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# An optimized production assignment algorithm for custom-made garments

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**A B S T R A C T**

Unlike mass-volume products, custom-made products provide multiple options at the ordering stage and therefore require a system flexible enough to accommodate these needs. This study developed a worker-balancing algorithm for custom-made products that enable equitable workload distribution across different numbers of workers. The key variables considered are task duration, the number of workers, and the type and complexity of the tasks involved in producing custom-made garments. The proposed algorithm is designed as an optimized production assignment by sequentially assigning the number of workers and tasks for each production operation. The main steps of the algorithm are as follows: (1) calculate the basic pitch time (BPT); (2) determine the number of workers and the time per worker required for the highest-level task; and (3) redistribute the workload between the highest-level task and the second-highest-level task. The algorithm was applied to generate production assignments for scenarios involving four to seven workers. The outcomes of the proposed method were compared with the current five-worker assignment in use. The results show that balance efficiency increased from 69.9 % to 83 %. To further validate the algorithm, a production process was modelled and simulated using a discrete-event systems simulation tool. The simulation confirmed the reliability of the balance efficiency, as labour utilization closely matched the calculated balance efficiency. This study is significant because it addresses workload balancing in small-scale, custom-made garment production. Moreover, it offers a practical approach to distributing task durations that accounts for both worker competencies and the specific nature of the tasks performed.

**A R T I C L E   I N F O**

*Keywords:*
Custom-made garment;
Flexible manufacturing system;
Garment production management;
Line balancing;
Workload distribution;
Discrete-event simulation;
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## 1. Introduction

In recent years, there has been a notable shift toward sustainability and customization within the apparel industry. Companies are increasingly adopting strategies to offer customized clothing, allowing them to differentiate their products while addressing environmental concerns. This trend effectively circumvents traditional issues related to excess inventory, which not only strains resources but also contributes to significant waste, thereby promoting a more sustainable fashion ecosystem. The rise of custom-made garments has been driven by a decline in the sewing workforce and a diminishing base for mass production, leading companies to embrace miniaturization and specialized production techniques. Such adaptations enable a transition to a production system characterized by multi-product, small-volume outputs. Consequently, this shift demands innovative approaches to production line design and management aimed at enhancing efficiency, reducing costs, and maintaining competitiveness.

Recent research highlights the critical importance of sophisticated production management in this evolving landscape. Effective production management involves careful measurement of working times and the strategic organization and analysis of task processing. The objective is to create an optimal work environment that minimizes inefficiencies, reduces delays, and decreases defects, ultimately boosting productivity [1]. Historically, studies have largely focused on line balancing within mass production frameworks, aiming to optimize the output of ready-to-wear garments [2-8]. However, there is an urgent need for research that specifically addresses optimal process allocation in bespoke clothing production, particularly concerning individual worker skill levels in a pre-order context. This approach not only aligns production more closely with actual market demand but also enhances resource utilization and worker capabilities, paving the way for a more sustainable and responsive manufacturing process.

The fashion industry's pivot toward custom-made garments presents unique challenges and opportunities in production management. This study introduces an innovative worker-balancing algorithm tailored specifically to address these dynamics. The essence of this algorithm lies in its capacity to adeptly allocate tasks among a variable number of workers, ensuring that each individual is assigned duties that align with their skills and the demands of the production schedule.

Central to this approach is the consideration of several critical factors: the task time required for each garment component, the fluctuating number of workers, and the varying types and difficulty levels of tasks. The algorithm is designed to optimize production efficiency by systematically assigning the right number of workers to each task, based on a detailed analysis of these factors. This method promises to enhance the productivity of custom garment production and ensures smoother operational flow, reducing bottlenecks and optimizing resource use.

By implementing this algorithm, manufacturers are equipped to maintain high efficiency while adapting to the bespoke needs of their clients. This study seeks to demonstrate the algorithm's effectiveness in real-world scenarios, thereby providing a robust framework for decision-makers in the apparel industry to enhance their operational strategies.

## 2. Literature review

The Assembly Line Balancing Problem (ALBP) in mass production systems has been a focus of study since the 1970s, leading to the development of empirical problem-solving methods [9-17]. The ALBP can be categorized into two main types: minimizing the number of workstations given fixed tasks, task times, and precedence relationships, and minimizing task times for assigned workstations. In mass-produced clothing, production levels tend to be consistent from day to day, with tasks structured to maintain flow and reduce delays, thereby balancing the time required for individual tasks along the production line. Once a production assignment is established, it often remains unchanged for extended periods. Moreover, traditional mass production approaches do not account for variations in worker skill levels when determining task times, as there is typically a fixed arrangement of workers assigned to each task. This model operates under the assumption that sufficient personnel and equipment can be allocated to bottleneck tasks, often leading to time inefficiencies.

The most widely adopted method for addressing the ALBP in mass production is the Ranked Position Weighted (RPW) method [18-20]. This approach involves assigning a cycle time, then calculating the number of required workstations or vice versa. With the advent of flexible production systems in 2000, researchers shifted their focus to solving the ALBP within flexible manufacturing contexts, which differ significantly from mass production systems, leading to the creation of analytical methods for mixed-model ALBPs [21, 22]. There is also research on optimizing industrial decision-making and operational production by applying genetic algorithms [23, 24].

