5	938,292	68,698	61,708	84,8208	0.0081
27	46	17	6	938,744	68,246	61,256	85,5496	0.0081
28	47	19	7	939,25	67,74	60,75	86,246	0.0081
29	48	1	8	939,748	67,242	60,252	86,9472	0.0081
30	49	3	9	940,244	66,746	59,756	87,6496	0.0057
31	50	5	10	940,476	66,514	59,524	88,5104	0.0057
32	51	10	1	940,482	66,508	59,518	89,5068	0.0057
33	52	12	2	940,488	66,502	59,512	90,5032	0.0057
34	53	14	3	940,566	66,424	59,434	91,4564	0.0057
35	54	16	4	940,65	66,34	59,35	92,406	0.0057
36	55	18	5	940,664	66,326	59,336	93,3976	0.0057
37	56	20	6	940,664	66,326	59,336	94,3976	0.0057

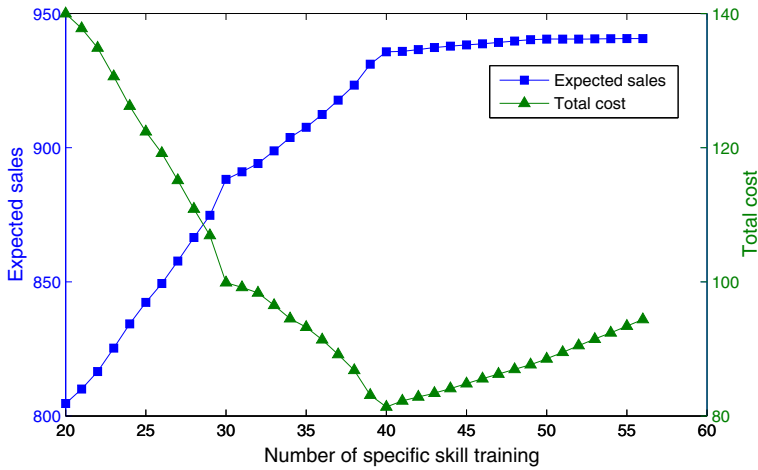


Fig. 2 Expected sales and total cost with different number of specific skill training

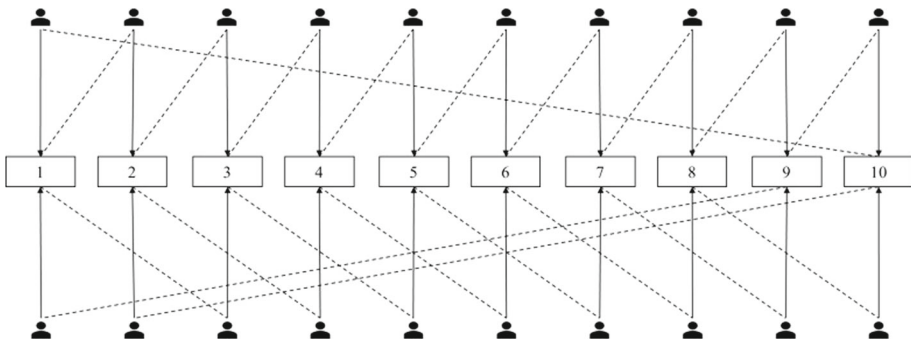


Fig. 3 Skill configuration for 10 product types

the parameters that we use. In the subsequent sections, we analyze the performance variation with different demands and cost conditions.

### 4.2 Impact of demand parameter

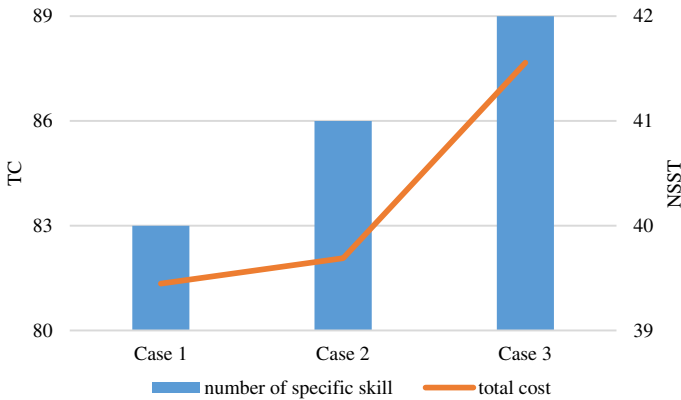
Based on the results of the basic experiments, we conduct experiments to investigate how demand-related parameters, e.g., the CPM, CoF, and NPT, impact the system cost and skill configuration.

