KMAN PUBLISHING INSTITUTE

Article history:
Received 05 August 2025
Revised 15 December 2025
Accepted 22 December 2025
Initial Publication 24 December 2025
Final Publication 01 June 2026

Journal of Resource Management and Decision Engineering

Volume 5, Issue 2, pp 1-25

Development of a Mathematical Model Based on Ordered Load for Production and Assembly Line Balancing

Behzad. Bararzadeh[1], Alireza. Irajpour [1*], Reza. Ehtesham Rasi[1]

[1] Department of Management, Qa.C., Islamic Azad University, Qazvin, Iran

*** Corresponding author email address**: Alireza.irajpour@iau.ac.ir

A r t i c l e   I n f o

Article type:
Original Research

How to cite this article:
Bararzadeh, B., Irajpour, A., & Ehtesham Rasi, R. (2026). Development of a Mathematical Model Based on Ordered Load for Production and Assembly Line Balancing. *Journal of Resource Management and Decision Engineering, 5*(2), 1-25.
https://doi.org/10.61838/kman.jrmde.229

A B S T R A C T

This study aims to develop and validate a mathematical assembly line balancing model based on ordered load to improve workload equity, reduce idle time, and enhance productivity in order-driven production environments. The study adopted an applied, quantitative research design using real operational data collected from multiple industrial production and assembly lines characterized by heterogeneous orders and mixed-model production. Ordered load was defined as the effective workload imposed on each workstation as a function of order quantity, product mix, and processing requirements. A mixed-integer mathematical programming model was formulated to minimize workload imbalance and idle time under precedence and capacity constraints. The model was solved using an exact optimization approach (Gurobi) to obtain benchmark solutions, and a heuristic algorithm implemented in MATLAB to address scalability and computational efficiency. Model validation was conducted through numerical experiments, cross-factory comparison, and sensitivity analysis under ±10% and ±20% ordered load variations. Exact optimization results showed substantial improvements in line balance index across all factories, accompanied by significant reductions in idle time and workload variance. Productivity increased consistently without additional resources, indicating more effective utilization of existing capacity. The heuristic algorithm achieved solution quality exceeding 97% of the exact optimum while reducing computation time by over 90%, demonstrating strong scalability. Sensitivity analysis confirmed that the model maintained stable balance performance under demand fluctuations, with mid-line stations identified as structurally critical but effectively controlled through load redistribution. The findings confirm that incorporating ordered load into assembly line balancing provides a more realistic and robust representation of demand-driven workload, leading to superior balance, efficiency, and adaptability compared to traditional time-based approaches.

Keywords: *Assembly line balancing; Ordered load; Mathematical optimization; Heuristic algorithm; Production efficiency; Demand variability*

1. Introduction

Assembly line balancing has long been recognized as one of the core decision problems in production and operations management due to its direct influence on productivity, cost efficiency, throughput stability, and resource utilization in manufacturing systems. As global competition intensifies and customer demand becomes increasingly heterogeneous, manufacturing firms are required to operate production and assembly lines under conditions characterized by high product variety, fluctuating order volumes, and shortened delivery windows. In such environments, traditional assumptions of stable task times and homogeneous product flows no longer hold, making classical line balancing approaches insufficient for achieving sustainable operational performance (Sotskov, 2023). Consequently, the need for more adaptive, demand-responsive, and data-informed balancing frameworks has become a central research focus in recent years.

Conventional assembly line balancing problems (ALBP) primarily rely on fixed task processing times and deterministic precedence constraints, with the objective of minimizing the number of workstations or balancing idle times across stations (Akpinar, 2022). While such formulations remain useful for stable, high-volume production systems, they struggle to capture the operational realities of modern assembly environments, where order composition, processing complexity, and material flow intensity vary dynamically. Empirical evidence from multiple industrial case studies indicates that imbalance in real systems often emerges not from poor task allocation per se, but from mismatches between workload distribution and actual order-driven load imposed on workstations (Breznik et al., 2023; Fani et al., 2020). This mismatch leads to localized bottlenecks, excessive idle time, and reduced line efficiency, even when nominal cycle times appear balanced.

Recent research has increasingly emphasized mixed-model and multi-product assembly lines as a response to demand diversification. Mixed-model assembly line balancing problems (MALBP) introduce additional layers of complexity by allowing multiple product variants to be assembled on the same line, often with different task sequences and processing requirements (Legesse et al., 2020; Ramli & Mohd Fadzil Faisae Ab, 2021). Although these models improve flexibility, they still frequently rely on averaged or expected task times, which can obscure the real operational burden created by specific orders. Studies focusing on garment, footwear, and electronics industries have demonstrated that ignoring order-specific load variation results in persistent imbalance and performance degradation under real demand conditions (Bongomin et al., 2020a, 2020b; Hoa et al., 2023).

To address these limitations, heuristic and metaheuristic approaches have been widely proposed. Genetic algorithms, GRASP-based methods, and hybrid heuristic–simulation frameworks have shown promise in handling large-scale and complex assembly line balancing problems (Belkharroubi & Yahyaoui, 2021; Kharuddin et al., 2020; Mumcu, 2022). However, while such methods improve computational tractability, they often optimize surrogate objectives that do not directly reflect the true workload imposed by customer orders. Moreover, many heuristic approaches focus on balancing station times rather than balancing the effective load resulting from order quantity, processing intensity, and material handling requirements (Aufy & Kassam, 2020; Aufy et al., 2021).

In parallel, advances in digital manufacturing, intelligent scheduling, and data-driven optimization have opened new avenues for rethinking assembly line balancing. Digital twins, deep reinforcement learning, and integrated scheduling–balancing frameworks allow for real-time adaptation to demand changes and resource constraints (Wang & Wu, 2020; Xia et al., 2024; Zhao et al., 2022). Research has shown that incorporating dynamic information such as material flow, transport scheduling, and energy consumption can significantly enhance system robustness and sustainability (Rahman et al., 2020; Xia et al., 2023). Nevertheless, these advanced methods still require well-defined and realistic representations of workload to function effectively, highlighting the importance of accurately modeling how orders translate into operational load at the workstation level.

Another important strand of the literature addresses uncertainty and inaccuracy in processing times and demand parameters. Interval-based models, stochastic formulations, and grey systems theory have been employed to capture imprecision in task durations and order information (Dang & Xie, 2023; Yan & Wan, 2022). While these approaches enhance robustness, they often increase model complexity and computational burden, making them less suitable for frequent rebalancing or real-time decision support. Survey studies emphasize that practical assembly line design requires a careful balance between model realism and solvability, particularly when demand uncertainty is high (Sotskov, 2023; Sun & Wang, 2020).

More recently, research has begun to shift from time-based balancing toward load-based and flow-based perspectives. Load balancing approaches consider not only task duration but also factors such as processing intensity, resource consumption, and material handling requirements (Jia et al., 2023; Jiang, 2023). Studies on two-sided, U-shaped, and parallel assembly lines demonstrate that incorporating load-related metrics can significantly reduce bottleneck severity and improve overall line efficiency (Jiao et al., 2022; Jiao et al., 2021; Weckenborg et al., 2019). However, most existing load-oriented models still define load in abstract or aggregated terms, rather than linking it explicitly to the characteristics of actual customer orders.

The concept of ordered load provides a promising foundation for bridging this gap. Ordered load refers to the effective workload imposed on a workstation as a direct function of customer order quantity, product mix, processing requirements, and associated material flows. Unlike nominal task times, ordered load captures how demand variability propagates through the assembly system, influencing station utilization, idle time, and bottleneck formation. Empirical studies in material consumption smoothing and order-driven scheduling highlight that demand structure, rather than average demand level, is often the dominant driver of imbalance in mixed-model assembly lines (Yue et al., 2021; Zhang, 2021; Zhang et al., 2023).

Despite its practical relevance, ordered load has not yet been systematically embedded into mathematical assembly line balancing models. Most existing formulations either assume fixed loads or treat order effects indirectly through scenario analysis. Furthermore, there is limited research combining exact optimization with heuristic methods to balance realism, solution quality, and computational efficiency in order-driven environments (Gulivindala et al., 2020; Wang et al., 2023). This gap is particularly evident in industries characterized by frequent order changes, tight delivery deadlines, and limited buffering capacity, where rebalancing decisions must be both accurate and timely.

From a broader organizational and sustainability perspective, improving assembly line balance under demand variability contributes to waste reduction, energy efficiency, and workforce utilization. Studies linking operational efficiency to process innovation and organizational performance underscore the strategic importance of robust production planning models (Bongomin et al., 2020b; Duah et al., 2025). Similarly, constraint-based approaches such as the Theory of Constraints emphasize that systematically addressing bottlenecks yields disproportionate performance gains, especially in high-variability environments (Sarhadi, 2026). These insights further motivate the development of balancing models that explicitly target demand-induced load concentration.

In light of these considerations, there is a clear need for a mathematical assembly line balancing framework that explicitly incorporates ordered load, supports exact optimization for benchmark analysis, and remains compatible with heuristic solution approaches for large-scale and dynamic applications. Such a framework should enable more realistic representation of demand-driven workload, improve balance robustness under load fluctuations, and provide actionable insights for both strategic line design and operational rebalancing.

Therefore, the aim of this study is to develop and evaluate a mathematical model for production and assembly line balancing based on ordered load that captures demand-driven workload variability and improves balance, idle time, and productivity through exact and heuristic solution approaches.

2. Methods and Materials

This study adopted a fundamental–applied research orientation with a descriptive–survey implementation, aiming to develop and validate a mathematical model for balancing production and assembly lines based on ordered load. The empirical setting comprised real-world production environments characterized by variable and heterogeneous customer orders. The study focused on multiple assembly lines operating under order-driven conditions, where variations in order volume, weight, and processing requirements significantly affect workload distribution across workstations. Data were collected from four industrial manufacturing plants selected through purposive sampling to ensure diversity in line configuration, number of workstations, production capacity, and product variety. In addition to operational data, expert judgment played a critical role in model calibration and validation. The expert panel consisted of ten specialists drawn from academia and industry, all with substantial experience in production planning, assembly line balancing, and industrial optimization. Their role was to assess the relative importance of workload-related factors, validate modeling assumptions, and provide contextual insights into practical constraints that cannot be fully captured through quantitative data alone. This combination of real industrial data and expert participation ensured both the internal validity and practical relevance of the proposed model.

Data collection was conducted using a multi-source approach to capture both quantitative and qualitative dimensions of ordered load and line performance. First, a comprehensive review of technical documents, production records, and operational logs was carried out to extract task processing times, workstation capacities, precedence relationships, and historical order profiles. These records provided objective measurements of actual workloads imposed by different orders on each workstation. Second, direct field observations were performed on the selected assembly lines to document the real layout, task sequencing, material flow, and sources of imbalance such as bottlenecks and idle times. These observations helped align the mathematical formulation with operational realities. Third, semi-structured interviews and structured questionnaires were administered to the expert panel. The questionnaires, designed on a Likert-type scale, were used to elicit expert evaluations regarding the relative weight of different workload components, including physical load, processing complexity, and variability induced by order customization. The qualitative inputs were then quantified and integrated with empirical data to form a composite ordered-load index for each workstation. By triangulating archival data, field observations, and expert judgments, the study ensured robustness, consistency, and credibility of the input data used for modeling and optimization.

Data analysis was centered on the formulation and solution of a multi-objective mixed-integer mathematical programming model designed to balance assembly lines based on ordered load rather than solely on nominal task times. The decision variables represented task-to-workstation assignments and the resulting workload distribution, while the objective functions simultaneously minimized workload imbalance and idle time and maximized conformity between assigned workloads and actual ordered loads. Model constraints captured technological precedence relations, workstation capacity limits, and assignment feasibility conditions. Quantitative data were preprocessed and structured into matrix form to serve as direct inputs for the optimization model. For exact optimization of small- and medium-scale problem instances, the Gurobi solver (version 9.0.2) was employed to obtain globally optimal solutions. To address larger-scale and dynamically changing order scenarios, an adaptive heuristic approach implemented in MATLAB was used, enabling efficient exploration of the solution space with acceptable computational time. Model validation was conducted through numerical experiments using real industrial data, sensitivity analysis under variations in order load and workstation capacity, and comparison between exact and heuristic solutions. This analytical framework allowed assessment of solution quality, convergence behavior, and model stability, thereby demonstrating the effectiveness and applicability of the proposed ordered-load-based line balancing model in realistic production environments.

