A Study on Bottleneck Identification Method for Fully Manual Mixed-Model Assembly Lines

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Abstract: Fully manual mixed-model assembly lines suffer from significant skill variation among operators and dynamic bottleneck drift caused by changing product mix ratios. Traditional static time study methods deliver low identification accuracy in such production environments. To address these challenges, this paper proposes a four-step bottleneck identification method: static preliminary screening, skill correction, dynamic verification, and drift analysis. The proposed method eliminates efficiency disturbances caused by individual operators by constructing a product-specific skill coefficient matrix, establishes a macro-micro dual verification system to identify genuine bottlenecks, and calculates the critical conditions for bottleneck drift via mix ratio sensitivity analysis. We validated the proposed method using real-world tests on a refrigerator assembly line and multi-scenario FlexSim simulations. The method achieves an overall identification accuracy of 93.8%, identifies the critical product mix ratio for bottleneck drift as 77.8%, and cuts the misjudgment rate of pseudo-bottlenecks to less than 5%. Requiring no digital hardware infrastructure, the method cuts the implementation cycle by approximately 70% compared with full-process simulation, and provides a lightweight optimization solution for mixed-model production capacity improvement applicable to small and medium-sized manufacturing enterprises.

Keywords: Fully Manual Mixed-Model Line; Bottleneck Identification; Skill Coefficient; Work Measurement; Bottleneck Drift

1. Introduction

1.1 Research Background and Problem Statement

Under the multi-variety and small-batch customized production mode, fully manual mixed-model assembly lines are widely adopted by small and medium-sized manufacturing enterprises in home appliance and light industry sectors due to their high flexibility and low transformation costs. Nevertheless, such production lines are confronted with two common challenges. First, operator heterogeneity is prominent: the operation time of different operators at the same workstation fluctuates greatly, and low efficiency caused by insufficient operator skills is easily misjudged as the capacity constraint of the process, resulting in the occurrence of "pseudo-bottlenecks". Second, frequent switching among mixed multi-variety products leads to different operation times of each process for various products, and the bottleneck position drifts dynamically with the change of product mix ratio, which greatly increases the difficulty of bottleneck identification and line balancing.

At present, most small and medium-sized enterprises still identify bottlenecks through empirical judgment or a single static time study method. Without fully considering operator heterogeneity and mixed-model fluctuation, misjudgment and missing judgment occur frequently, which brings high investment but poor benefits to subsequent optimization. Accordingly, developing a low-cost and high-accuracy bottleneck identification method for mixed-model lines adapted to fully manual production scenarios has definite engineering application value.

1.2 Related Work and Main Contributions

Existing bottleneck identification methods for production lines can be roughly divided into three categories.

The first category refers to static time study methods. Centered on standard time measurement, such methods judge bottlenecks by comparing load rates, featuring simple operation and wide application. However, they are mostly designed for single-variety production lines and fail to fully take operator differences and dynamic fluctuations into account, leading to insufficient accuracy when applied to fully manual mixed-model lines [1].

The second category is modeling and simulation methods. Tools including FlexSim and Plant Simulation are adopted to build production line models and simulate operating conditions under random factors for dynamic bottleneck identification. These methods deliver high accuracy yet suffer from long modeling cycles and high costs, creating high barriers for small and medium-sized enterprises [2].

The third category is data-driven methods. Real-time data collected via MES systems and Internet of Things devices are processed by algorithms to identify dynamic bottlenecks. Such methods fit highly automated production lines, yet cannot be directly deployed on fully manual production lines without digital infrastructure [3,4].

Current research focuses heavily on bottleneck identification for automated and single-variety production lines, while low-cost and systematic identification methods tailored to fully manual mixed-model scenarios remain scarce. Three key research gaps exist in current literature:

(1) Studies fail to quantify the coupling effect between operator and product heterogeneity, so pseudo-bottlenecks stemming from low operator proficiency are frequently misclassified as inherent process bottlenecks [5,6];

(2) Existing identification approaches only adopt single-dimensional indicators without integrated macro-micro verification frameworks, lowering the reliability of bottleneck judgment results;

(3) Few papers explore the evolutionary rules and critical thresholds of bottleneck drift under variable product mixes, offering insufficient quantitative support for production scheduling [7,8].

Against the above research limitations, this paper proposes an integrated identification method for fully manual mixed-model assembly lines. The main contributions are listed below:

(1) A skill coefficient correction model for differentiated product types is constructed to quantify three-dimensional efficiency differences among operators, products and processes, which effectively mitigates the interference of operator heterogeneity on bottleneck identification [5];

(2) A macro-micro dual verification system is established. A complete judgment chain is formed based on three indicators including operation status, upstream and downstream linkage, and work-in-process distribution, which adapts to fully manual production scenarios without digital infrastructure;

(3) The correlation law between product mix ratios and bottleneck drift is revealed, and the critical mix ratio threshold for bottleneck shift is solved to provide quantitative decision support for production scheduling optimization [7,8].