In the manufacturing system relevant to this study, task times among workers are assumed to vary according to a statistical distribution due to automation in the equipment. While statistical methods are effective in mass production environments characterized by repetitive tasks, custom garment manufacturing presents unique challenges, as task times can differ significantly based on individual worker skill levels. Consequently, a different approach to the ALBP is warranted. Typically, a small custom garment production process involves three to five workers and focuses on fulfilling a single order. Therefore, further research is essential to develop efficient and cost-effective production systems for custom garment manufacturing. Integrating techniques from mass production systems could yield optimal solutions for producing custom-made garments.

Given that custom-made garments are produced on demand, daily production levels can vary significantly. This variability arises from differences in fabric and design for each individual garment, necessitating a system that is sufficiently flexible to accommodate these changes. Enhancing productivity and quality in custom-made garment production requires efficient process organization by aligning production factors—such as machinery and personnel—with specific orders and configuring task orders accordingly. Generally, custom-made production relies on a small number of workers, each performing multiple tasks with various tools. Thus, it is critical to allocate tasks based on the functional skill levels of the workers.

To analyse the efficient production of custom-made clothing, Choi [25] developed twelve combinations of worker and equipment numbers, establishing balanced efficiency based on Processing Time (PT) discrepancies among workers in each combination. However, Choi's study lacks specificity regarding the task allocation process within these combinations. Production efficiency can vary significantly in garment manufacturing, influenced by the method of task allocation and equipment layout, even when the number of workers and machines is constant. Recent advancements in line balancing for clothing production have also incorporated artificial intelligence [26], highlighting the ongoing evolution in this field.

## 3. Research methodology

### 3.1 Development process of a worker-balancing algorithm

The development process for the worker-balancing algorithm began with a careful selection of specific custom-made garment items and their corresponding manufacturers. This initial step ensured that the study remained focused on real-world applications where increased production efficiency could offer significant benefits. The primary case study involved on-demand production of custom-made formal shirts, providing a clear and controlled environment to validate the algorithm’s efficacy, with the potential for broader application across the custom garment industry.

Following the selection of garment types and manufacturing partners, the algorithm was implemented, leading into an extensive data collection phase. This critical phase involved gathering detailed data essential for optimizing production assignments. The collected data included:

- Garment Production Requirements: Information on the types of cuts required for each garment.
- Machine Resources: The specific types and quantities of sewing machines available in the production process.
- Worker Resources: The number of workers, along with their individual skill levels and proficiencies.
- Task Specifications: Type, difficulty level, and estimated completion time for each task, organized by process step.

This data provided a foundational understanding of the resources and variables involved, allowing the algorithm to balance worker assignments effectively. The structured approach enabled the application of the algorithm within a controlled, data-rich environment and allowed for refinement and adaptation based on real-time insights.

This methodical development process not only enabled the algorithm to demonstrate clear improvements in efficiency but also provided evidence of its adaptability. Although the primary focus was on formal shirts, the principles and techniques developed show promising flexibility, making the algorithm applicable to a broad range of custom-made clothing products. This adaptability enhances the findings’ relevance and scalability, offering a practical solution to meet the industry’s diverse and evolving needs.

*Standard process analysis of custom-made shirts of the target company*

This study focuses on custom-made men's formal shirts manufactured on demand by the target company. The shirt design, shown in Fig. 1, involves an eight-hour working day with a team of five workers: one in cutting, two in sewing, one as an assistant, and one in finishing. The sewing process is divided into two stages: preparation and pre-processing followed by assembling and part-making. Specific tasks within these stages are assigned to lock-stitch and specialized sewing machines based on production requirements.

The company operates on a straight-line production system adapted to a multi-product, small-volume model, which requires workers to perform various tasks. Each worker moves between equipment stations according to the specific demands of the production process. Fig. 2 illustrates the target manufacturer's worksite layout, where individual sewing stations are equipped with various sewing machines tailored to different garment assembly needs. The production floor layout is strategically designed to optimize workflow and reduce unnecessary movement, essential for maintaining efficiency in a small-volume, custom production setting.

In this study, the composition of the workforce, production assignments, and task completion times were carefully analysed. This analysis provided the foundational data for developing a worker-balancing algorithm tailored to the target company's production system. The algorithm was designed to optimize task assignments by balancing workloads across the available workforce, based on these real-time observations.

*Setting standard task time based on skilled workers*

Establishing precise standard task times is essential for optimizing production in custom garment manufacturing. This study set standard task times by observing the work of highly skilled domestic experts with over 30 years of experience in specialized areas. The expert team included one worker dedicated to cutting, two specializing in both general and specialized sewing tasks, one assistant, and one focused on finishing.

To ensure consistent measurement, each expert performed their task on five consecutive shirt cuts, all in the same design, allowing for accurate benchmarking. Task times were meticulously recorded for each shirt as a discrete unit of measurement. This approach not only reflects the high skill and efficiency of seasoned workers but also establishes a reliable baseline that accounts for the various specialized sewing operations involved.

This method leverages the proficiency and speed of experienced workers to represent peak productivity levels, providing a strong framework for estimating maximum potential efficiency in shirt production. The resulting standard task times play a critical role in calibrating the worker-balancing algorithm, ensuring it aligns with realistic, high-performance scenarios.

Setting these standards also aids in streamlining operations and serves as a vital metric for evaluating production strategies, making them applicable to different levels of workforce expertise across the industry.