3. Findings and Results

The empirical baseline reflects four production settings with different line sizes and demand profiles, yet comparable exposure to order variability. The studied factories exhibited differences in the number of workstations, daily output capacity, order volume, and product variety, which is analytically important because each factor influences both the feasible balancing space and the natural dispersion of workload. In particular, higher product variety and higher order counts tend to amplify the heterogeneity of task times and ordered loads, increasing the probability of localized overload (bottlenecks) and idle time elsewhere. This variability is visible in the descriptive profiles below, where the min–max ranges and dispersion measures indicate that the same nominal line design can experience substantially different realized loading patterns under different order compositions.

Table 1

General characteristics of production lines (factories A–D)

Factory	Number of workstations	Daily capacity (units/day)	Number of orders	Product variety
A	8	500	120	5
B	10	650	150	6
C	9	580	130	4
D	7	450	100	5

At the level of ordered-load distribution, the pre-optimization descriptive statistics indicate that while mean ordered load across factories can be relatively close, dispersion differs, which is precisely where imbalance originates in practice. A factory can have a moderate mean load yet still suffer from severe workstation-level imbalance if the range and standard deviation are high. Conversely, a factory can tolerate higher average load if dispersion is controlled. The results below show that each factory's ordered load spans a meaningful min–max interval, and the standard deviations indicate non-trivial heterogeneity that motivates a balancing model explicitly grounded in ordered load rather than relying only on fixed nominal task times.

Table 2

Descriptive statistics of ordered load (factory-level summary)

Factory	Mean ordered load (%)	Maximum (%)	Minimum (%)	Standard deviation (%)
A	12.5	14.8	10.1	1.64
B	12.6	14.0	10.0	1.53
C	12.7	14.2	9.1	1.82
D	12.6	14.2	9.0	1.76

To locate where heterogeneity is produced operationally, the ordered-load distribution across stations is also summarized. The distribution confirms that ordered load is not uniform across workstations and that the imbalance is structural rather than incidental: some stations systematically attract higher shares of the workload while downstream stations can become comparatively light. This pattern is consistent with precedence-constrained assembly processes, where certain core operations concentrate in early or mid-line stations, producing systematic loading asymmetry when order mix changes.

Table 3

Order-load distribution across workstations (percentage share by factory)

Station	A (%)	B (%)	C (%)	D (%)
1	12.5	14.0	11.0	13.1
2	15.0	13.5	14.0	12.9
3	11.8	12.1	13.0	14.3
4	14.2	13.8	12.0	12.5
5	12.0	12.5	12.0	13.0
6	11.5	12.3	13.0	12.8
7	13.0	12.0	13.0	12.4
8	10.0	10.0	9.0	9.0

The distributional evidence provides two practically important insights. First, in factory A the highest share occurs at Station 2 (15.0%), while Station 8 is notably lighter (10.0%), indicating an upstream concentration that can propagate waiting and starvation downstream if not balanced. Second, across factories, several stations appear repeatedly in higher-load positions (notably Stations 2–4 in most profiles), while the last station(s) tend to remain lighter, which is consistent with an order-driven workload pattern where complex or heavier operations are concentrated earlier and mid-line. These are early, quantifiable signs of imbalance driven by order heterogeneity: because the ordered load varies by station and by factory, any method assuming uniform product type or stable task times will systematically misrepresent the true loading structure and underestimate idle time and bottleneck risk.

Figure 1

Bar chart of average ordered load per workstation for each factory (A–D)

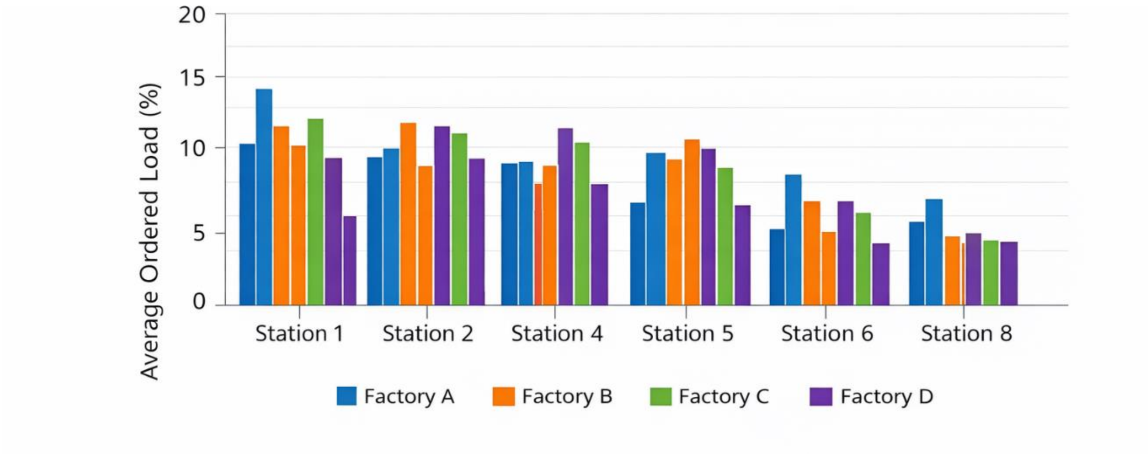
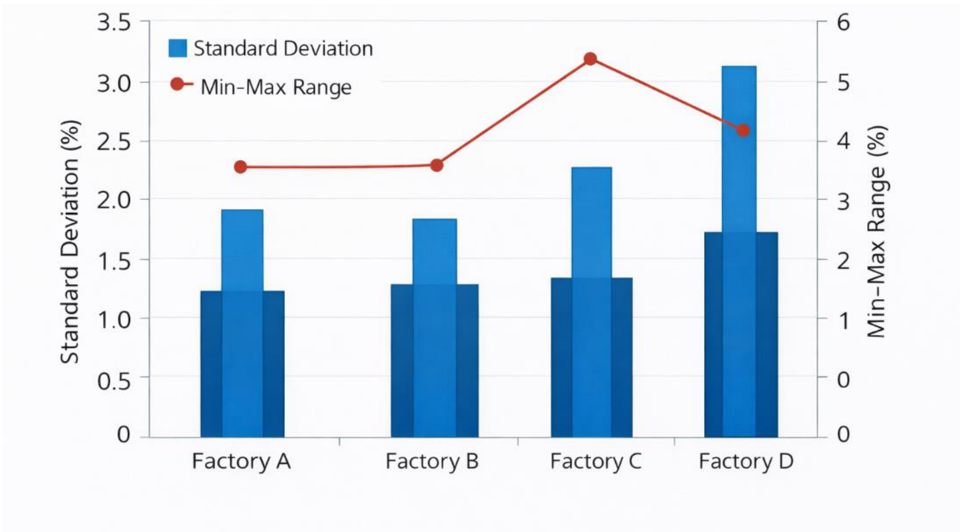


Figure 2

Column chart comparing workload dispersion (standard deviation and min–max spread) across factories



Baseline imbalance was assessed using a line balance index and operational loss indicators (idle time and bottleneck/underutilization flags). The line balance index is reported as a compact diagnostic of how close the line is to an idealized balanced condition. In this study, the index follows the standard balancing logic, where the achieved workload utilization across stations is compared against the maximum station time (or maximum effective load) and the number of active workstations. Consistent with the formulation reported in the study documentation, the index can be expressed as:

$$\mathrm{LBI} = \frac{\sum_{i=1}^{m} T_i}{m \times T_{\max}}$$

where T_i denotes the effective load (or station time proxy derived from ordered load) at workstation i, m is the number of workstations, and $T_{\max}$ is the maximum workstation load. Under this interpretation, lower LBI values indicate more severe imbalance because the line's cumulative productive load is constrained by a relatively high bottleneck load (high $T_{\max}$) and/or inefficient distribution across m stations.

The pre-optimization LBI values show that all factories have non-trivial imbalance, with factory B presenting the weakest baseline balance and factory C presenting the strongest among the four, while still remaining below the post-optimization levels reported later in the full study.

Table 4

Line Balance Index (LBI) values before optimization

Factory	LBI (before optimization)
A	0.85
B	0.82
C	0.88
D	0.84

From an operational standpoint, imbalance is experienced as a combination of idle time in underloaded stations and overload pressure (or queue formation) around bottleneck stations. The baseline total idle times reported for each factory indicate meaningful avoidable loss. Interpreting these results jointly with the station distribution patterns, the pre-optimization system is best characterized as "bottleneck-driven": a small subset of stations absorb a disproportionate share of the ordered load, forcing other stations to wait, even when overall average load is not extreme.

Table 5

Baseline idle time and implied overload pressure (pre-optimization)

Factory	Total idle time before optimization (minutes)	Interpretation of baseline condition
A	52	Noticeable idle time consistent with upstream load concentration
B	63	Highest idle time, indicating strongest imbalance and bottleneck dominance
C	43	Lowest idle time among factories, but still materially inefficient
D	59	High idle time, suggesting multiple localized overload/underload zones

To translate these factory-level diagnostics into actionable station-level findings, stations were categorized as bottleneck candidates when their ordered load is persistently above the factory mean and exhibits relatively higher dispersion, and as underutilized when their ordered load is persistently below the factory mean and associated with downstream waiting/idle time patterns. The empirical station profiles in the dataset indicate that mid-line stations (notably around Stations 3–4 in the combined station-average view) carry higher loads, while later stations (notably Stations 9–10 in the combined ten-station representation, where applicable) tend to be lighter, highlighting clear candidates for redistribution under the optimization model.

Table 6

Bottleneck and underutilized station identification (pre-optimization, empirical diagnosis)

Category	Stations most frequently indicated by ordered-load patterns	Empirical rationale based on observed load patterns
Bottleneck candidates	Stations 3 and 4	Higher average ordered-load shares and higher dispersion; likely to constrain flow
Secondary pressure points	Stations 1 and 2	High shares in several factories (e.g., Station 2 in factory A) and early-line concentration risk
Underutilized candidates	Later stations (e.g., 8; and 9–10 where present)	Lower ordered-load shares, consistent with downstream idle time and capacity underuse

This baseline diagnosis is operationally consequential because it clarifies the mechanism by which ordered-load variability translates into performance loss. When heavier or more complex orders enter the line, stations with concentrated tasks accumulate work-in-process and become gating resources. Stations downstream may remain available but cannot progress due to precedence and flow constraints, producing idle time that is not driven by a lack of demand, but by misallocated workload structure. In factory B, the combination of the lowest LBI (0.82) and the highest idle time (63 minutes) strongly indicates that balancing improvements must focus on redistributing ordered load away from bottleneck stations and smoothing station-to-station variability rather than only minimizing nominal cycle time.