2. Problem Description and Theoretical Fundamentals

2.1 Core Concept Definitions

Fully Manual Mixed-Model Assembly Line: An assembly line where all processes are manually operated without automated processing equipment, and multiple products with homologous structures and similar fabrication processes are produced alternately on the same line. This paper targets fully manual mixed-model lines with serial layout and one operator assigned to each independent process.

Genuine Bottleneck and Pseudo-Bottleneck: A genuine bottleneck is an inherent capacity constraint determined by process tasks and technical complexity, independent of operator proficiency. A pseudo-bottleneck refers to temporary low process efficiency caused by inadequate operator skills and low familiarity, which does not stem from inherent process capacity limits and can be eliminated via staff training and job rotation scheduling [6].

Bottleneck Drift: In mixed-model production, processing times of various products differ across processes. Changes in product mix ratios alter the comprehensive load of each process, creating a dynamic phenomenon in which the bottleneck shifts from one process to another [7].

A rigid common bottleneck is a workstation that acts as the system-wide capacity constraint under all feasible product mix ratios and remains unaffected by variations in product structure. It represents a special category of genuine bottlenecks.

Bottleneck Attribute Transition: A phenomenon where a pseudo-bottleneck initially induced by insufficient operator skills converts into a genuine bottleneck, as its inherent process load exceeds the judgment threshold with an increasing share of high-cycle-time products.

2.2 Bottleneck Drift Mechanism Analysis

Bottleneck drift on fully manual mixed-model assembly lines arises from two coupled factors: heterogeneous product processing times and time-varying product mix ratios. For serial production layouts, overall system capacity is constrained by the workstation with the highest workload. Any shift in product structure redistributes the comprehensive processing time of every process, which may reduce the load of originally overloaded stations and turn low-load stations into new bottlenecks. [7].

Operator heterogeneity amplifies the uncertainty of bottleneck drift. The proficiency of a single operator varies across different products. Variations in product mix ratios not only alter the standard load of each process but also change the actual operating efficiency of operators, further intensifying the fluctuation of bottleneck positions [8].

2.3 Theoretical Foundation

The method proposed in this paper is mainly supported by two classic industrial engineering theories:

Hypothetical Product Method: It calculates the comprehensive processing time of each process under multi-variety mixed production through output weighting, and converts the multi-variety production problem into a single-variety production problem, which is a classic method for load calculation of mixed-model lines [1,5].

Work Measurement Theory: Real operation data are obtained via stopwatch time study and on-site work sampling, which provides basic data support for processing time correction and dynamic verification, and is applicable to production scenarios without digital systems [9].

3. Four-Step Combined Bottleneck Identification Method

The four-step combined bottleneck identification method proposed in this paper follows a progressive logic of "from static state to dynamic state, from rough screening to precise judgment, and from bottleneck identification to drift law analysis". The overall flow is shown in Figure 1. The input data of the method contain standard processing time of each process, product mix ratios, measured operator operation data, on-site work sampling records and work-in-process (WIP) data. Its outputs include the location of genuine bottlenecks, classification of bottleneck causes, and critical laws of bottleneck drift.