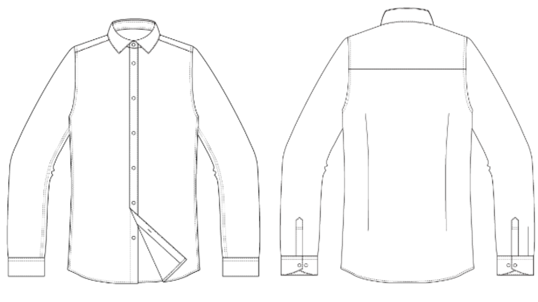

**Fig. 1** Men's formal slim shirt design

**Fig. 2** Custom-made men's formal shirts factory

*Development of worker-balancing algorithm for the production of custom-made garments*

The development of a worker-balancing algorithm tailored specifically for custom-made shirt production marks a significant step forward in garment manufacturing efficiency. This process begins with defining several essential parameters: the type of task, the difficulty level of each task, and the conversion rules for assigning tasks to each worker. These parameters ensure the algorithm is customized to meet the specific requirements of custom shirt production.

Built around these parameters, along with the standard task times established from empirical observations of skilled workers, the algorithm is designed to streamline task management across the production line. This structured framework allows for efficient task allocation that optimizes the workflow and maximizes resource use.

To illustrate the practical application of the algorithm, it was tested with a five-person production team. Each team member was assigned tasks aligned with both their individual skillsets and the overall production needs. This strategic allocation leverages the strengths of each worker, enhancing productivity and ensuring high-quality outputs. The successful implementation and observed effectiveness of the algorithm underscore its potential to transform custom garment manufacturing by aligning detailed task characteristics with worker capabilities.

*Simulation and verification of worker-balancing algorithm for custom-made garment production*

To validate the worker-balancing algorithm for custom-made shirt production, a simulation was conducted using a timed Petri net approach. This method is well-suited for modelling the complex dynamics of discrete-event systems such as custom garment production. For this study, GPEN-Sim, a specialized tool for modelling and simulating discrete-event systems, was used to rigorously test and evaluates the balance efficiency of the proposed algorithm [27].

During simulation, labor utilization—a key metric for assessing production efficiency—was closely monitored. Results from the algorithm's performance were compared with those of the existing system, providing a direct efficiency benchmark. This comparative analysis demonstrated significant improvements in balance efficiency, reinforcing the algorithm's potential to enhance productivity and optimize resource use in custom-made garment production. The concrete evidence gathered from this simulation strongly supports the adoption of this algorithm as a productivity-boosting tool in the industry.

### 3.2 Development of the algorithm

*Standard process analysis of custom-made formal shirts*

The production process for custom-made, slim-fit formal shirts follows a standardized sequence of 43 tasks, as outlined in Fig. 3. Unlike in mass production, where cutting tasks are generally excluded from sewing process analyses, cutting is integral to custom production because it occurs with each individual order. In mass production, cuts are made in large batches, making individual cuts less relevant to the sewing process. However, custom shirt production requires unique cuts for each order, influencing the overall process flow.

In this study, cutting is performed automatically using a laser cutter guided by digital patterns stored on a computer. Each custom shirt differs in size and fabric, so it is essential to assign a unique product number to each cut piece for identification and tracking. As each piece progresses through the assembly process, steps are included to verify matching product numbers, ensuring that all components belong to the same shirt.

The machines used in production include four lockstitch machines, one double-felled seam machine, a button-sewing machine, a buttonhole machine, and an ironing machine. This range of equipment supports the varied and precise tasks required for assembling custom-made shirts.