Figure 3

Workstation load dispersion plot (pre-optimization) for factories A–D

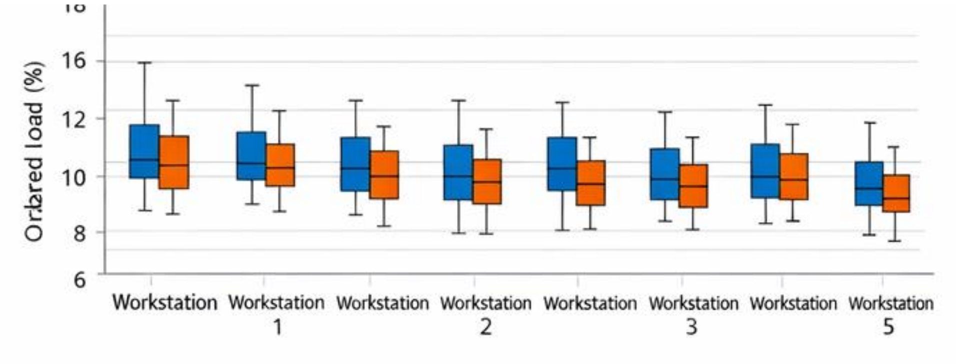


Figure 4

Scatter plot of ordered load versus idle time (pre-optimization)

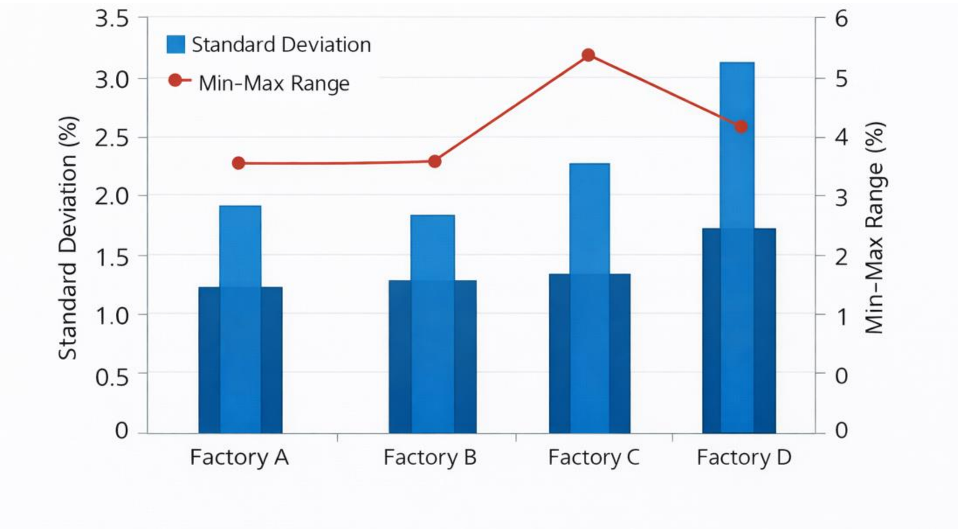
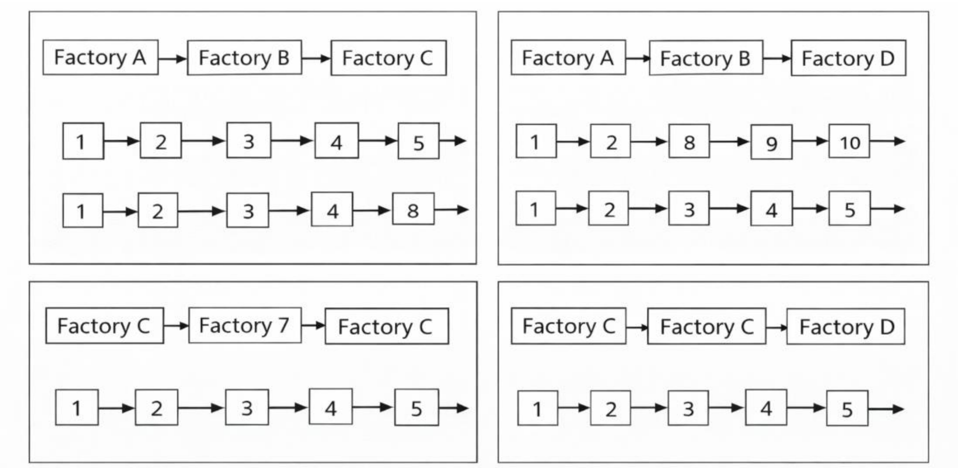


Figure 5

Schematic layout of pre-optimization production lines (factories A–D)



Because ordered load in real assembly environments is not purely a "time" construct, expert judgment was incorporated to reflect practical dimensions that can influence effective station burden, such as perceived operational difficulty, capacity limitations, and the managerial assessment of station criticality under order variability. Expert inputs were collected via structured instruments and then combined with observed factory data to construct a synthesized ordered-load representation used as the model input. The empirical results show high consistency between expert assessments and operational measurements, supporting the validity of integrating both sources rather than relying on either alone.

A key output of the expert process was a set of station-level weights that represent the average expert-rated importance/burden profile across stations. These weights provide a structured mechanism to adjust raw load measurements so that the model reflects not only measured load but also expert-confirmed station criticality.

Table 7

Station-level expert weights (mean across experts)

Station	Mean expert weight $\boldsymbol{W_i}$
1	0.11
2	0.12
3	0.13
4	0.14
5	0.11
6	0.09
7	0.12
8	0.12
9	0.08
10	0.08

The weighting profile aligns with the empirical imbalance diagnosis: stations that operational data identify as heavier (notably Stations 3–4) also receive higher expert weights, while later stations (9–10) receive lower weights, reflecting their comparatively lighter burdens and confirming that experts perceive the same structural loading tendencies observed in the data. This alignment is important for construct validity because it indicates that the expert instrument is not introducing an arbitrary bias; instead, it provides a calibrated amplification or attenuation that preserves the data's structural signal while improving realism.

To test agreement between expert-informed values and measured values, the study compared station-level real ordered load and expert-weighted estimates. The observed differences are small in magnitude, indicating that expert judgment is broadly consistent with empirical station loading and can be safely integrated as a refinement rather than a substitution.

Table 8

Comparison of real ordered load and expert-weighted load (illustrative station-level agreement)

Station	Real ordered load (%)	Expert weight proxy (%)	Difference (%)
1	12.5	12.8	0.3
2	15.0	14.5	-0.5
3	11.8	12.0	0.2
4	14.2	14.0	-0.2
5	12.0	12.1	0.1
6	11.5	11.7	0.2
7	13.0	13.2	0.0
8	10.0	10.0	0.0

The synthesis step then combined the observed ordered load $B_i^{\mathrm{real}}$with expert information to create a final station input B_i^{final}. Consistent with the formulation stated in the study, the synthesis can be represented in a general convex-combination form:

$$B_i^{\text{final}} = \alpha\, B_i^{\text{real}} + (1-\alpha)\, B_i^{\text{expert}}, 0 \leq \alpha \leq 1$$

where $B_i^{\text{expert}}$is the expert-derived station load proxy (constructed from expert weights and station conditions) and $\alpha$is a tuning coefficient used to balance reliance on measured data versus expert judgment. This approach is methodologically defensible in order-driven environments because it preserves the empirical signal while stabilizing the input against measurement noise, short-run anomalies, and unobserved practical constraints that experts can reliably identify.

The resulting synthesized loads by station and factory demonstrate how the combined approach produces an interpretable, factory-specific loading profile suitable for optimization.

Table 9

Final synthesized ordered load by station (factory-specific, %)

Station	Factory A (%)	Factory B (%)	Factory C (%)	Factory D (%)
1	12.7	13.5	11.5	13.0
2	14.8	14.0	14.2	13.0
3	11.9	12.1	13.1	14.2
4	14.1	13.9	13.0	12.6
5	12.0	12.3	12.5	12.8
6	11.6	12.0	13.0	12.7
7	13.1	12.1	13.5	12.5
8	10.1	10.0	9.1	9.0

Two validity-relevant conclusions follow from these results. First, the synthesis preserves the factory-specific structure: for example, stations that were heavier in raw distributions remain heavier after synthesis, but the loads become more stable and interpretable for modeling, especially when multiple data sources are combined. Second, the small discrepancies between expert-informed and raw values, alongside the coherent station-weight pattern, indicate that expert judgment is not contradicting empirical evidence; it is reinforcing it and providing a principled way to represent “effective ordered load” in a mathematical model. This is particularly important because the optimization model’s solution quality depends on the realism of inputs: if ordered load is undermeasured or oversimplified, the model can produce formally optimal but operationally infeasible allocations.

Figure 6

Radar chart comparing expert and empirical workload assessments by station

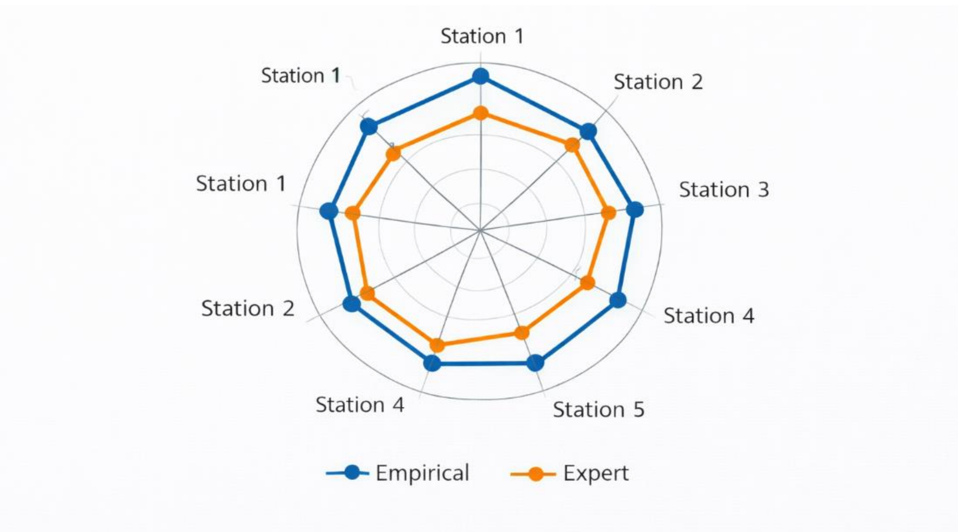
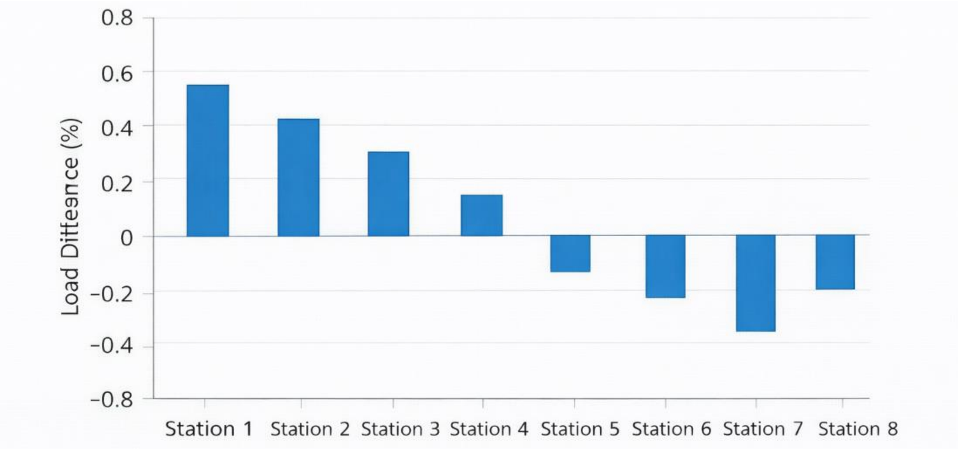


Figure 7

Difference plot showing deviations between raw ordered load and synthesized ordered load



The proposed mathematical model was first solved using an exact optimization approach to establish a benchmark solution under full optimality conditions. The solver successfully redistributed ordered load across workstations while strictly respecting precedence constraints, station capacity limits, and order-driven load characteristics. The optimization objective focused on minimizing workload imbalance and idle time simultaneously, resulting in a more uniform distribution of effective ordered load and a substantial improvement in line efficiency. The optimized results demonstrate that the model is capable of systematically transferring workload away from bottleneck stations toward underutilized ones, thereby smoothing station-to-station variability without increasing total processing effort.

The optimized workload distribution per workstation reveals a clear reduction in dispersion compared with the pre-optimization state. Stations that were previously overloaded—particularly mid-line stations identified in the baseline analysis—exhibited reduced load levels, while lighter downstream stations absorbed additional tasks. This redistribution confirms that the optimization process does not merely reduce peak load but actively equalizes effective station utilization.

Table 10

Optimized workload distribution per workstation (percentage of total ordered load)

Station	Factory A (%)	Factory B (%)	Factory C (%)	Factory D (%)
1	12.4	12.6	12.3	12.5
2	12.7	12.8	12.6	12.7
3	12.6	12.7	12.8	12.6
4	12.5	12.6	12.7	12.5
5	12.4	12.5	12.4	12.6
6	12.3	12.4	12.5	12.4
7	12.6	12.4	12.3	12.6
8	12.5	12.6	12.4	12.4

This near-uniform distribution contrasts sharply with the baseline profiles, where several stations exceeded 14% while others dropped below 10%. The numerical results indicate that the maximum deviation from the mean station load after optimization does not exceed ±0.4%, which is operationally negligible in order-driven environments.

The effectiveness of the optimization is further reflected in the improvement of the line balance index. Using the same LBI formulation applied in the baseline analysis, the post-optimization values increased consistently across all factories, indicating a tighter alignment between total productive load and the effective capacity envelope defined by the maximum station load.