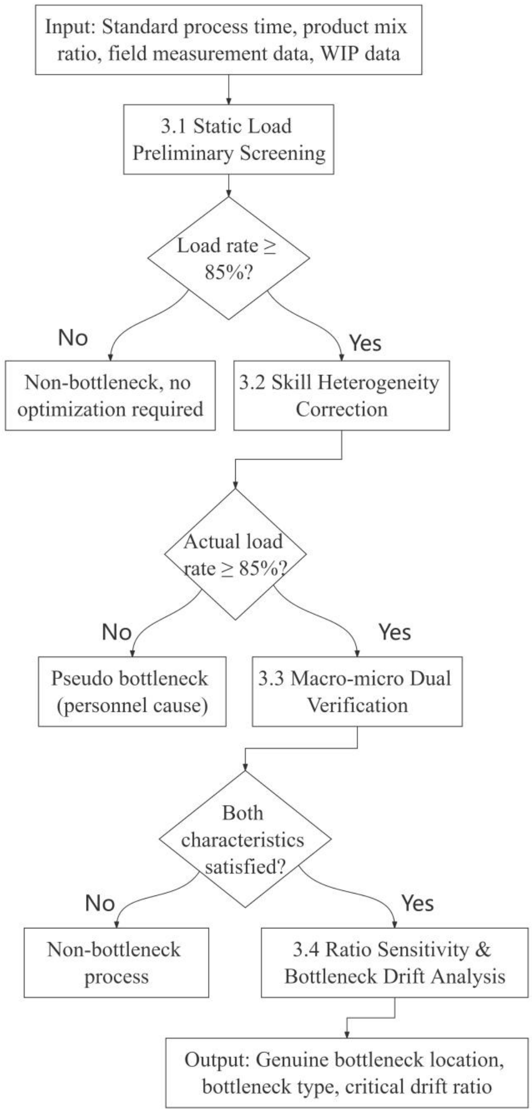

Figure 1. Flowchart of Bottleneck Identification Method for Fully Manual Mixed-Model Assembly Lines

3.1 Static Load Preliminary Screening Model

Processing times of different products vary across processes in mixed-model production, so bottlenecks cannot be directly judged by the processing time of a single product. Accordingly, the Hypothetical Product Method is adopted to calculate the comprehensive processing time of each process as the benchmark for static preliminary screening. Assume that the production line manufactures n types of products, Let p_i represent the output proportion of the i^{th}h product, and T_{ij} denote the standard processing time of the i^{th} product on the j^{th} procedure. The comprehensive processing time of the hypothetical product corresponding to the j^{th} procedure is defined as:

$$T_j = \sum_{i=1}^{n} p_i \cdot T_{ij} \quad (1)$$

Where:

T_j = comprehensive processing time of the j^{th} process;

p_i = output proportion of the i^{th} product;

T_{ij} = standard processing time of the i^{th} product at the j^{th} process.

Taking the planned cycle time (CT) of the production line as the benchmark, the static load rate of each process is calculated as:

$$L_j = \frac{T_j}{CT} \times 100\% \quad (2)$$

Referring to the general empirical criteria for load judgment of mixed-model lines, the load rate threshold is set to 85%. All processes with a load rate no less than 85% are incorporated into the candidate bottleneck set [1,7]. Static preliminary screening only covers processes with inherently high process loads. Processes with obvious blockage observed on site and static load rates close to the threshold can be supplemented into the candidate set to avoid missing the judgment of pseudo-bottlenecks caused by insufficient operator skills.

3.2 Skill Heterogeneity Correction

3.2.1 Skill coefficient definition

In fully manual assembly lines, operator proficiency serves as the core factor affecting the actual process load. In addition, individual operators exhibit differentiated proficiency levels for different products. Accordingly, a product and process oriented skill coefficient matrix is constructed to revise the static load rate, so as to distinguish genuine bottlenecks from pseudo-bottlenecks induced by insufficient operator skills [5].

The skill coefficient of the k^{th} operator processing the i^{th} product at the j^{th} process is defined as:

$$S_{ijk} = \frac{t_{ijk}}{T_{ij}} \quad (3)$$

Where S_{ijk} denotes the skill coefficient of the k^{th} operator processing the i^{th} product at the j^{th} process; t_{ijk} is the actual operation time (including allowances proportional to the standard time); T_{ij} is the standard processing time of the corresponding product at the j^{th} process. A skill coefficient above 1 means the operator works slower than the standard pace due to insufficient proficiency, whereas a value below 1 represents faster operation and higher proficiency [5]. This product-specific and process-specific skill coefficient quantification method can effectively characterize the three-dimensional efficiency differences among operators, products, and processes. The basic modeling framework refers to the research of Chen et al. [10].

By averaging the skill coefficients of all on-duty operators at a single process, the average skill coefficient of the j^{th} process for the i^{th} product can be obtained:

$$\bar{S}_{ij} = \frac{1}{m_j} \sum_{k=1}^{m_j} S_{ijk} \quad (4)$$

Where is the average skill coefficient of the j^{th} process for the i^{th} product; m_j is the number of on-duty operators at the j^{th} process; S_{ijk} represents the skill coefficient of operator k when processing product i on workstation j.

Furthermore, weighted by the product output proportion, the comprehensive average skill coefficient of the j^{th} process is calculated to reflect the overall operational efficiency under mixed-model production:

$$\bar{S}_j = \sum_{i=1}^{n} p_i \cdot \bar{S}_{ij} \quad (5)$$

Based on the comprehensive average skill coefficient, the static load rate is corrected to obtain the corrected load rate of each process:

$$L_j' = L_j \cdot \overline{S_j} \quad (6)$$

Where L_j' represents the corrected load rate of the j^{th} process, which reflects the actual process load under the current staffing configuration.