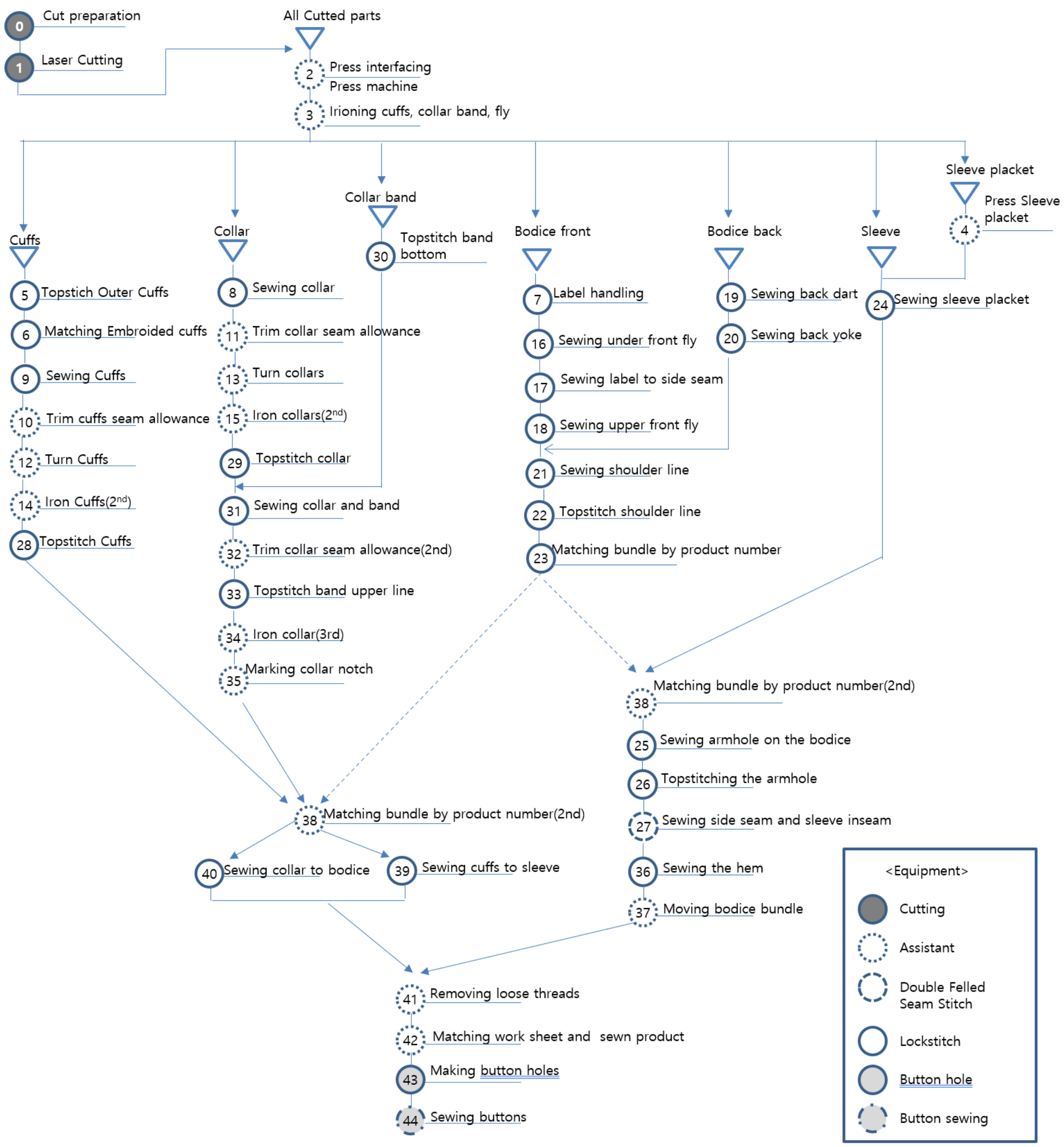


**Fig. 3** Standard process chart for custom-made men's formal shirts manufactured on demand

### *Results of setting standard task time based on skilled workers*

Standard task time represents the time required to complete a specific unit of work at an average pace. In this study, each step in the custom-made formal shirt production was segmented based on task characteristics, and the time needed for each task was measured and set as the standard. For a single shirt, the average task time across all processes is 3,130 seconds. A breakdown of average task times for each process is provided in Table 1.

This segmentation and time setting allow for a realistic assessment of production efficiency and form the basis for the worker-balancing algorithm, aligning it with the precise demands of custom garment production.

**Table 1** Task time, task type, and task level according to customized formal shirts standard process

| Process No. | Process | Equipment | Task type | Task level | Task time |
|---|---|---|---|---|---|
| 0 | Cut preparation | PC | A | 1 | 83 |
| 1 | Laser cutting | Laser cutting machine | A | 1 | 446 |
| 2 | Press interfacing | Press | B | 1 | 249 |
| 3 | Iron cuffs, collar band, fly (1st) | Iron | B | 1 | 175 |
| 4 | Press sleeve placket | Press, Iron | B | 1 | 53 |
| 5 | Topstitch outer cuffs | Lockstitch | C | 3 | 36 |
| 6 | Match embroidered cuffs | Handwork | C | 3 | 8 |
| 7 | Label handling | Hand work | C | 3 | 9 |
| 8 | Sew collar | Lockstitch | C | 3 | 37 |
| 9 | Sew cuffs | Lockstitch | C | 3 | 25 |
| 10 | Trim cuffs seam allowance | Scissors | B | 1 | 34 |
| 11 | Trim collar seam allowance | Scissors | B | 1 | 31 |
| 12 | Turn cuffs | Iron | B | 1 | 18 |
| 13 | Turn collars | Iron | B | 1 | 29 |
| 14 | Iron cuffs (2nd) | Iron | B | 1 | 36 |
| 15 | Iron collars (2nd) | Iron | B | 1 | 50 |
| 16 | Sew under front fly (R) | Lockstitch | C | 3 | 23 |
| 17 | Sew label to side seam | Lockstitch | C | 3 | 8 |
| 18 | Sew upper front fly (L) | Lockstitch | C | 3 | 70 |
| 19 | Sew back dart | Lockstitch | C | 3 | 38 |
| 20 | Sew back yoke | Lockstitch | C | 3 | 27 |
| 21 | Sew shoulder line | Lockstitch | C | 3 | 50 |
| 22 | Topstitch shoulder line | Lockstitch | C | 3 | 70 |
| 23 | Match bundle by product number (1st) | Hand work | C | 3 | 10 |
| 24 | Sew sleeve placket | Lockstitch | C | 3 | 142 |
| 25 | Sew armhole on the bodice | Lockstitch | C | 3 | 121 |
| 26 | Topstitch the armhole | Lockstitch | C | 3 | 80 |
| 27 | Sew side seam and sleeve inseam | Double felled seam stitch | C | 3 | 115 |
| 28 | Topstitch cuffs | Lockstitch | C | 3 | 51 |
| 29 | Topstitch collar and band | Lockstitch | C | 3 | 65 |
| 30 | Topstitch band bottom | Lockstitch | C | 3 | 51 |
| 31 | Sew collar and band | Lockstitch | C | 3 | 59 |
| 32 | Trim collar seam allowance (2nd) | Scissors | C | 3 | 28 |
| 33 | Topstitch band upper line | Lockstitch | C | 3 | 38 |
| 34 | Iron collar (3rd) | Iron | B | 1 | 23 |
| 35 | Mark collar notch | Hand work | B | 1 | 47 |
| 36 | Sew the hem | Lockstitch | C | 3 | 46 |
| 37 | Move bodice bundle | Hand work | B | 1 | 7 |
| 38 | Match bundle by product number (2nd) | Hand work | B | 1 | 22 |
| 39 | Sew cuffs to sleeve | Lockstitch | C | 3 | 88 |
| 40 | Sew collar to bodice | Lockstitch | C | 3 | 137 |
| 41 | Remove loose threads | Hand work | B | 1 | 99 |
| 42 | Match work sheet and sewn product | Hand work | B | 1 | 22 |
| 43 | Make buttonholes | Buttonhole | D | 1 | 181 |
| 43 | Sew buttons | Button sewing | D | 1 | 93 |