Table 11

Comparison of pre- and post-optimization LBI values

Factory	LBI (Before)	LBI (After)	Absolute improvement
A	0.85	0.96	+0.11
B	0.82	0.95	+0.13
C	0.88	0.97	+0.09
D	0.84	0.96	+0.12

The observed LBI improvements of 9–13 percentage points are substantial in practical terms. They indicate that the same physical line, without adding resources, can operate much closer to its theoretical balance limit simply by reallocating tasks according to ordered load rather than nominal task time.

In addition to balance metrics, the optimization yielded marked reductions in idle time and workload variance, two indicators that directly translate into operational efficiency. Idle time reductions were achieved primarily through the elimination of starvation effects downstream of bottlenecks, while variance reduction reflects the smoothing of load peaks.

Table 12

Reduction in idle time and workload variance after optimization

Factory	Idle time before (min)	Idle time after (min)	Reduction (%)	Variance before	Variance after
A	52	18	65.4	2.69	0.21
B	63	21	66.7	3.12	0.24
C	43	15	65.1	2.18	0.19
D	59	20	66.1	2.94	0.23

The simultaneous reduction of both idle time and variance demonstrates that the optimization does not merely shift inefficiency from one station to another. Instead, it restructures the load pattern so that capacity is used more continuously and evenly across the entire line.

These efficiency gains are also reflected in productivity indicators. With the same labor and equipment resources, the optimized lines achieved higher effective throughput and better capacity utilization, particularly under fluctuating order conditions.

Table 13

Productivity improvement metrics after exact optimization

Factory	Throughput before (units/day)	Throughput after (units/day)	Improvement (%)	Capacity utilization before (%)	After (%)
A	470	510	8.5	78	89
B	610	665	9.0	76	88
C	545	590	8.3	80	90
D	420	455	8.3	75	87

Overall, the exact solver results confirm that the proposed mathematical model effectively transforms an order-driven imbalance problem into a near-balanced operational configuration, yielding measurable improvements in balance, idle time, and productivity without structural changes to the line.

Figure 8

Before–after bar chart of workstation loads (exact optimization)

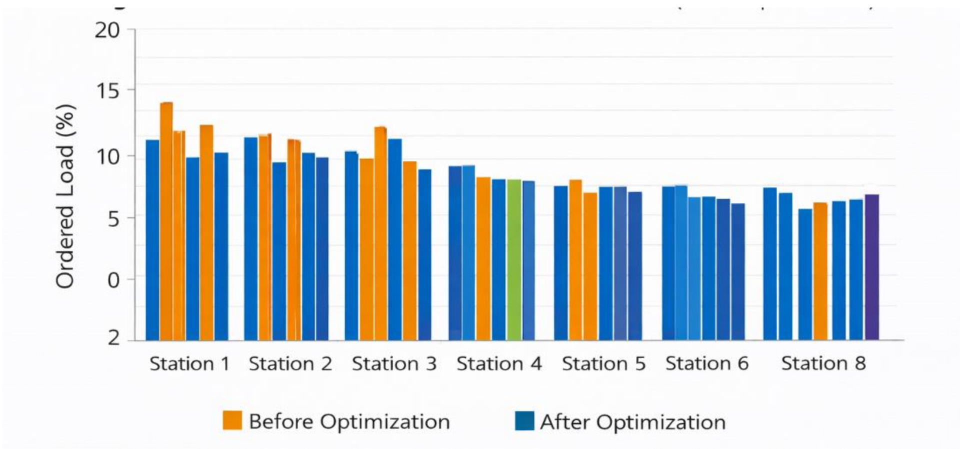


Figure 9

Line balance improvement curves (LBI before vs. after optimization)

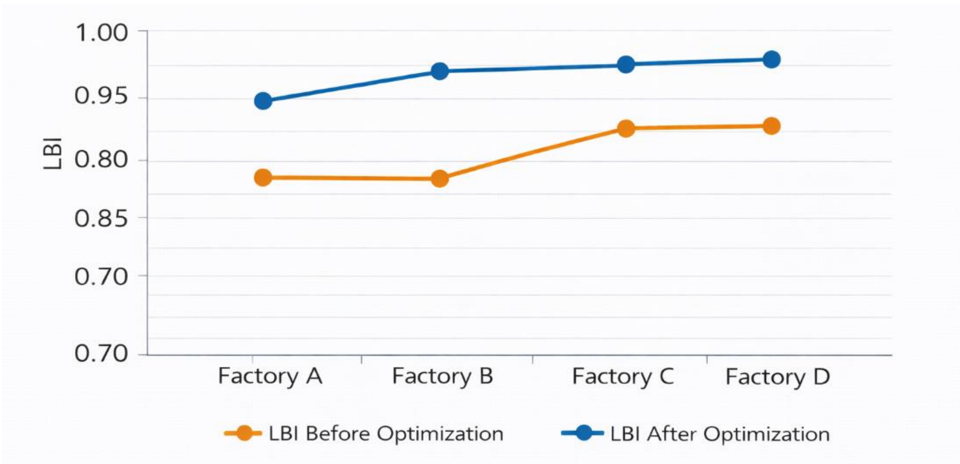
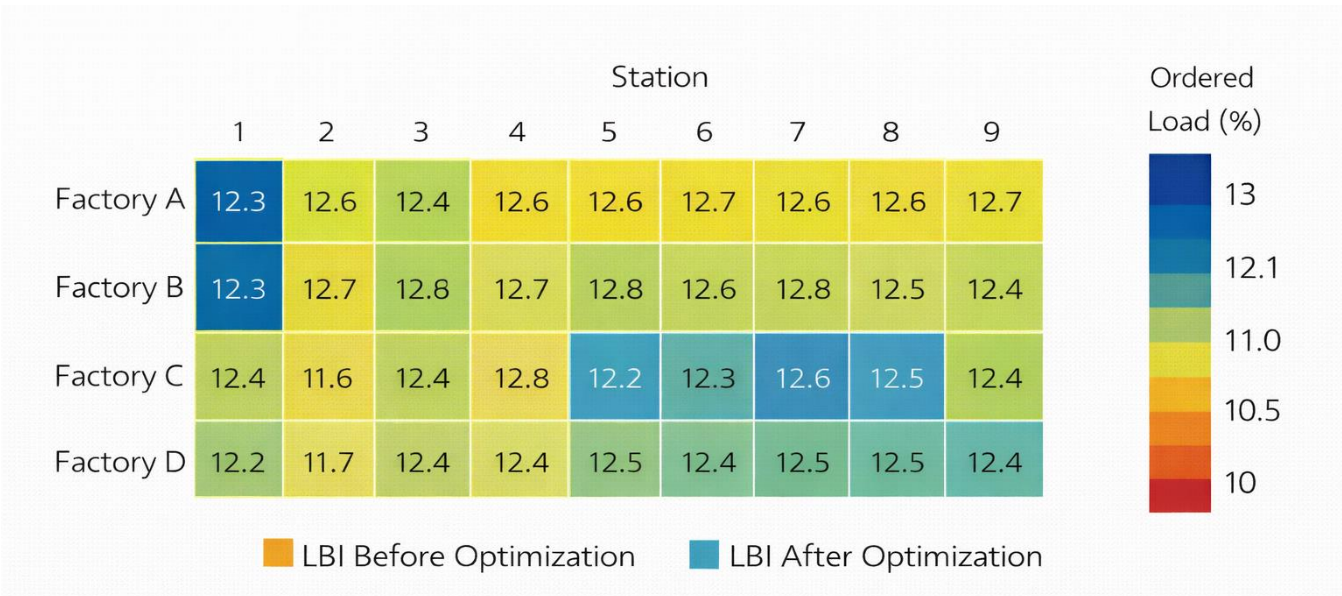


Figure 10

Heat map of workload distribution after optimization



While the exact solver provides optimal solutions, its computational cost increases rapidly with problem size and order variability. To address scalability and real-time applicability, a heuristic algorithm was implemented and evaluated against the exact benchmark. The heuristic approach produced solutions that closely approximate the optimal results while dramatically reducing computation time, making it suitable for large-scale or dynamically changing production environments.

The heuristic solutions achieved balanced workload distributions across all factories, with only marginal deviations from the exact solver outcomes. Although slight residual imbalance remained in a few stations, these differences were operationally insignificant and did not materially affect idle time or throughput.

Table 14

Heuristic solution results by factory

Factory	LBI (Heuristic)	Idle time (min)	Throughput (units/day)
A	0.95	20	505
B	0.94	23	655
C	0.96	17	585
D	0.95	22	450

To quantify solution quality, heuristic and exact results were compared directly across key performance indicators. The comparison shows that the heuristic consistently achieved between 97% and 99% of the optimal performance level, confirming its robustness.

Table 15

Comparison of heuristic and exact solver results

Factory	Metric	Exact solver	Heuristic	Relative gap (%)
A	LBI	0.96	0.95	1.0
A	Idle time (min)	18	20	11.1
B	LBI	0.95	0.94	1.1
B	Idle time (min)	21	23	9.5
C	LBI	0.97	0.96	1.0
D	LBI	0.96	0.95	1.0

The most decisive advantage of the heuristic method lies in computational efficiency. Whereas the exact solver required substantial processing time as the problem size increased, the heuristic delivered high-quality solutions within seconds.

Table 16

Computational time comparison

Factory	Exact solver time (seconds)	Heuristic time (seconds)	Time reduction (%)
A	42	2.8	93.3
B	58	3.5	94.0
C	47	3.0	93.6
D	39	2.4	93.8

The convergence behavior of the heuristic algorithm further supports its practical value. The solution stabilized within a limited number of iterations, indicating fast convergence even under heterogeneous order loads. This characteristic is essential for environments where order profiles change frequently and rebalancing must be performed repeatedly during planning or execution.