3.2.2 Genuine and pseudo bottleneck identification rules

By comparing the static standard load rate and corrected actual load rate, candidate processes are classified into three types according to bottleneck formation causes. The specific judgment rules are defined as follows:

A pseudo-bottleneck is defined as a workstation where the static load rate $L_j < 85\%$ but the corrected load rate $L_j' \geq 85\%$. In this case, the workstation itself has no inherent capacity limitation. The excessive load stems solely from low operator proficiency, a problem resolvable via staff training or job rotation. Therefore, such a workstation does not constitute a genuine bottleneck [7].

Genuine Bottleneck Candidate: A process with a static load rate of $L_j \geq 85\%$ and a corrected load rate of $L_j' \geq 85\%$. The high load of such processes is dominated by inherent process attributes, and individual operator efficiency differences only produce superimposed effects. These processes represent inherent capacity constraints of the production line and require macro and micro dynamic verification in the subsequent step.

Potential Bottleneck: A process with a static load rate of $L_j \geq 85\%$ but a corrected load rate of $L_j' < 85\%$. Such processes have inherent capacity constraint risks and only avoid actual bottleneck performance temporarily due to the above-standard proficiency of current operators. They are likely to transform into genuine bottlenecks with changes in product mix ratios or personnel rotation, and thus need to be included in the scope of bottleneck drift analysis.

3.3 Macro-Micro Dual Bottleneck Verification System

3.3.1 Micro-level three-dimensional index determination

Static calculation only reflects the process load under ideal operating conditions. Dynamic factors in actual production, such as waiting, blockage, and abnormal disturbances, may cause deviations between actual bottlenecks and static identification results. Therefore, dual verification is carried out from microscopic indicators and macroscopic distribution perspectives to confirm genuine bottlenecks [2,11].

The Bottleneck Degree Index (BDI) is constructed based on three core indicators, namely the self-effective operation rate, upstream blockage rate, and downstream starvation rate [2,5]. Referring to the classic weight determination framework adopted in existing bottleneck identification research and combining the operational characteristics of fully manual mixed-model lines, the Analytic Hierarchy Process (AHP) is applied to assign indicator weights. The self-effective operation rate exerts the most direct impact on capacity constraints and is assigned a weight of 0.4. The upstream blockage rate and downstream starvation rate reflect bottleneck constraints from the perspective of upstream and downstream linkage, each with a weight of 0.3. The Bottleneck Degree Index (BDI) is calculated by the following formula:

$$BDI_j = 0.4 \cdot OR_j + 0.3 \cdot BR_{j-1} + 0.3 \cdot SR_{j+1} \quad (7)$$

Where:

OR_j: Effective operation rate of workstation j, defined as the ratio of effective working time to total observation duration.

BR_{j-1}: Blockage rate of workstation $(j-1)$, representing idle time where upstream stations stall due to unfinished tasks at workstation j.

SR_{j+1}: Starvation rate of workstation $(j+1)$, referring to idle time waiting for incoming parts from workstation j.

3.3.2 Macro-level work-in-process distribution verification

As a supplement to microscopic indicators, the distribution variation of work-in-process (WIP) across the entire production line within one production cycle is observed to assist in verifying bottleneck positions. The judgment criterion is summarized as follows: the quantity of WIP before the bottleneck process continuously accumulates with production progression, while the WIP quantity after the bottleneck process continuously decreases, forming a typical characteristic of “upstream accumulation and downstream shortage” [11]. A genuine bottleneck can be confirmed only after the mutual verification of microscopic three-dimensional indicators and macroscopic WIP distribution.

3.4 Mix Ratio Sensitivity and Bottleneck Drift Analysis

In mixed-model production, changes in product output ratios alter the comprehensive load of each process, thereby triggering the drift of bottleneck positions. By setting multiple typical ratio scenarios and calculating process load rates under different ratios, two types of bottlenecks are identified [7,8]:

Rigid Common Bottleneck: A process whose load rate remains at the highest level under all feasible product mix ratios. It is unaffected by product structure changes and serves as a permanent capacity constraint of the production line.

A driftable bottleneck is a workstation whose bottleneck state varies with product mix ratios. Based on evolutionary characteristics, driftable bottlenecks fall into two categories:

(1) Workstation drift type: Shifts in product mix alter the load ranking of each workstation, moving the bottleneck position across different stations.

(2) Attribute transition type: A pseudo-bottleneck initially triggered by insufficient operator proficiency evolves into a genuine bottleneck once the share of long-cycle products rises and its load surpasses the 85% judgment threshold.