*Definition of variables and rules of the worker-balancing algorithm*

The variables used in the worker-balancing algorithm include the task type and task level to define the processes of nature.

The task type is determined by whether the nature of the process is clearly distinguished, regardless of the task level. In other words, if there are "two types of tasks," this means it is efficient for a worker to specialize in each task. The production of custom-made formal shirts in this study has four task types: cutting (A); assistant (B), including press interfacing, ironing, and handwork; sewing (C); and finishing (D), including making buttonholes and button sewing.

The task level represents the degree of skill required in the process. The task level can be estimated by considering the period of training and experience needed for the task to be performed. In sewing tasks, there are cases in which it is possible or not possible to switch between tasks, depending on the worker's skill. In other words, if the highest task level of worker A is 3, worker A can perform all tasks 1, 2, and 3. However, if worker B's highest task level is 1, worker B can only perform task 1. Therefore, tasks should be assigned to each worker considering the maximum task level each worker can perform. In this study, considering the classifications of the workers' task levels, it is assumed that task level 1 can be performed with two months of training or experience, task level 2 with ten years, and task level 3 with 20 years. The task levels of the processes for custom-made formal shirt production, the target of this study, are set as follows: Cutting (A) = level 1; Assistant (B) = level 1; Sewing (C) = level 3; and Finishing (D) = level 1. Table 1 shows the types and levels of each task.

*Development of the worker-balancing algorithm*

In this study, an algorithm to optimize the production process were developed according to the number of workers based on the pre-data mentioned above for customized production assignments and the conversion rules. The basic concept of the algorithm is to make the total task time divided by the number of workers (BPT: basic pitch time) closer to that of each worker's task time.

The algorithm proceeds as follows: calculate the BPT → determine the number of workers and the time per worker for the highest-level task → determine the number of workers and the time per worker for the second highest-level task → redistribute the times of workers for the highest-level task and the times of workers for the second-highest-level task.

In this algorithm, the number of workers and the time taken for the highest-level tasks are set first when allocating tasks to workers. This enables us to redistribute the work of a lower-level task to workers of highest-level tasks if the time of the low-level task worker is set larger than the highest-level worker's time. This is because the highest-level task worker can perform the lower-level tasks. Furthermore, assigning tasks to each worker is done to assign as many consecutive tasks as possible so that workers can memorize the tasks and perform them more efficiently. The algorithm is based on several assumptions, as shown below. The specific process is shown in Figure 3 which presents a comprehensive flowchart detailing the step-by-step process involved in the manufacturing of custom-made shirts. The diagram begins with the initial 'Cut preparation' phase, involving tasks such as laser cutting and the interfacing of various parts, setting the foundational stage for the garment assembly.

*Basic assumptions for the worker-balancing algorithm*

1. The task type-level is divided into the following four categories:

   A-1 = Cutting; level 1, B-1 = Assistant; level 1
   C-3 = Sewing; level 3, D-1 = Finishing; level 1

2. There are only two task levels (level 1 and level 3).
3. The lowest task level (level 1) allows the task to be switched between workers, even if the task type is different.
4. A sewing (level 3) worker (C-3) can perform Assistant (level 1) tasks (B-1).

*Worker-balancing algorithm process*

| | Pseudo code | Note |
|---|---|---|
| 1.BPT calculation | BPT = tT / nT<br>Calculate the total task time by task type (tA, tB, tC, tD). | tT is total process time;<br>nT is total number of workers |
| 2. Determine number of workers (nC) for C-3 task | nC = ceil(tC / BPT) | nC is umber_of_workers_C3 required for the highest-level task;<br>tC is total task time of the highest-level task (C-3) |