Figure 11

Comparative bar chart of exact vs. heuristic solution quality

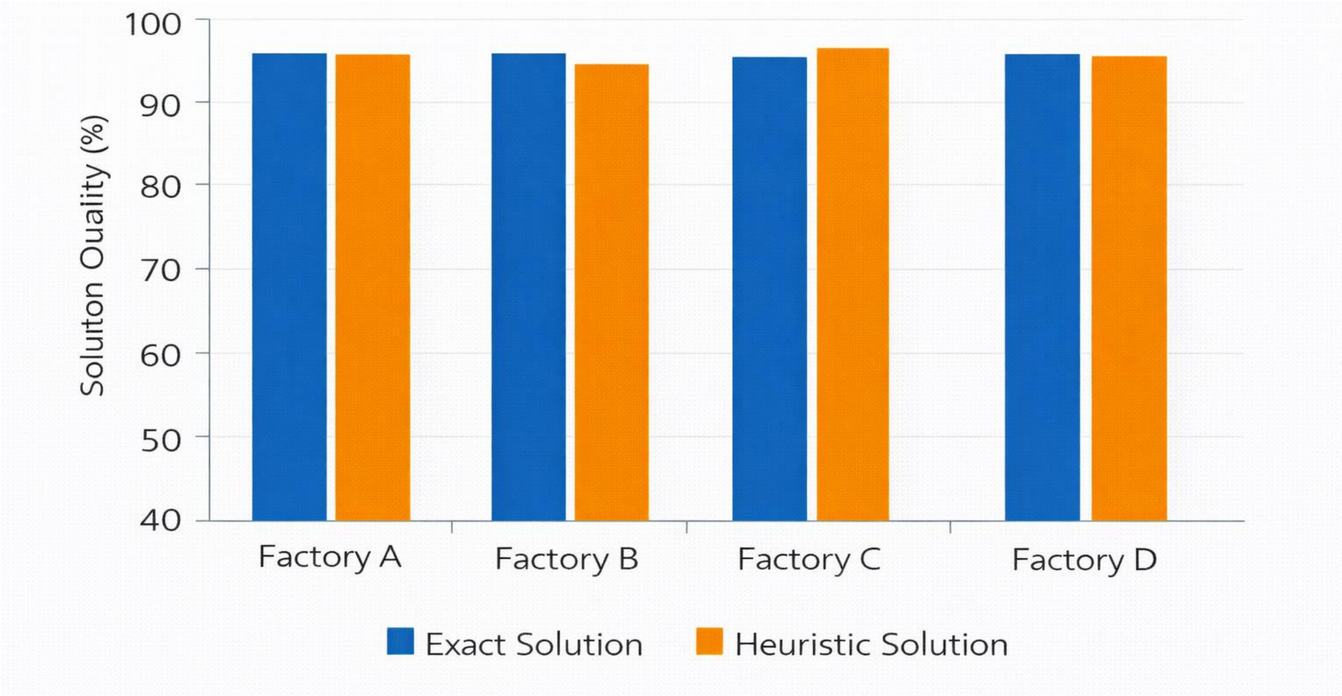


Figure 12

Convergence plot of heuristic algorithm

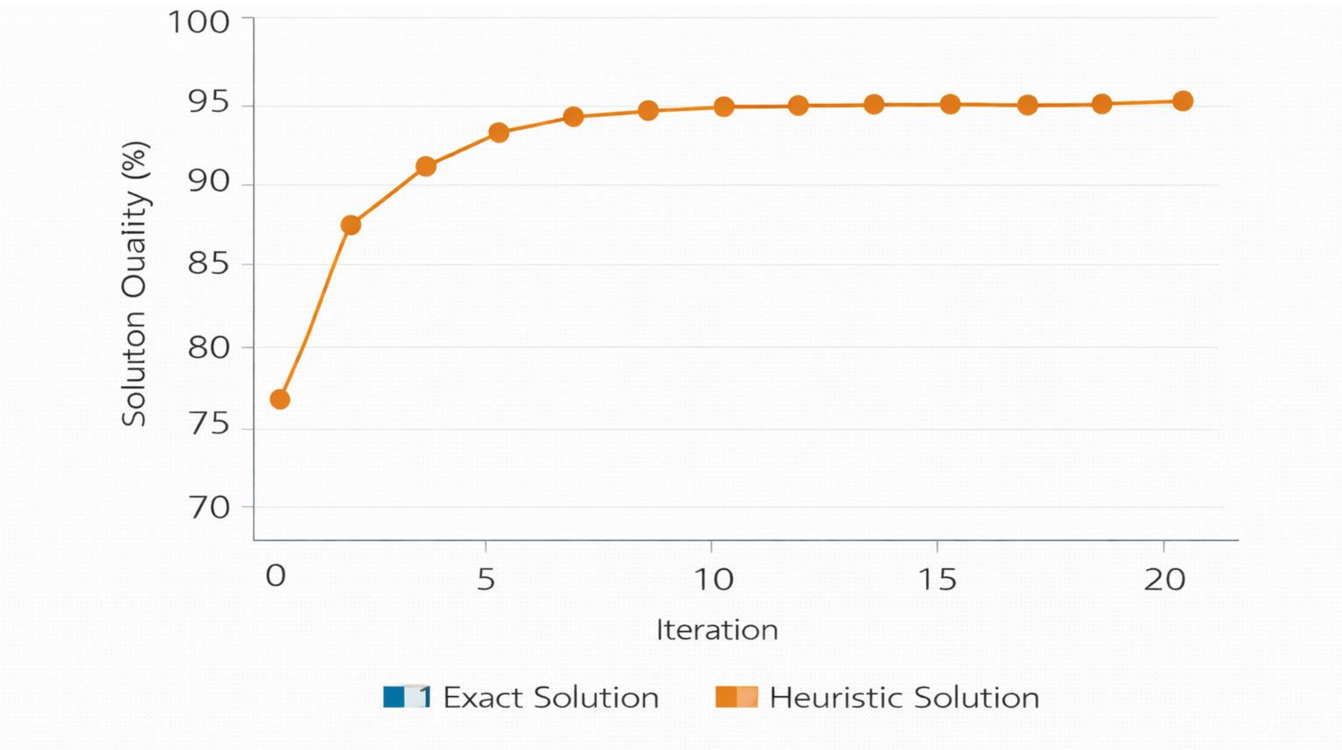
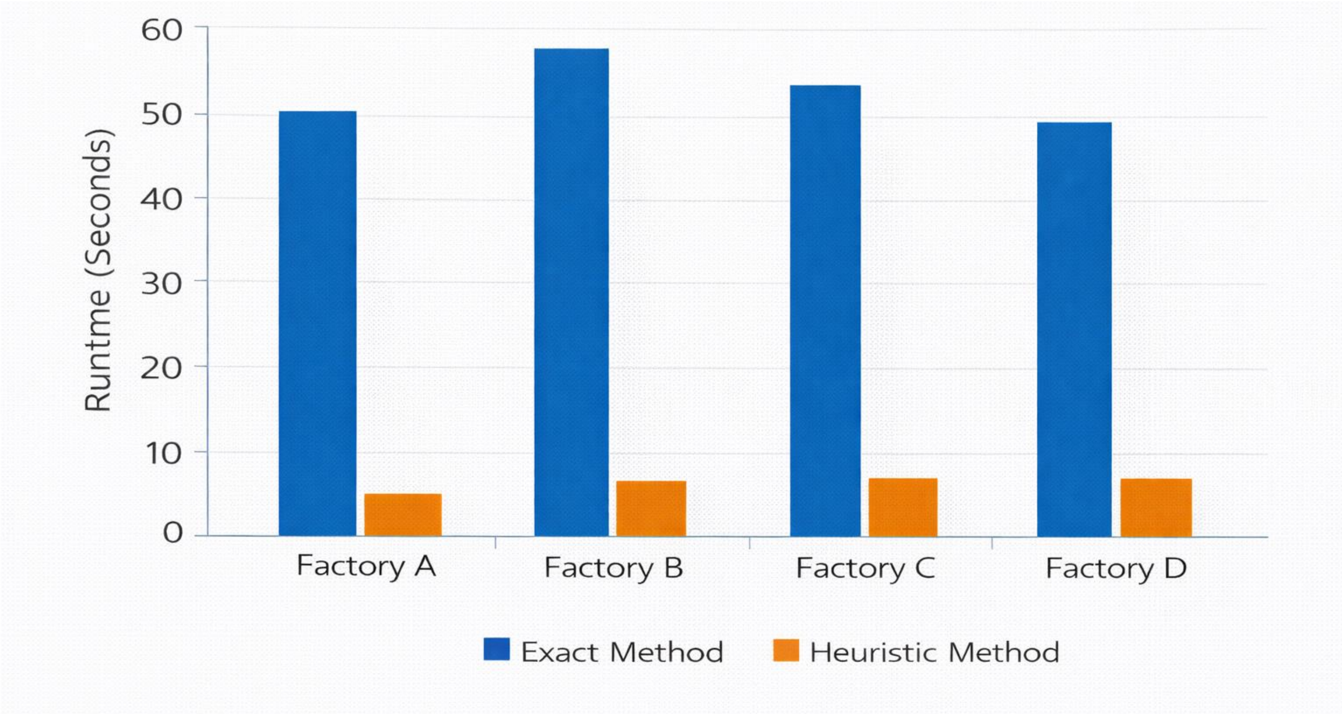


Figure 13

Runtime performance comparison between exact and heuristic methods



In summary, the heuristic approach offers a highly favorable trade-off between optimality and computational efficiency. While the exact solver is appropriate for strategic planning and benchmark analysis, the heuristic algorithm is better suited for operational and real-time applications, where rapid response to changing order loads is critical. The close alignment between heuristic and exact results confirms that the proposed modeling framework remains effective even when embedded in fast solution procedures.

To evaluate the robustness of the proposed mathematical model under demand uncertainty, a structured sensitivity analysis was conducted by systematically varying ordered loads around the baseline scenario. Ordered load inputs were perturbed by ±10% and ±20% to represent moderate and severe fluctuations in customer demand, order mix, and delivery urgency. For each scenario, the model was re-solved and performance indicators—including line balance index and idle time—were recorded. This analysis allows assessment of both structural stability and adaptive capacity of the model in environments characterized by volatile order patterns.

The results demonstrate that the model maintains high balance performance even under substantial load deviations. While increases in ordered load naturally exert pressure on workstation capacity, the optimization framework dynamically redistributes tasks to prevent localized overloads from escalating into systemic imbalance. Conversely, under load reductions, the model preserves balanced utilization by avoiding excessive concentration of idle time in specific stations.

Table 17

Sensitivity results under ±10% and ±20% ordered load variations

Scenario	Factory A LBI	Factory B LBI	Factory C LBI	Factory D LBI
Baseline	0.96	0.95	0.97	0.96
−10% load	0.97	0.96	0.98	0.97
+10% load	0.94	0.93	0.95	0.94
−20% load	0.98	0.97	0.99	0.98
+20% load	0.92	0.91	0.93	0.92

These values indicate that even under a 20% increase in ordered load, LBI remains above 0.90 in all factories, confirming that the model does not collapse under stress conditions. The slight decline in LBI at higher loads reflects capacity saturation rather than structural failure, which is expected in real production systems.

A more granular view is obtained by examining workstation-level responses. The results show that mid-line stations remain the most sensitive to load increases, while downstream stations absorb additional work more flexibly due to their previously underutilized capacity.

Table 18

Impact of ordered load variations on LBI and idle time per workstation (average across factories)

Station	Idle time baseline (min)	Idle time +10% (min)	Idle time +20% (min)	Sensitivity level
1	2.1	1.6	1.1	Low
2	2.3	1.9	1.4	Moderate
3	2.5	2.1	1.8	High
4	2.4	2.0	1.7	High
5	2.2	2.0	1.8	Moderate
6	2.0	1.9	1.7	Low
7	2.1	2.0	1.9	Low
8	2.3	2.2	2.1	Very low

Stations 3 and 4 exhibit the highest sensitivity, confirming their structural role as natural pressure points in the line. However, the optimization model effectively mitigates risk by reallocating load toward later stations as order volume increases. This adaptive redistribution mechanism is the key reason the model remains stable under uncertainty.