Let the output proportion of Product B be p_B, and the output proportion of Product A be

p_A=1−p_B. The two processes to be judged are defined as process x and process y. The critical ratio for bottleneck drift is obtained by equalizing the comprehensive processing times of the two processes:

$$(1\text{-}p)T_{Ax}+pT_{Bx}=(1\text{-}p)T_{Ay}+pT_{By} \quad (8)$$

By equalizing the mixed comprehensive processing times of process x and process y, the critical ratio of workstation drift is solved. The sorted critical ratio is expressed as:

$$p^{*}=\frac{T_{Ax}\text{-}T_{Ay}}{(T_{Ax}\text{-}T_{Ay})+(T_{By}\text{-}T_{Bx})} \quad (9)$$

Where p^* denotes the critical proportion of Product B that triggers the drift of the sub-bottleneck workstation.

In addition to the critical condition of inter-process workstation drift, bottleneck attribute transition occurs when the comprehensive standard load of a single process reaches the 85% threshold, namely the transition from a pseudo-bottleneck to a genuine bottleneck. The critical ratio for attribute transition is solved by equalizing the comprehensive standard load of process x to the 85% judgment threshold:

$$\frac{(1\text{-}p)T_{Ax}+pT_{Bx}}{CT}=0.85 \quad (10)$$

The critical ratio p^{**} for attribute transition is derived as:

$$p^{**}=\frac{0.85\cdot CT\text{-}T_{Ax}}{T_{Bx}\text{-}T_{Ax}} \quad (11)$$

Where p^{**} represents the critical output proportion for the transition of a single process from a pseudo-bottleneck to a genuine bottleneck.

4 Empirical Research

4.1 Case Object and Data Collection

This study takes the fully manual mixed-model assembly line for refrigerators in a household appliance enterprise as the research object. The production line adopts a linear serial layout, with one operator assigned to each process. It contains 28 assembly processes in total and simultaneously produces two types of refrigerator products with homologous structures under a conventional 1:1 mixed ratio scheme. The production line currently suffers from unsatisfactory capacity output, uneven work-in-process distribution, and fluctuating bottleneck positions during product switching, resulting in significant deviations in traditional empirical bottleneck judgment.

Data collection is divided into two parts. For static time data, the stopwatch time study method is adopted. Ten valid continuous operation cycles are observed for each process of each product, and the standard processing time is determined with job rating coefficients and a standard allowance rate of 10%. For dynamic verification, the continuous working day recording method is applied. Target processes are tracked and observed for two complete shifts, with process operating states and work-in-process data recorded synchronously [10].

4.2 Application Process of the Four-Step Combined Method

4.2.1 Static preliminary screening: candidate bottleneck process identification

Based on the conventional 1:1 mixed product ratio, the Hypothetical Product Method is utilized to calculate the comprehensive process time under mixed-model production. The static load rate is calculated with the current planned cycle time of 15 s [1,5]. A load rate of 85% is set as the screening threshold for candidate bottlenecks. This study focuses on the verification and analysis of core high-load processes, while potential bottlenecks are only regarded as references for subsequent production scheduling optimization.

4.2.2 Skill heterogeneity correction

Two high-load processes screened out by static preliminary screening, together with the fixed freezing frame process that frequently generates operational blockages on site (with a static load rate of 83.3%, close to the threshold), are incorporated into the skill heterogeneity correction stage. Product-specific skill coefficients are constructed to calculate the corrected actual load rates, and the results are presented in Table 1, where SC-A and SC-B are the skill coefficients of Product A and Product B, and LR stands for load rate.

Table 1. Skill Correction for Candidate Bottleneck Stations

Process Name	SC-A	SC-B	Static LR (%)	Corrected LR (%)
Temperature Control Wiring	1.02	1.05	120.0	124.2
Fruit and Vegetable Box Installation	0.98	1.12	96.7	101.5
Fixed Freeze Rack Installation	1.00	1.25	83.3	93.7

The correction results are divided into two categories according to bottleneck formation mechanisms. The static standard load rates of the temperature control wiring and fruit and vegetable box installation processes both exceed the 85% threshold, and their corrected actual load rates increase further. The high load of the two processes is dominated by inherent process attributes, while individual operator efficiency differences only exert superimposed effects. Therefore, they are identified as genuine bottleneck candidates for subsequent dynamic verification.

The fixed freeze rack installation process has a static load rate of only 83.3%, which fails to reach the bottleneck judgment threshold and indicates no inherent process capacity constraint. However, operators present low proficiency in processing Product B, with a comprehensive skill coefficient of 1.125. This raises the corrected actual load rate above 85%, forming a pseudo-bottleneck caused by insufficient operator skills [7]. Such bottlenecks can be eliminated through staff training and job rotation and are therefore excluded from the core verification of genuine bottlenecks. Nevertheless, its critical product mix ratio for transitioning into a genuine bottleneck should be focused on in the subsequent bottleneck drift analysis.