#### 4.2.1 Composition of product mix

To evaluate the impact of different CPMs, we consider three typical demand conditions, shown in Table 6. The values in the table represent the mean demand for each product type in cases of varying demand. Case 1 is the basic experiment described in Sect. 4.1. Cases 1–3 represent three levels of difference in demand among product types; case 1 involves no difference among product types, and case 3 involves the maximum difference among product types. Without a loss of generality, we set the CoF as 0.5 for every product type in each case.

**Table 6** Demand for different product types

	Mean demand for different product types	CoF
Case 1	$d_k = 100, \forall k$	0.5
Case 2	$d_k \in [80, 120], \forall k, \sum_{k=1}^K d_k = 1000$	0.5
Case 3	$d_k \in [10, 190], \forall k, \sum_{k=1}^K d_k = 1000$	0.5



**Fig. 4** Optimal worker skill configuration for different cases

Through numerical experiments, we obtain the optimal worker skill training strategies for the three cases shown in Fig. 4. Both the NSST and TC increase with an increasing difference in the product mix. The NSST values are 40, 41, and 42 for cases 1, 2, and 3, while the TC are 81.3412, 82.0684, and 87.6672 respectively.

### 4.2.2 Coefficient of demand fluctuation

Different levels of demand fluctuation will impact the performance of SPS and the skill configuration. Here, the CoF is defined as  $\sigma/\mu$ . We set CoF as 0, 0.1, 0.2, 0.9 to represent the different levels of demand fluctuation. CoF = 0 represents the lowest level of demand fluctuation, while CoF = 0.9 represents the highest level of fluctuation. With the other parameters being the same as in the basic experiment, a comparison of different CoF values is shown in Fig 5. Although TC appears to invariably increase with an increasing CoF, some interesting discoveries are made. When  $CoF \leq 0.2$ , i.e., demand fluctuation is low, a group of workers in which half are single-skilled and half are multi-skilled is sufficient for obtaining the optimal cost. The arcs that connect the multi-skilled half of the worker group and the products constitute a long chain, which has been proven to be the most appropriate method of adding flexibility to a production system Deng and Shen (2015). When  $0.4 \leq CoF \leq 0.6$ , all the workers are trained to acquire two specific skills, and two long chains connect the products and workers. For  $CoF \geq 0.8$ , half of the workers are trained to acquire two specific skills, and the other half are trained to acquire three specific skills; thus, there are three long chains in this case. Therefore, multi-skill workers are not necessary when the demand is stable, and having workers with a limited number of specific skills can ensure almost optimal performance (e.g., the long chain skill configuration).