3. Determine task time of each C-3 worker

   3-1. Set the task time (tC1) of the first worker (C1)

| | |
|---|---|
| tmC1 = tC / nC | tmC1 is mean task time per worker for the highest-level task;<br>nC is number_of_workers_C3 |
| For each task in C-3 tasks:<br>Calculate endTime = currentTime + task.duration<br>If endTime is close to tmC1:<br>    If task.group == gC1a:<br>        Add task to list gC1a<br>    Else if task.group == gC1b:<br>        Add task to list gC1b<br>Update currentTime to endTime | Add the time of C-3 tasks in order, then extract two kinds of task groups (gC1a, gC1b) close to tmC1 |
| Set minTimeDiff = infinity<br>Set selectedGroup = null<br><br>For each task in gC1a:<br>Calculate timeDiff = abs(task.endTime – tmC1)<br>If timeDiff < minTimeDiff:<br>    Set minTimeDiff = timeDiff<br>    Set selectedGroup = gC1a<br><br>For each task in gC1b:<br>    Calculate timeDiff = abs(task.endTime – tmC1)<br>If timeDiff < minTimeDiff:<br>    Set minTimeDiff = timeDiff<br>    Set selectedGroup = gC1b<br>Return selectedGroup | Between gC1a and gC1b, select the group with the smaller time difference, where tmC1<br><br>selectedGroup = gC1 |

3-2. Set the task time (tC2) of the second worker (C2)

| | | |
|---|---|---|
| 3-2-1. | If last: tC2 = tC – tC1 | |
| 3-2-2. | If not last:<br>tmC2 = (tC - tC1) / nRC2 | nRC2 is number of workers, except C1;<br>tmC2 is mean time of one worker to determine second task C worker's time |
| | For each task in remaining C-3 tasks except Cg1:<br>If task.group != Cg1:<br>Calculate endTime = currentTime + task.duration<br>Update currentTime to endTime<br><br>Set minTimeDiff = infinity<br>Set selectedGroup = null<br><br>For each task in gC2a:<br>Calculate timeDiff = abs(task.endTime – tmC2)<br>If timeDiff < minTimeDiff:<br><br>Set minTimeDiff = timeDiff<br>Set selectedGroup = gC2a<br><br>For each task in gC2b:<br>Calculate timeDiff = abs(task.endTime – tmC2)<br>If timeDiff < minTimeDiff:<br>Set minTimeDiff = timeDiff<br>Set selectedGroup = gC2b<br><br>Return selectedGroup | Add the time of the remaining C-3 tasks, except Cg1, in order, then extract two kinds of task groups (gC2a, gC2b) close to tmC2.<br><br>Between gC2a and gC2b, select the group with the smaller time difference, with tmC2<br><br>Name the selected group gC2. |

3-3. Set the task time (tC3) of the third worker (C3)

| |
|---|
| If last: tC3 = tC – tC1 – tC2 |
| If not last: Determine tC3 in the same manner as in 3-2. |

4. Determine number of workers for level 1 tasks (A-1, B-1, D-1)

| | |
|---|---|
| nR = nT – nC | (nR is number of remaining workers, except C-3 workers) |

5. Determine time of each level 1 worker

5-1. Set the time of the first worker (A1) among the nR

| | |
|---|---|
| tR1 = tT – tC<br>tmR1 = tR / nR | Calculate the mean task time per worker for the highest-level task |
| For each level 1 task:<br>Calculate endTime = currentTime + task.duration<br>If endTime is close to tmR1:<br>If task.group is gR1a:<br>Add task to list gR1a<br>Else if task.group is gR1b:<br>Add task to list gR1b<br>Update currentTime to endTime | Add the time of the level 1 tasks in order, then extract two kinds of task groups (gR1a, gR1b) close to tmR1 |
| For each task in gR1a:<br>Calculate timeDiff = abs(task.endTime – tmR1)<br>If timeDiff is smaller than minTimeDiff:<br>Set minTimeDiff to timeDiff<br>Set selectedGroup to gR1a | Between gR1a and gR1b, select the group with the smaller time difference, with tmR1 |
| For each task in gR1b:<br>Calculate timeDiff = abs(task.endTime – tmR1)<br>If timeDiff is smaller than minTimeDiff:<br>Set minTimeDiff to timeDiff<br>Set selectedGroup to gR1b | Name the selected group gR1 |

5-2. Set the time of the second worker (A2) among the nR

| | |
|---|---|
| 5-2-1. | If last: tR2 = tR – tA1 |
| 5-2-2. | If not last, repeat the method used in 5-1. |
| | tR2 = tT – tC – tA1<br>tmR2 = tR2 / nR2<br>Add the time of the level 1 tasks in order, then extract two kinds of task groups (gR2a, gR2b) close to tmR2<br>Between gR2a and gR2b, select the group with the smaller time difference, with tmR2<br>Name the selected group gR2 |

5-3. Set the time of the third worker (A3) among the nR1

| | |
|---|---|
| 5-3-1. | If last: tA2 = tR1 – tA1 – tA2 |
| 5-3-2. | If not last, repeat the method used in No. 5-1. |

6. Decide whether to assign additional tasks to the highest-level task workers

| | |
|---|---|
| If task time of all C-3 workers > task time of B-work workers:<br>No task variation<br>Else if any C-3 worker's task time < task time of B-work workers:<br>Perform task variation | |
| Find the B-1 worker (Rx) with the largest task time<br>Find the C-3 worker (Cx) with the smallest task time<br><br>Transfer the task of Rx to Cx | Transfer the task of the B-1 worker with the largest task time (Rx) to the C-3 worker with the smallest task time (Cx) |
| Calculate the midpoint between tBx and tCx: midpoint = (tBx + tCx) / 2<br><br>Find the task group among tasks performed by Rx closest to midpoint<br>Assign this task group to Cx | Among the tasks performed by Rx, assign the task group closest to (tBx – tCx) / 2 to Cx. |

# 4. Results and discussion

## 4.1 Applying the worker-balancing algorithm

The proposed algorithm simulated a production assignment process for five workers (i.e., the same number of workers as the target manufacturer).