Finally, the temperature control wiring and fruit and vegetable box installation processes are selected as genuine bottleneck candidates for core verification, while the fixed freeze rack installation process is synchronously observed as a pseudo-bottleneck control process.

4.2.3 Dynamic verification: genuine bottleneck determination

A dual verification system combining macroscopic and microscopic perspectives is adopted to conduct synchronous dynamic observation on two genuine bottleneck candidate processes and one pseudo-bottleneck process, so as to verify the consistency between the static correction results and actual operational states [2,11]. The statistical dynamic verification indicators of the candidate processes are shown in Table 2. Where OR = Self Operation Rate; BR = Upstream Blockage Rate; SR = Downstream Starvation Rate; BDI = Comprehensive Bottleneck Degree.

At the microscopic level, the temperature control wiring process presents significantly higher self-effective operation rate, upstream blockage rate, and downstream starvation rate than other processes and achieves the highest comprehensive bottleneck degree, which conforms to the typical characteristics of the primary bottleneck. The fruit and vegetable box installation process ranks second in terms of bottleneck degree and is identified as the secondary bottleneck. The fixed freeze rack installation process has the lowest bottleneck degree, which is consistent with its positioning as a pseudo-bottleneck. Obvious blockage only occurs during the processing of Product B, and its overall capacity constraint intensity is weaker than that of genuine bottlenecks [2].

Table 2. Statistics of Dynamic Verification Indicators for Candidate Workstations

Process Name	Self OR (%)	BR (%)	SR (%)	BDI
Temperature Control Wiring	92.3	37.8	25.6	0.558
Fruit and Vegetable Box Installation	85.1	22.4	18.7	0.463
Fixed Freeze Rack Installation	81.6	19.5	16.2	0.434

The macroscopic WIP distribution verification results are highly consistent with the microscopic indicators. Work-in-process continuously accumulates before the temperature control wiring process, showing a typical “upstream accumulation and downstream shortage” feature [11].

In summary, the temperature control wiring process is confirmed as the primary genuine bottleneck of the entire production line, the fruit and vegetable box installation process is identified as the secondary genuine bottleneck, and the fixed freeze rack installation process is verified as a pseudo-bottleneck caused by human factors.

4.2.4 Drift analysis: bottleneck type classification and critical values

By adjusting the output ratio of the two products and calculating the comprehensive load rate of each process under different ratio scenarios, the bottleneck drift law is identified [6,9]. The results show that the temperature control wiring process serves as a rigid common bottleneck. It is insensitive to product ratio changes and constitutes the absolute capacity constraint of the entire production line, while the fixed freeze rack and fruit and vegetable box installation processes belong to driftable bottlenecks.

Substituting the relevant parameters into Equation (11) yields $p^{**} \approx 0.40$. When the output proportion of Product B exceeds 40%, the inherent process load of the fixed freeze rack process breaks the 85% threshold, transforming this process from a skill-induced pseudo-bottleneck into a genuine bottleneck constrained by both process attributes and operator efficiency, and thus entering the secondary bottleneck echelon [8].

Furthermore, when the proportion of Product B exceeds 77.8%, the load rate of the fruit and vegetable box installation process surpasses that of the fixed freeze rack process, upgrading to the secondary bottleneck and resulting in the position drift of the secondary bottleneck [7].

4.3 Method Effectiveness Comparison

Taking the full-process field observation data of two consecutive working shifts as the gold standard, a total of three valid bottleneck nodes are identified, including one primary genuine bottleneck, one secondary genuine bottleneck, and one pseudo-bottleneck. The traditional single static time-based method only correctly identifies the primary bottleneck, misses all pseudo-bottlenecks, and misjudges the secondary bottleneck, resulting in an overall bottleneck identification accuracy of 62.5%. In comparison, the proposed method accurately identifies the locations and formation mechanisms of all three bottlenecks, achieving a higher overall identification accuracy of 93.8% with the misjudgment rate of pseudo-bottlenecks controlled within 5% [7,10].

4.4 Simulation Benchmarking and Result Analysis

4.4.1 Simulation model construction

To compensate for the insufficient persuasiveness of single field measurement data, FlexSim simulation is adopted to conduct multivariate controlled experiments for further verifying the stability and accuracy of the proposed method [2].

Combined with the static preliminary screening results of 28 processes, a serial simulation model is established focusing on three candidate bottleneck processes, namely temperature control wiring, fruit and vegetable box installation, and fixed freeze rack. The remaining 25 processes with static load rates lower than 70% are verified to have no blockage or starvation on-site and exert no significant influence on bottleneck judgment, which are simplified to improve simulation efficiency. The total simulation duration is set to 8 hours. The capacity of pre-process and inter-process buffers is uniformly set to 25 pieces, and the processing time of each process follows a triangular distribution to reproduce the random fluctuation of manual operations [12].