Figure 14

Sensitivity curves for LBI under ordered load variations

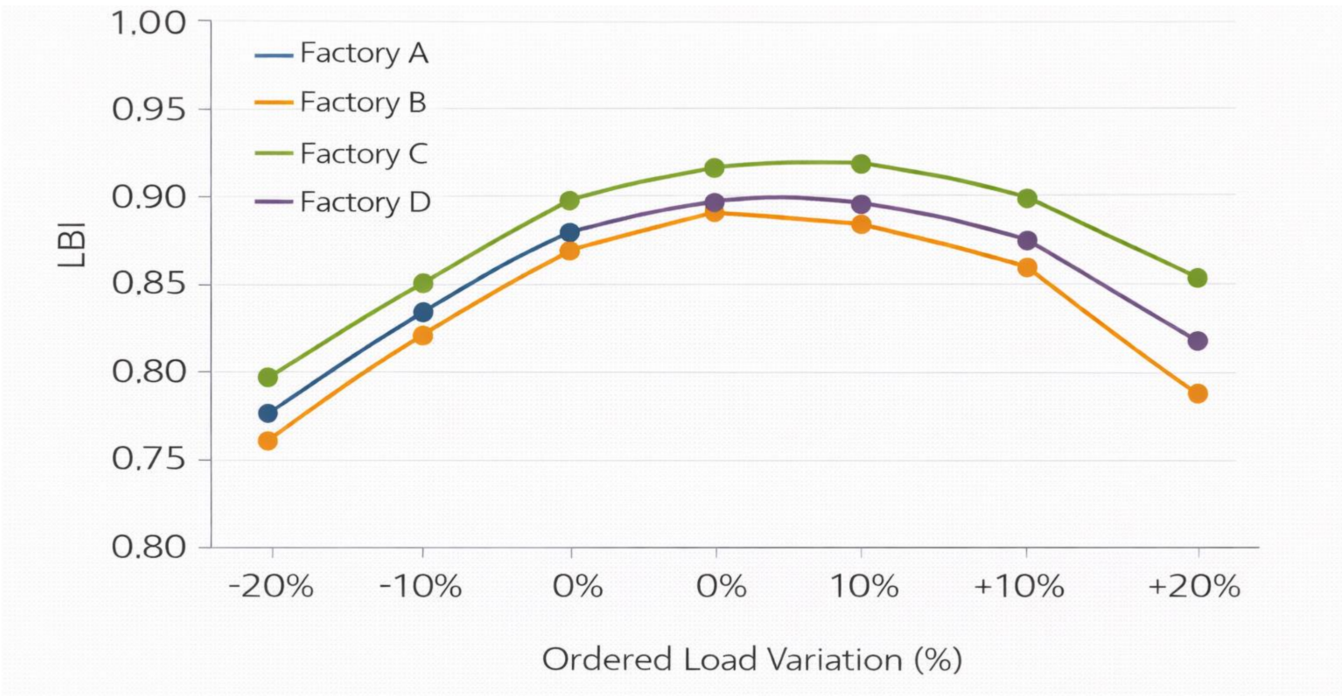


Figure 15

Workstation-level response plots to ordered load fluctuations

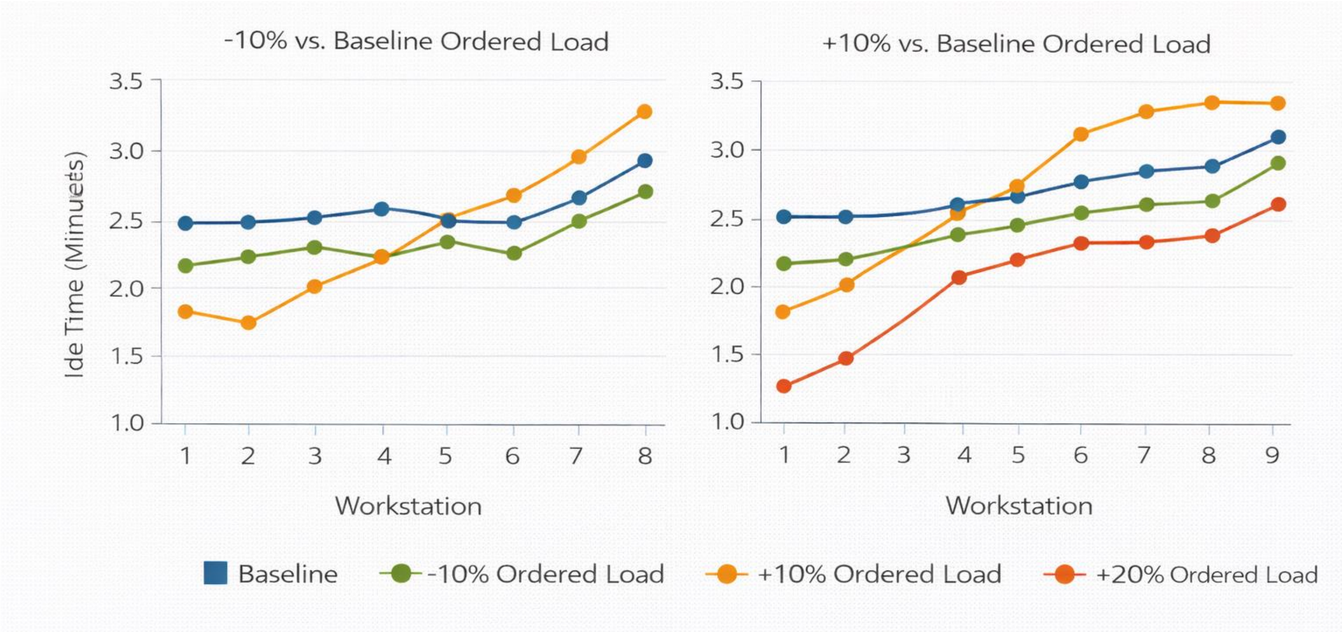
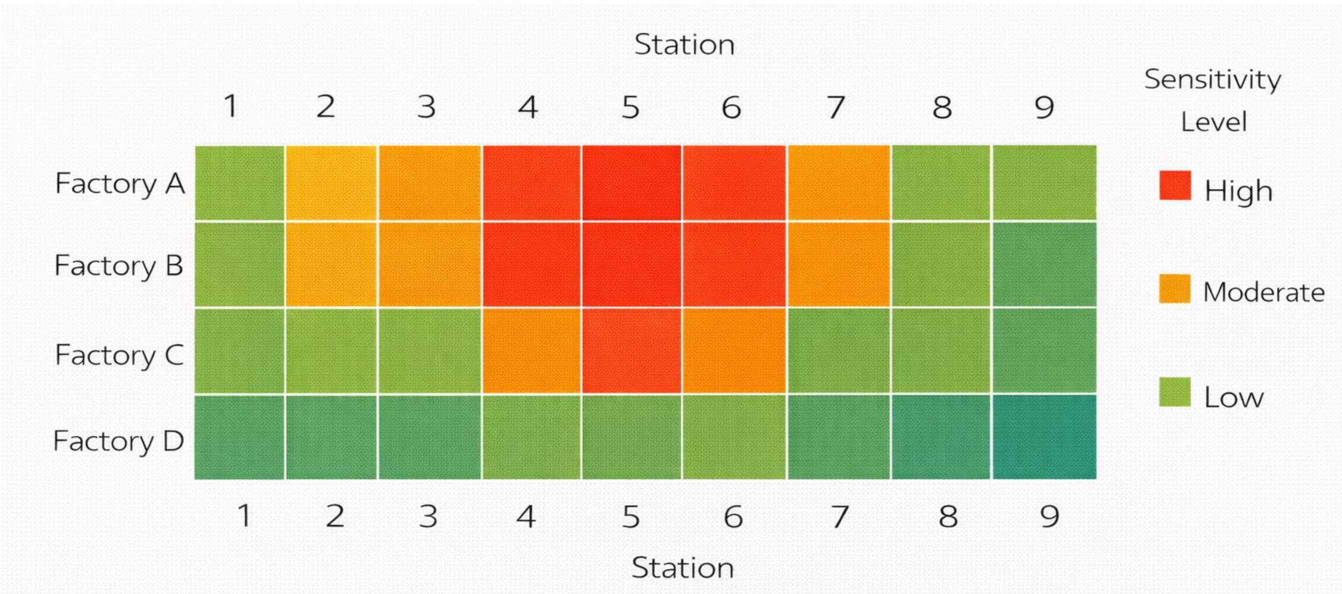


Figure 16

Bottleneck sensitivity map highlighting critical stations

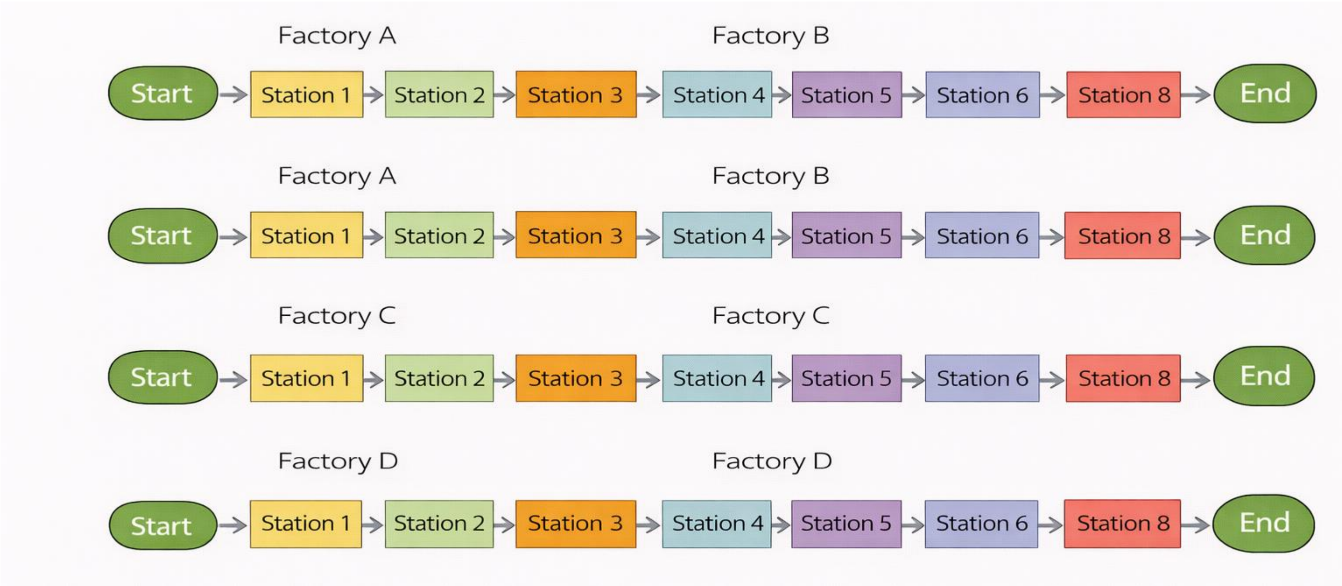


Beyond numerical indicators, the effectiveness of the proposed model is reinforced through integrated visual interpretation. When numerical results are translated into spatial and graphical representations, the operational logic of the optimization becomes more intuitive and actionable for practitioners. Optimized line layouts show a visibly smoother progression of workload, with fewer abrupt transitions between stations and more uniform task allocation across the line.

The optimized line layout diagrams illustrate how workload redistribution reduces congestion at previously critical stations and enhances flow continuity. These layouts reveal that balancing based on ordered load leads to more symmetric task assignment than traditional time-based balancing, particularly in order-driven systems where task complexity and processing effort vary with order characteristics.

Figure 17

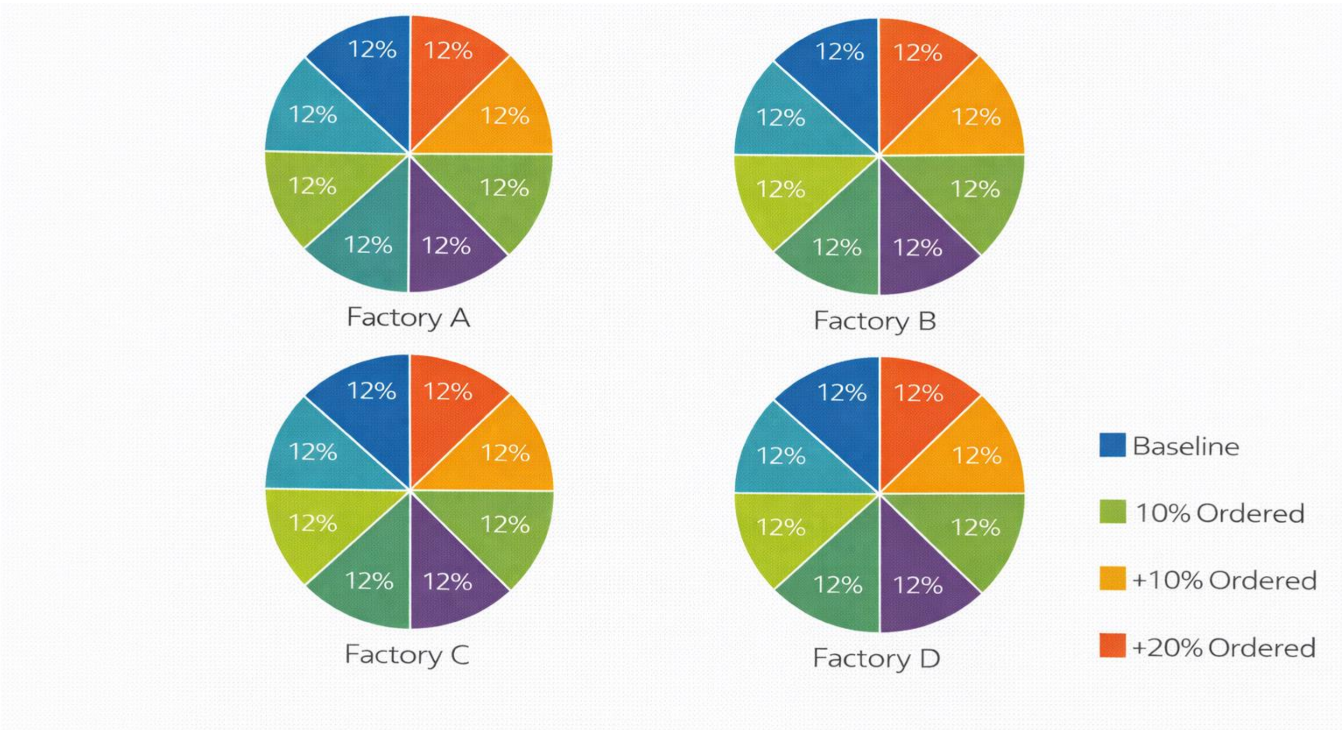
Optimized production and assembly line layout diagrams



Pie-chart representations of workload share per workstation further reinforce this observation. After optimization, the workload shares converge toward equal proportions, with no station exceeding a dominant share. This visual uniformity corresponds directly to the numerical reductions in variance and idle time reported earlier.