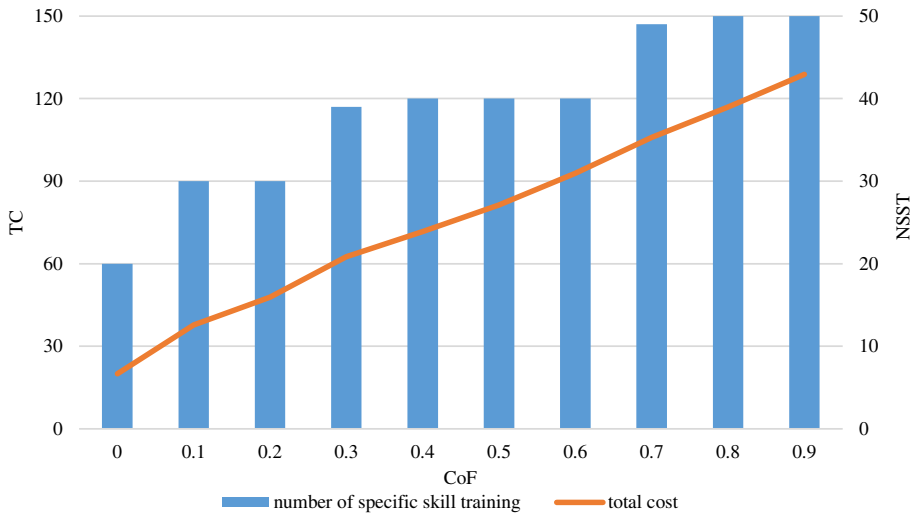


Fig. 5 Number of specific skill training and total cost with different CoFs

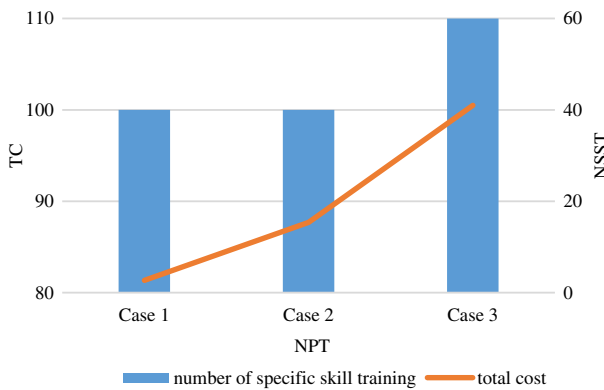


Fig. 6 Number of specific skill training and total cost with different NPTs

### 4.2.3 Number of product types

Although it appears that reasonable results can be obtained easily with a simple demand and supplement system, the differences in system performance and worker training strategies with different NPTs should be considered. For brevity, we evaluate the system performance and skill training strategy for cases 1–3 with NPT values of 10, 20, and 40. Without a loss of generality, we set (1) the number of workers with a capacity of 50 as 20; (2) the total demand for all product types as 1000 in each case; (3) CoF as 0.5 for every product type in each case.

The TCs for the cases with NPTs of 10, 20, and 40 are 81.3412, 87.7016, and 100.5052, respectively. For the same group of workers, TC and NSST increase with NPT, as shown in Fig. 6. The NSST is 40 for the NSTs of 10 and 20, while it is 60 for the NST of 40. The skill configurations for the three NPTs are shown in Figs. 3 and 7. It can be observed in the Fig. 3 that each of the product types can be served by four workers when the NST is 10. Meanwhile, there are two closed chains that connect the products and workers. However, the

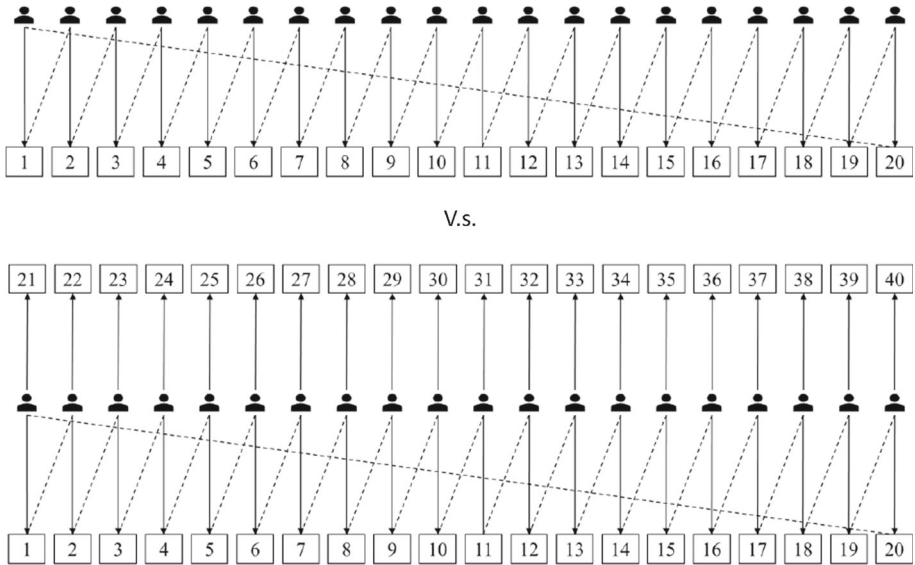


Fig. 7 Skill configuration of 20 and 40 product types

average numbers of workers that serve each product type are 2 and 1.5 for the NSTs of 20 and 40, respectively.

### 4.3 Impact of cost-related parameters

To analyze the impact of cost-related parameters, we conduct experiments with different training costs, coefficients of penalty cost for lost sales  $\alpha$ , and coefficients of penalty cost for idle capacity  $\beta$ ; the other parameters remain the same as in the basic experiment. The results are shown in Fig. 8a–c, where the bars represent workers with different numbers of skills, and the line represents the TC of the system. Evidently, TC increases with the training cost as well as the number of workers with few skills. As shown in Fig. 8a, when the training cost is 0, only 15 workers are trained to have three skills, while the other 5 have two skills. More workers are trained to less multi-skilled with an increase in the training cost. Three-skilled workers are not required until  $C \geq 0.4$ , while only half of the workers need to be trained to have two skills when  $C$  ranges from 2.9 to 5. With a high training cost over 5, single-skilled workers are the best choice for this system. For an NST of 10 in the extreme condition, in which the training cost is ignored, it is not necessary to train workers to acquire more than three specific skills. Figure 8b, c show that both TC and the number of skills of the workers increase with increasing  $\alpha$  and  $\beta$ . In Fig. 8b, half of the workers are trained to have two specific skills without considering the staff shortage cost. Meanwhile, multi-skill training is imperative when considering the staff shortage cost, especially with greater values of  $\alpha$ . Four two-skilled workers have to be trained to acquire another specific skill when  $\alpha \geq 1.76$ , and six more workers must be trained to acquire three skills when  $\alpha$  exceeds 1.88. As shown in Fig. 8c, all single-skilled workers can perform well when  $\beta \leq 0.08$ , while 10 of the workers need to be trained to acquire one more specific skill when  $0.12 \leq \beta \leq 0.2$ . When  $\beta$  reaches 1.96, 4 of the 20 two-skilled workers must be trained to have three skills. When  $\beta$  exceeds 2.08, the number of three-skilled workers required increases to 9.