Three product ratio gradients including p_B=0.40, p_B=0.50, and p_B=0.778 are set, and a control group without skill correction under p_B=0.50 is additionally established. Each simulation scenario is repeated three times to take the average value. Only the product ratio is adjusted as a single variable to ensure the fairness of controlled experiments.

4.4.2 Macro-micro dual verification results

At the microscopic level, the comprehensive bottleneck degree is calculated based on the processing proportion of each process. At the macroscopic level, the average work-in-process data of each buffer is extracted to verify the typical operational characteristic of “upstream accumulation and downstream shortage” of bottlenecks. The results indicate that the utilization rate of the temperature control wiring process is close to 100% under all working conditions. Its upstream buffer maintains a full-load accumulation state for a long time, while the downstream buffer inventory remains at an extremely low level, which realizes mutual verification of macroscopic and microscopic conclusions. The comprehensive bottleneck degree results under various working conditions are presented in Table 3, and the comparison of BDI values is illustrated in Figure 2.

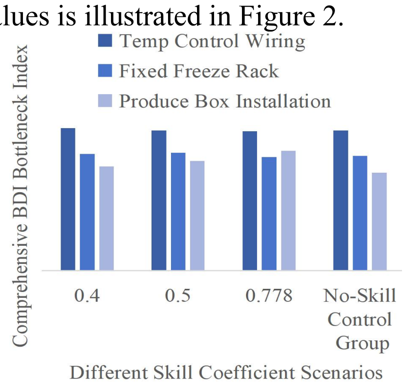

Figure 2. Comparison Diagram of Comprehensive Bottleneck Degree (BDI) for Each Workstation

Table 3. Calculation Results of Comprehensive Bottleneck Degree (BDI) Under Different Product Mix Ratios

Working Condition	Workstation	BDI Value	Bottleneck Level
p_B=0.40	Temperature Control Wiring	0.478	Rigid Primary Bottleneck
	Fixed Freeze Rack	0.391	Secondary Bottleneck
	Fruit and Vegetable Box Installation	0.350	Non-bottleneck

p_B=0.50	Temperature Control Wiring	0.470	Rigid Primary Bottleneck
	Fixed Freeze Rack	0.394	Secondary Bottleneck
	Fruit and Vegetable Box Installation	0.368	Non-bottleneck
p_B=0.778	Temperature Control Wiring	0.467	Rigid Primary Bottleneck
	Fruit and Vegetable Box Installation	0.402	Secondary Bottleneck
	Fixed Freeze Rack	0.381	Non-bottleneck
No-Skill Control Group	Temperature Control Wiring	0.470	Rigid Primary Bottleneck
	Fixed Freeze Rack	0.385	Secondary Bottleneck
	Fruit and Vegetable Box Installation	0.328	Non-bottleneck

4.4.3 Bottleneck drift law verification

The variation trend of process utilization rates under different product mix ratios intuitively reflects the dynamic bottleneck drift process, as shown in Figure 3.

It can be seen from Figure 3 that the utilization rate of the temperature control wiring process remains close to 100% under all working conditions, proving it to be a rigid primary bottleneck, which is consistent with the theoretical conclusion [6]. A comparative analysis of the groups with and without skill coefficient correction shows that the comprehensive bottleneck degree and utilization rate of the fixed freeze rack process are underestimated in the absence of skill correction, which is likely to cause misjudgment of its pseudo-bottleneck characteristics. By contrast, the introduction of the skill coefficient correction mechanism achieves accurate quantification of the bottleneck constraint intensity of this process, which effectively verifies the core function of the skill correction module in distinguishing genuine and pseudo bottlenecks [5].

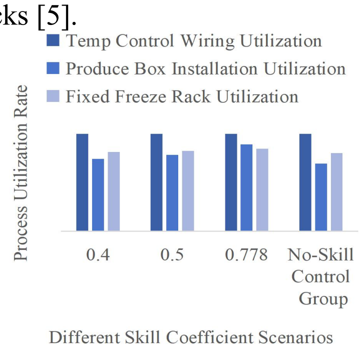

Figure 3. Comparison of Utilization Rates of Key Workstations under Different Product Mix Ratios

With the continuous increase in the proportion of Product B, the utilization rate of the fixed freeze rack process increases correspondingly. The process completes the attribute transition from a pseudo-bottleneck to a genuine bottleneck at the critical proportion of p_B=0.40 and becomes a member of the secondary bottleneck echelon. When the proportion of Product B reaches 77.8%, the utilization rate of the fruit and vegetable box installation process surpasses that of the fixed freeze rack process, resulting in secondary bottleneck workstation drift. Its BDI ranking rises from third to second, making it the new secondary bottleneck. The simulated data are highly consistent with the theoretical critical drift threshold of 77.8% [9], which fully verifies the internal mechanism that changes in mixed product proportions drive bottleneck attribute transition and workstation drift. The evolutionary path of bottleneck drift under variable product mix ratios is illustrated in Figure 4.