In this study, the algorithm is applied to produce custom-made formal shirts. The resulting production assignment and balance efficiencies are presented in Table 2. In addition, the results of production assignments using the proposed algorithm for four, six, and seven workers are shown in Table 3. Furthermore, the results were compared for five workers currently used by the shirt manufacturer and the results for five workers based on the proposed algorithm. The results show that the balance efficiency improved from 69.9 % to 83 % shown in Table 4.

The production assignment process using the worker-balancing algorithm for five workers is as follows:

1. $BPT = \frac{3130}{5} = 626$ tA = 529, tB = 895, tC = 1432, tD = 274

2. $nC1 = \frac{1432}{625} = 2.3 \cong 2$

3. $tmC = \frac{tC}{nC} = \frac{1432}{2} = 716$

3-1. gC1a process = 5–9, 16–25 process → tgC1a(time of gC1a) = 674
→ dt = tgC1a – tmC1 = 674 – 716 = –84

gC1b = 5–9, 16–26 process → tgC1b(time of gC1b) = 754
→ dt = tgC1b – tmC1 = 754 – 716 = 76
→ Select tC1b in which dt is smaller
→ tC1 = 754

3-2. Set C2 worker time:
tC2 = tC – tC1 = 1432 – 754 = 678

4. nR = nT – nC = 3

5. Set time of A1 worker (first of three workers)

5-1. tR = tT(3130) – tC(1432) = 1698
tmR1 = tR/ remaining workers = 1698 / 3 =566
gR1a = 0–1 = 557
gR1b = 0–1, 4 =582
Select tR1a, where the difference with tmR1 is smaller → tR1 = 557

5-2. Set time of A2 worker (second of three workers)
tR2 = tT(3130) – tC(1432) – tA1(557) = 1141
tmR2 = tR2 / remaining workers = 1141 / 2 = 570.5
gR2a = 2–12 = 560
gR2b = 2–13 = 589

5-3. Set time of A3 worker (last of three workers)
tA31 = tT(3130) – tC(1432) – tA1(557) – tA2(560) = 581

6. The C-3 workers' time is greater than the level 1 workers' time. Thus, terminate the production assignment process

**Table 2** Results of production assignment for the five-worker team

| Worker | Task type level | Task number | Task time (s) |
|---|---|---|---|
| A1 | A-1 | 0–1 | 557 |
| B1 | B-1 | 2–4, 10–12 | 560 |
| C1 | C-3 | 5–9, 16–26 | 754 |
| C2 | C-3 | 27–33, 36, 39–40 | 678 |
| D1 | D-1 | 13–15, 34–35, 37–38, 41–42 43–44 | 581 |
| | | Total | 3130 |
| | | BPT | 626 |
| | | Balance efficiency | 83 % |

Notes:
Balance efficiency = 3130 / (754 × 5) × 100 = 83 %
A-1: Cutting (level 1); B-1: Assistant (level 1); C-3: Sewing (level 3); D-1: Finishing (level 1)

**Table 3** Results of production assignment using the proposed algorithm by number of workers

| | Production assignment using the proposed algorithm | | | |
|---|---|---|---|---|
| Number of workers | 4 | 5 | 6 | 7 |
| Net working time (s) | 3130 | 3130 | 3130 | 3130 |
| BPT (s) | 782.5 | 626 | 521.7 | 447.1 |
| Bottleneck time (s) | 850 | 754 | 557 | 553 |
| Balance efficiency (%) | 92.1 | 83 | 93.6 | 80.8 |

**Table 4** Comparison of production assignment in use and proposed algorithm for five workers

| | Production assignment based on the proposed algorithm | Current production assignment |
|---|---|---|
| Number of workers | 5 | 5 |
| Net working time (s) | 3130 | 3130 |
| BPT (s) | 626 | 626 |
| Bottleneck time (s) | 754 | 895 |
| Balance efficiency (%) | 83 | 69.9 |

When balance efficiency increases from 69.9 % to 83 %, the production time becomes 1.19 times faster, allowing for 1.19 times more production output within the same timeframe. Additionally, as production time decreases, the labor cost can be reduced since less time is required to produce the same quantity.

### 4.2 Simulation and verification of worker-balancing algorithm for custom-made garment production

The Petri net model of this sewing process is shown in Fig. 4. This graphical representation helps visualize the dynamic interactions and dependencies within the production line. It includes multiple nodes and transitions, representing the various tasks, decision points, and workflow sequences in the custom-made shirt manufacturing process.

The simulation conditions used to evaluate the worker-balancing algorithm are as follows:

- number of workers: 4,
- input lot size: 5,
- input interval: 50 min,
- operation time: 2400 min,
- task assignment scheduling: FIFO (First-In, First-Out).