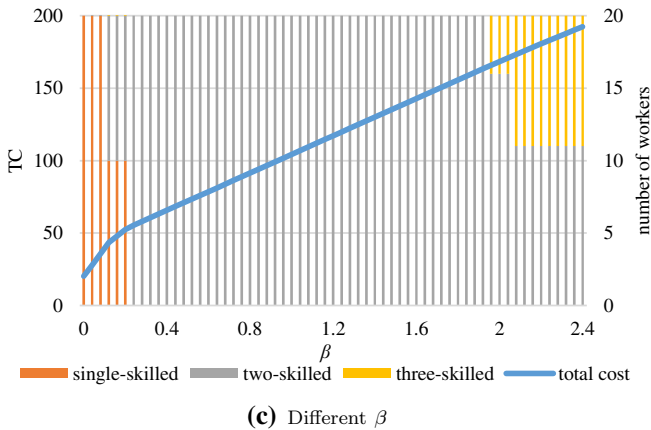
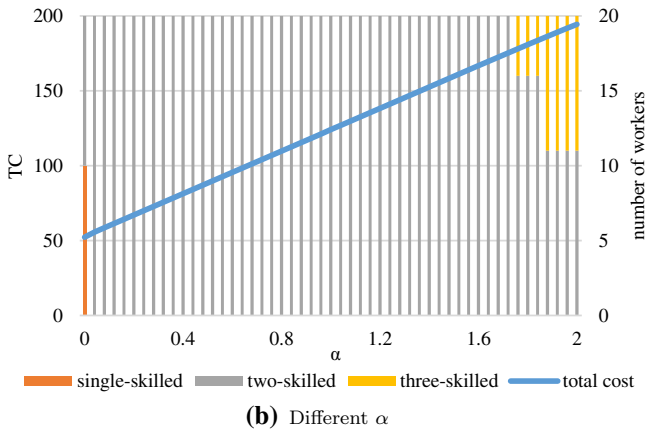
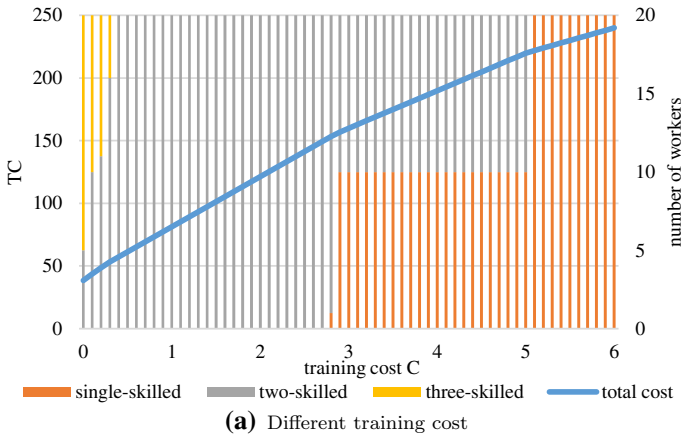


Fig. 8 Total cost and skill configuration with different cost parameters

## 5 Conclusion

This study focused on multi-skill training of workers for SPS implementation under uncertain demands. A stochastic optimization model was formulated to minimize the cost of SPS under uncertain demand while considering training cost, staff shortage cost, and staff surplus cost. Herein, a specific skill was defined as the skill to process one type of product completely by oneself. The key problem is deciding how the workers should be trained to acquire specific skills when handling an uncertain demand. The proposed model was solved using a proposed algorithm via simulation. Experimental results indicate that with appropriate skill training, partially multi-skilled workers can perform almost the same as fully skilled workers who have only a single skill. Both NSST and TC increase with an increasing 1) difference in CPM, 2) CoF, and 3) NPT. The number of skills possessed by workers increases with decreasing training cost and with increasing staff shortage cost and staff surplus cost.

Although the proposed model can readily handle SPS skill configuration problems under uncertain demand, it would be worthwhile to study problems with more complicated relations between products and specific skills (e.g., one product requiring several specific skills). Other parameters that can be considered include the facility cost of building a seru, and establishing an SPS with known skill configurations of certain staff.

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