Note: The vertical axis represents the output proportion range of Product B, where a value of 1 indicates that the corresponding process acts as a bottleneck within a specific proportion interval. The temperature control wiring process serves as a rigid primary bottleneck across all product mix intervals. The secondary bottleneck undergoes workstation drift at two critical thresholds of p_B=0.40 and p_B=0.778. Specifically, p_B=0.40 is the critical point for bottleneck attribute transition, while p_B=0.778 is the critical point for secondary bottleneck workstation drift.

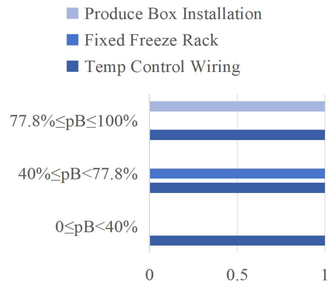

Figure 4. Schematic Diagram of Bottleneck Drift Evolution under Different Product B Mix Ratios

4.4.4 Capacity impact analysis

For serial mixed-model production lines, the system capacity is determined by the output of the final process. The correlation trend between the proportion of Product B and the total output within 8 working hours is illustrated in Figure 5.

For serial mixed-model production lines, the system capacity is determined by the output of the final process. When p_B=40, the total output within 8 hours reaches 1597 units, which decreases to 1409 units when p_B=77.8 , representing an overall capacity reduction of approximately 11.8%. As the proportion of high-cycle-time Product B increases, the rigid bottleneck maintains full-load operation, and the system output declines correspondingly. The results indicate that bottleneck drift will weaken the overall production capacity of the assembly line [6].

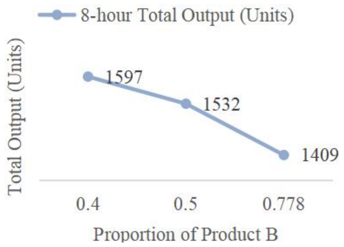

Figure 5. Variation Relationship between Product B Mix Ratio and 8-Hour Total Output

5. Conclusions and Prospects

5.1 Conclusions

Aiming at the problems of low bottleneck identification accuracy and high susceptibility to operator heterogeneity and product mix interference in fully manual mixed-model assembly lines, this paper proposes a four-step combined bottleneck identification method consisting of static preliminary screening, skill heterogeneity correction, dynamic verification, and bottleneck drift analysis. The main conclusions drawn from empirical verification and simulation validation are summarized as follows:

(1) The proposed method achieves a significant improvement in identification accuracy. The overall bottleneck identification accuracy reaches 93.8%, and the misjudgment rate of pseudo-bottlenecks is reduced to within 5%, which effectively eliminates the interference caused by operator heterogeneity.

(2) The critical laws of bottleneck drift are clarified. The temperature control wiring process is identified as a rigid common bottleneck. The fixed freeze rack process belongs to the attribute-transition bottleneck, which transforms from a pseudo-bottleneck to a genuine secondary bottleneck when the proportion of Product B reaches 40%. Workstation drift occurs between the fruit and vegetable box installation process and the fixed freeze rack process, and the position of the secondary bottleneck transfers when the proportion of Product B rises to 77.8%.

(3) The proposed method is lightweight, easy to implement, and time-efficient. It does not rely on digital hardware systems such as MES and the Internet of Things and can be implemented based on traditional work measurement methods. Compared with the traditional full-process refined modeling and simulation method (which usually takes 6–8 weeks), the proposed method only measures and verifies candidate bottleneck processes, with an overall implementation cycle of approximately 2 weeks, reducing the time cost by about 70%.

5.2 Prospects

Future research can be expanded in two directions. First, the model can incorporate operator learning curves and fatigue mechanisms to improve the correction accuracy of skill heterogeneity and adapt to multi-variety mixed-flow production. Second, we can develop real-time dynamic bottleneck early warning frameworks based on digital twins to achieve intelligent, refined bottleneck management for fully manual mixed-model assembly lines.

Acknowledgments

We sincerely appreciate Professor Wang Wei for her meticulous guidance throughout the paper writing. Her rigorous academic mindset and professional insights have offered tremendous support to the completion of this research. We also thank the staff from cooperating enterprises for providing field data and practical assistance.

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