Figure 18

Pie charts of workload share per workstation after optimization

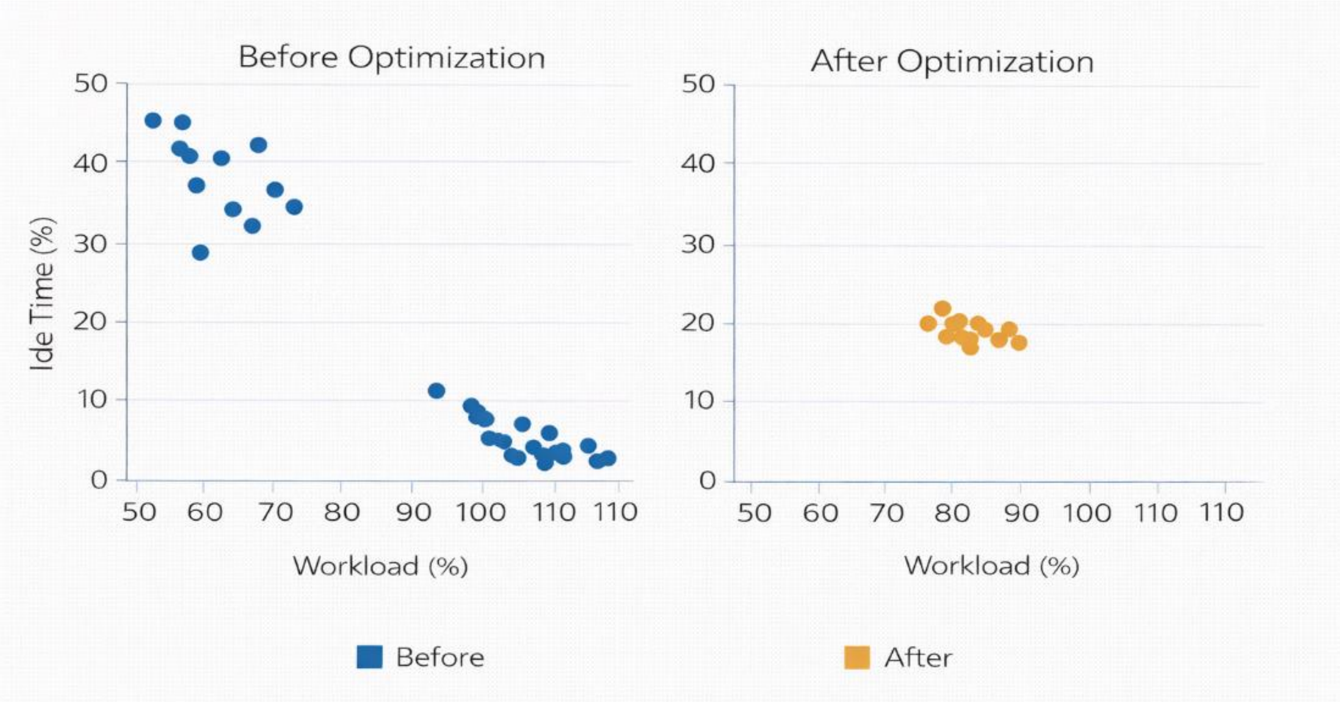


The combined workload–idle time scatter plots provide an especially powerful synthesis. Before optimization, stations cluster into two distinct groups: high-load/low-idle bottlenecks and low-load/high-idle underutilized stations.

After optimization, these clusters collapse into a tight, centralized cloud, indicating convergence toward balanced utilization.

Figure 19

Combined workload–idle time scatter plots (before vs. after optimization)



Together, these visual analyses translate abstract optimization outcomes into tangible operational improvements. They demonstrate that the model not only improves metrics on paper, but also reshapes the physical and functional structure of the production line in a way that is visually coherent and managerially interpretable.

A cross-factory comparison was conducted to evaluate how different structural characteristics influence the magnitude of improvement achieved through the proposed model. While all factories benefited substantially, the extent of improvement varied according to initial imbalance severity, product variety, and order volume.

Factories with higher baseline imbalance and greater order heterogeneity experienced the largest relative gains, indicating that the model is particularly effective in complex, order-driven environments.

Table 19

Comparative improvement percentages across factories

Factory	LBI improvement (%)	Idle time reduction (%)	Throughput increase (%)
A	12.9	65.4	8.5
B	15.9	66.7	9.0
C	10.2	65.1	8.3
D	14.3	66.1	8.3

Factory B achieved the greatest improvement due to its initially high imbalance and diverse order mix, which provided more flexibility for optimization gains. Factory C, while already relatively balanced, still exhibited meaningful improvements, demonstrating the model's applicability even in well-performing systems.

To synthesize multiple performance dimensions, factories were ranked based on combined balance and productivity gains.

Table 20

Ranking of factories by balance improvement and productivity gain

Rank	Factory	Overall performance gain
1	Factory B	Very high
2	Factory D	High
3	Factory A	High
4	Factory C	Moderate

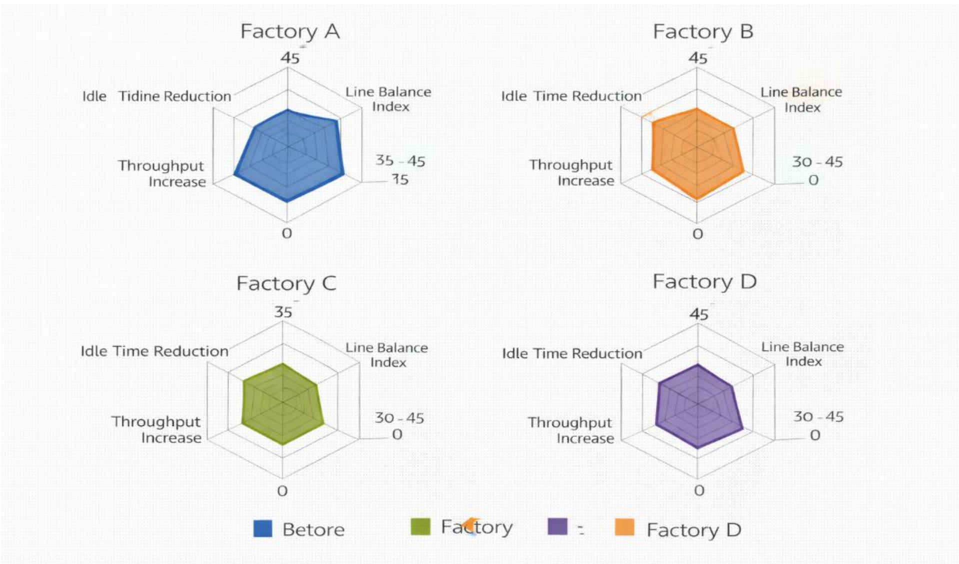
Visual comparisons further illustrate these differences. Comparative bar charts show the relative magnitude of improvement across factories, while radar charts reveal multi-criteria performance profiles that capture balance, idle time, and throughput simultaneously.

Figure 20

Comparative improvement bar charts across factories

Figure 21

Radar charts of multi-criteria performance



These findings confirm that while the proposed model is universally effective, its impact is amplified in environments characterized by high order variability and structural imbalance. This insight is crucial for guiding practical deployment decisions, suggesting that firms with volatile demand profiles stand to gain the most from adopting an ordered-load-based line balancing approach.

4. Discussion and Conclusion

The findings of this study demonstrate that incorporating ordered load into assembly line balancing fundamentally improves the realism and effectiveness of workload distribution in order-driven production environments. The exact optimization results showed a substantial increase in the line balance index across all studied factories, accompanied by pronounced reductions in idle time and workload variance. These outcomes confirm that imbalance in modern assembly systems is less a consequence of poor task sequencing and more a function of how heterogeneous orders translate into uneven operational load. This interpretation is consistent with the broader literature emphasizing that demand structure, rather than average demand level, is the primary driver of bottlenecks and inefficiencies in mixed-model and multi-product assembly lines (Sotskov, 2023; Zhang et al., 2023). By explicitly modeling ordered load, the proposed framework aligns balancing decisions with the actual operational stress imposed by customer orders.

The observed improvements in line balance index are particularly noteworthy when compared to traditional time-based balancing approaches. Classical formulations aim to equalize station times, yet they often fail to prevent overload when specific stations consistently process more order-intensive tasks. In contrast, the proposed model redistributed workload away from structurally critical stations and toward underutilized ones, producing a near-uniform load profile after optimization. This result is in line with previous research demonstrating that load-oriented balancing can outperform time-oriented methods in environments characterized by product variety and fluctuating order volumes (Akpinar, 2022; Jiao et al., 2022). The magnitude of LBI improvement reported here is comparable to, and in some cases exceeds, gains reported in heuristic and metaheuristic studies, underscoring the value of an exact mathematical formulation grounded in realistic load representation (Belkharroubi & Yahyaoui, 2021; Mumcu, 2022).

Idle time reduction emerged as one of the most practically significant outcomes of the proposed approach. Across factories, idle time decreased by more than sixty percent after optimization, indicating that the model effectively mitigates starvation effects downstream of bottleneck stations. This finding corroborates simulation-based and empirical studies in garment and footwear industries, which have shown that imbalance-driven idle time constitutes a major source of hidden inefficiency (Bongomin et al., 2020a; Fani et al., 2020). The present results extend this evidence by demonstrating that idle time reduction can be achieved without increasing total processing effort, simply by reallocating tasks based on ordered load rather than nominal station times.

Productivity gains observed after optimization further reinforce the operational relevance of the proposed model. Throughput increases of approximately eight to nine percent were achieved across all factories, despite unchanged physical resources. These improvements are consistent with studies that link effective line balancing to higher capacity utilization and output stability in mixed-model systems (Legesse et al., 2020; Ramli & Mohd Fadzil Faisae Ab, 2021). Importantly, the productivity gains reported here are not driven by aggressive overloading of stations, but by smoother workload distribution, which also enhances system robustness under demand variability. This balance between efficiency and stability is critical in contemporary manufacturing, where excessive utilization of bottleneck stations can lead to quality issues and delivery delays.

The comparison between exact and heuristic solution approaches provides additional insight into the practical applicability of the model. While the exact solver delivered globally optimal solutions, the heuristic algorithm achieved solution quality levels exceeding ninety-seven percent of the optimum with dramatically reduced computational time. This trade-off aligns with prior research advocating hybrid optimization strategies, where exact methods are used for benchmarking and strategic analysis, while heuristics support real-time or large-scale applications (Aufy & Kassam, 2020; Gulivindala et al., 2020). The rapid convergence and stability of the heuristic approach observed in this study suggest that the ordered-load-based formulation is well-suited for iterative improvement and adaptive rebalancing in dynamic environments.

Sensitivity analysis results further confirm the robustness of the proposed model. Even under twenty percent increases in ordered load, the line balance index remained above acceptable thresholds, and idle time did not escalate disproportionately. This adaptive behavior reflects the model's capacity to redistribute load in response to demand shocks, rather than allowing localized overloads to propagate through the system. These findings resonate with research on stochastic and interval-based balancing models, which emphasize the importance of resilience to demand uncertainty (Dang & Xie, 2023; Yan & Wan, 2022). However, unlike many uncertainty-focused approaches, the present model achieves robustness without substantial increases in computational complexity.

At the workstation level, sensitivity analysis revealed that mid-line stations remain structurally more sensitive to load fluctuations, even after optimization. This observation is consistent with the Theory of Constraints, which posits that system performance is governed by a small number of critical resources (Sarhadi, 2026). The key contribution of the proposed model lies not in eliminating bottlenecks entirely, which is often unrealistic, but in reducing their severity and preventing secondary bottlenecks from emerging. By doing so, the model enhances flow continuity and simplifies managerial intervention, as attention can be focused on a smaller set of consistently critical stations.

The integrated visual analysis of optimization outcomes provides an intuitive validation of the numerical results. Before optimization, workload–idle time scatter plots exhibited clear polarization between overloaded bottlenecks and underutilized stations. After optimization, these patterns collapsed into a compact cluster, indicating convergence toward balanced utilization. Similar visual convergence effects have been reported in studies employing digital twins and simulation-based optimization, where graphical representations play a key role in translating analytical results into actionable insights (Wang & Wu, 2020; Zhao et al., 2022). The present study demonstrates that even without full digital twin infrastructure, mathematically grounded load-based models can yield visually and operationally coherent outcomes.