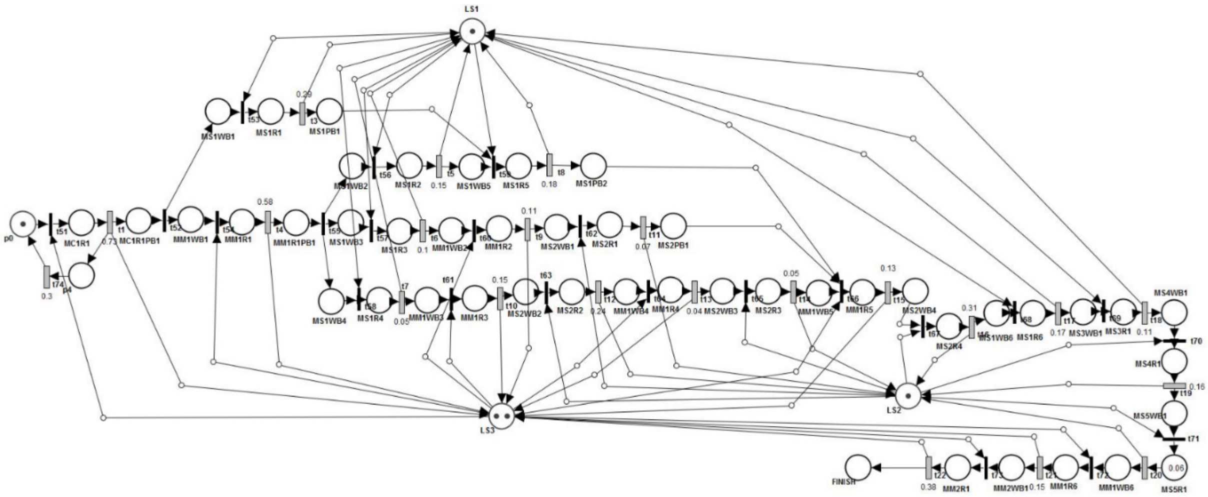

**Fig. 4** Petri net model of the production process of custom-made shirts

The simulation results presented in Table 5 provide data on:

- the number of task executions per station,
- total time spent per station,
- labor utilization percentage,
- resource usage and cost metrics.

However, the cost-related outputs show a reporting issue: both "Sum resource usage costs" and "Sum working costs" appear as NaN% of total.

This anomaly was caused by either zero-initialized values or incomplete entries in the simulation's cost parameter fields. As a result, the simulation software (GPEN-Sim) was unable to compute valid percentages for cost utilization. These figures were excluded from the performance analysis and do not affect the primary simulation results related to labor utilization and balance efficiency.

Despite this, the main result is reliable. The balance efficiency achieved through the proposed production assignment (with 4 workers) is 92.1 %, meaning the workload was nearly equal among all workers. By contrast, in mass production systems—where one worker is assigned to one fixed task—the balance efficiency often correlates closely with machine utilization only.

Here, due to multi-task assignments and potential wait times, small differences can exist. Nonetheless, the labor utilization calculated from the simulation was 90.2 %, which is very close to the algorithm's predicted balance efficiency. The difference of only 2.1 % supports the validity of the proposed approach.

**Table 5** Simulation results using "Timed Petri net modelling" and "GPEN-Sim"

| Resource usage summary | | | Line efficiency and cost calculations | |
|---|---|---|---|---|
| | Total occasions | Total time spent (s) | Number of labor group | K = 3 |
| | | | Total number of labors | K = 4 |
| LS1 | 222 | 2327 | Total operation time (s) | 2400 |
| Ls2 | 157 | 2079 | Labor time (s) | 9600 |
| Ls3 | 210 | 4251 | Total time at stations (s) | 8657 |
| | | | Utilization of labors | 90.1771 % |
| | | | Sum resource usage costs | 0 (NaN% of total) |
| | | | Sum working costs | 0 (NaN% of total) |

## 5. Conclusion

In conclusion, this study presents a novel approach to managing the production of custom-made garments through the development of a worker-balancing algorithm tailored to small-batch manufacturing environments. By analysing key variables such as task duration, worker skill level, and task complexity, the algorithm effectively distributes workloads to optimize production efficiency. When applied to a five-worker team, the algorithm demonstrated a notable improvement in balance efficiency—from 69.9 % to 83 %. Additional simulations using a Petri net model confirmed the reliability of this result, with labour utilization rates closely aligning with the computed balance efficiency, showing a margin of error of only 2.1 %. While this study focused on men's formal shirts, the structure of the algorithm is flexible enough to extend to other garment types, such as jackets, pants, and dresses.

There are, however, several limitations. The current algorithm assumes static conditions, such as fixed worker availability, consistent task durations, and no production interruptions. It does not yet address mid-shift changes in worker availability, machine breakdowns or downtime, urgent rush orders or real-time disruptions, rework cycles or error corrections, or the involvement of temporary or partially trained workers with limited task capabilities. These limitations constrain the algorithm's adaptability in dynamic production environments. To address these challenges, future studies should explore integrating metaheuristic optimization techniques (e.g., genetic algorithms or swarm intelligence) to discover globally optimal worker-task configurations. Real-time scheduling systems capable of dynamic task reassignment in response to operational disruptions should also be considered. Stochastic modelling of machine downtime and worker performance variability would improve robustness. User-friendly software tools based on the algorithm would further support its adoption in industrial practice. By extending this work in these directions, manufacturers can achieve greater flexibility and resilience in custom garment production, aligning with the industry's transition toward mass customization and sustainable practices.

Future research should expand the algorithm's application to a wider range of custom garments with varying task complexities and workforce structures. Additionally, incorporating parameters such as machine availability and individual performance variation could enhance the algorithm's effectiveness across diverse manufacturing settings. Developing user-oriented software based on this algorithm would further facilitate its practical deployment, enabling more efficient scheduling and resource allocation.

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