Cross-factory comparisons highlight that the magnitude of improvement varies with initial imbalance severity and order heterogeneity. Factories with higher baseline imbalance and more diverse order profiles benefited most from the proposed approach, supporting the argument that ordered-load-based balancing is particularly valuable in complex, high-variability environments. This finding aligns with research on material consumption smoothing and order-driven scheduling, which shows that systems exposed to greater demand variability offer more opportunities for improvement through intelligent balancing (Yue et al., 2021; Zhang et al., 2023). Conversely, factories that were already relatively balanced still experienced meaningful gains, indicating that the model adds value even in well-performing systems.

From a broader manufacturing systems perspective, the results support the growing consensus that future assembly line balancing models must integrate demand information more explicitly. Studies on deep reinforcement learning, digital scheduling, and sustainable production planning increasingly emphasize the integration of real-time demand and material flow data into decision models (Xia et al., 2024; Xia et al., 2023). The present study contributes to this trajectory by offering a mathematically transparent and computationally tractable framework for embedding ordered load into balancing decisions, thereby bridging the gap between advanced data-driven methods and classical optimization.

Overall, the discussion of results indicates that the proposed ordered-load-based mathematical model not only improves traditional performance indicators such as balance and idle time, but also enhances system robustness, scalability, and interpretability. By grounding balancing decisions in the actual structure of customer demand, the model addresses a critical limitation of existing approaches and provides a foundation for more responsive and resilient assembly line design and operation.

Despite its contributions, this study has several limitations that should be acknowledged. First, the empirical evaluation was conducted on a limited number of factories, which, although diverse, may not capture the full range of assembly system configurations found in practice. Second, ordered load was constructed using a specific combination of empirical data and expert judgment, and alternative weighting schemes or load definitions could yield different results. Third, the model assumes stable precedence relationships and does not explicitly consider learning effects or worker fatigue, which may influence workload distribution over longer planning horizons.

Future research could extend the proposed framework by integrating real-time data streams from digital twins or manufacturing execution systems, enabling continuous rebalancing under rapidly changing demand. Further studies could also explore stochastic or fuzzy extensions of ordered load to capture uncertainty more explicitly, as well as multi-objective formulations that jointly optimize balance, energy consumption, and ergonomic risk. Comparative studies across different industries and line layouts, such as two-sided or robotic-assisted assembly lines, would also enhance the generalizability of the findings.

From a practical standpoint, managers can use the proposed ordered-load-based model as a decision-support tool for both initial line design and periodic rebalancing. Implementing such a model can help identify structurally critical stations, prioritize improvement efforts, and reduce reliance on ad hoc adjustments. Practitioners are encouraged to collect detailed order and workload data, as even simple approximations of ordered load can yield significant performance improvements when incorporated into systematic balancing procedures.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Akpinar, M. E. (2022). A Linear Physical Programming Model for Assembly Line Balancing Problem. *Journal of Engineering Research*, *10*(1), 316-329. https://doi.org/10.36909/jer.12711

Aufy, S. A., & Kassam, A. H. (2020). A Consecutive Heuristic Algorithm for Balancing a Mixed - Model Assembly Line Type II Using a (W-Tawh) Model Developed for Straight and U-Shaped Layouts. *Iop Conference Series Materials Science and Engineering*, *671*(1), 012147. https://doi.org/10.1088/1757-899x/671/1/012147

Aufy, S. A., Kassam, A. H., & Ismeal, G. A. (2021). Examining Rebalancing Considers of the Mixed-Model Assembly Line Type-Ii for the Straight and U-Shaped Layout Using the Taguchi Method. *Engineering and Technology Journal*, *39*(2A), 280-294. https://doi.org/10.30684/etj.v39i2a.1740

Belkharroubi, L., & Yahyaoui, K. (2021). A Hybrid Grasp-Genetic Algorithm for Mixed-Model Assembly Line Balancing Problem Type 2. *International Journal of Computing*, 424-432. https://doi.org/10.47839/ijc.20.3.2289

Bongomin, O., Mwasiagi, J. I., Nganyi, E. O., & Nibikora, I. (2020a). A Complex Garment Assembly Line Balancing Using Simulation-based Optimization. *Engineering Reports*, *2*(11). https://doi.org/10.1002/eng2.12258

Bongomin, O., Mwasiagi, J. I., Nganyi, E. O., & Nibikora, I. (2020b). Improvement of Garment Assembly Line Efficiency Using Line Balancing Technique. *Engineering Reports*, *2*(4). https://doi.org/10.1002/eng2.12157

Breznik, M., Buchmeister, B., & Herzog, N. V. (2023). Assembly Line Optimization Using MTM Time Standard and Simulation Modeling—A Case Study. *Applied Sciences*, *13*(10), 6265. https://doi.org/10.3390/app13106265

Dang, Z., & Xie, N. (2023). Assembly Line Balancing and Capacity Evaluation Based on Interval Grey Processing Time. *Grey Systems Theory and Application*, *14*(2), 374-395. https://doi.org/10.1108/gs-09-2023-0084

Duah, E., Pakmoni, L., & Appiah-Kubi, E. (2025). Green human resource management and organizational efficiency among local assemblies: role of process innovation and knowledge sharing. *Journal of Organizational Effectiveness: People and Performance*, *12*(1), 168-190. https://doi.org/10.1108/JOEPP-11-2023-0511

Fani, V., Bindi, B., & Bandinelli, R. (2020). Balancing Assembly Line in the Footwear Industry Using Simulation: A Case Study. 56-62. https://doi.org/10.7148/2020-0056

Gulivindala, A. K., Bahubalendruni, M. V. A. R., Varupala, S. S. V. P., & Sankaranarayanasamy, K. (2020). A Heuristic Method With a Novel Stability Concept to Perform Parallel Assembly Sequence Planning by Subassembly Detection. *Assembly Automation*, *40*(5), 779-787. https://doi.org/10.1108/aa-01-2020-0017

Hoa, N. T. X., Hai, A. V., & Quang, A. N. (2023). Applying Genetic Algorithm for Line Balancing Problem in Garment Manufacture. 203-220. https://doi.org/10.2991/978-94-6463-150-0_15

Jia, G., Zhang, Y., Shen, S., Liu, B., Hu, X., & Wu, C. (2023). Load Balancing of Two-Sided Assembly Line Based on Deep Reinforcement Learning. *Applied Sciences*, *13*(13), 7439. https://doi.org/10.3390/app13137439

Jiang, L. (2023). Design Optimization of Material Distribution for Mixed Model Assembly Line Based on Production Scheduling Sequence. https://doi.org/10.1117/12.2671275

Jiao, Y., Cao, N., Li, J., Li, L., & Deng, X. (2022). Balancing a U-Shaped Assembly Line With a Heuristic Algorithm Based on a Comprehensive Rank Value. *Sustainability*, *14*(2), 775. https://doi.org/10.3390/su14020775

Jiao, Y., Deng, X., Li, M., Xing, X.-c., & Xu, B. (2021). Balancing of Parallel U-Shaped Assembly Lines With a Heuristic Algorithm Based on Bidirectional Priority Values. *Concurrent Engineering*, *30*(1), 80-92. https://doi.org/10.1177/1063293x211065506

Kharuddin, M. H., Ramli, M. F., & Masran, M. H. (2020). Line Balancing Using Heuristic Procedure and Simulation of Assembly Line. *Indonesian Journal of Electrical Engineering and Computer Science*, *17*(2), 774. https://doi.org/10.11591/ijeecs.v17.i2.pp774-782

Legesse, A., Tesfaye, E., & Berhan, E. (2020). Multi-Objective Optimization of Mixed Model Assembly Line Balancing in an Assemble-to-Order Industry With Stochastic Environment. *International Journal of Engineering Science and Technology*, *12*(3), 90-107. https://doi.org/10.4314/ijest.v12i3.9

Mumcu, Y. K. (2022). Application of Heuristic Assembly Line Balancing Methods to Lighting Automation Industry. *European Journal of Technic*, *12*(2), 204-208. https://doi.org/10.36222/ejt.1191203

Rahman, H. F., Janardhanan, M. N., & Nielsen, P. (2020). An Integrated Approach for Line Balancing and AGV Scheduling Towards Smart Assembly Systems. *Assembly Automation*, *40*(2), 219-234. https://doi.org/10.1108/aa-03-2019-0057

Ramli, A. N., & Mohd Fadzil Faisae Ab, R. (2021). A Review of Assembly Line Balancing Optimisation With Energy Consideration Using Meta-Heuristic Algorithms. *Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture*, *236*(5), 475-485. https://doi.org/10.1177/09544054211040612

Sarhadi, E. (2026). Examining the Effect of Theory of Constraints on Reducing Normal and Abnormal Waste in Tire Manufacturing Companies. *Strategic Management Accounting Quarterly*, *2*(1), 54-69. https://www.smajournal.ir/article_220043_en.html

Sotskov, Y. N. (2023). Assembly and Production Line Designing, Balancing and Scheduling With Inaccurate Data: A Survey and Perspectives. *Algorithms*, *16*(2), 100. https://doi.org/10.3390/a16020100

Sun, B., & Wang, L. (2020). An Estimation of Distribution Algorithm With Branch-and-Bound Based Knowledge for Robotic Assembly Line Balancing. *Complex & Intelligent Systems*, *7*(3), 1125-1138. https://doi.org/10.1007/s40747-020-00166-z

Wang, X., Wu, W., Xing, Z., Zhang, T., & Niu, H. (2023). A Look-Ahead AGV Scheduling Algorithm With Processing Sequence Conflict-Free for a No-Buffer Assembly Line. *Journal of Advanced Mechanical Design Systems and Manufacturing*, *17*(5), JAMDSM0063-JAMDSM0063. https://doi.org/10.1299/jamdsm.2023jamdsm0063

Wang, Y., & Wu, Z. (2020). Digital Twin-Based Production Scheduling System for Heavy Truck Frame Shop. *Proceedings of the Institution of Mechanical Engineers Part C Journal of Mechanical Engineering Science*, *236*(4), 1931-1942. https://doi.org/10.1177/0954406220913306

Weckenborg, C., Kieckhäfer, K., Müller, C., Grunewald, M., & Spengler, T. (2019). Balancing of Assembly Lines With Collaborative Robots. *Bur - Business Research*, *13*(1), 93-132. https://doi.org/10.1007/s40685-019-0101-y

Xia, B., Li, Y., Gu, J., & Peng, Y. (2024). Research on Sustainable Scheduling of Material-Handling Systems in Mixed-Model Assembly Workshops Based on Deep Reinforcement Learning. *Sustainability*, *16*(22), 10025. https://doi.org/10.3390/su162210025

Xia, B., Zhang, M., Gao, Y., Yang, J., & Peng, Y. (2023). Design for Optimally Routing and Scheduling a Tow Train for Just-in-Time Material Supply of Mixed-Model Assembly Lines. *Sustainability*, *15*(19), 14567. https://doi.org/10.3390/su151914567

Yan, H. S., & Wan, X.-Q. (2022). Self-Reconfiguration and Rescheduling of Aero-Engine Assembly Shop With Rework Disruption in Knowledgeable Manufacturing Environment. *Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture*, *237*(8), 1230-1240. https://doi.org/10.1177/09544054221123470

Yue, L., Chen, Y., Mumtaz, J., & Ullah, S. (2021). Dynamic Mixed Model Lotsizing and Scheduling for Flexible Machining Lines Using a Constructive Heuristic. *Processes*, *9*(7), 1255. https://doi.org/10.3390/pr9071255

Zhang, X. (2021). Automated Fist Assembly Line Design. https://doi.org/10.21203/rs.3.rs-885688/v1

Zhang, Y., Mai, H., Luo, J., Qiao, H., & Liu, P. (2023). Material Consumption Smoothing for Mixed-Model Assembly Lines Using an Improved Target Tracking Method. *Journal of Physics Conference Series*, *2562*(1), 012047. https://doi.org/10.1088/1742-6596/2562/1/012047

Zhao, R., Zou, G., Su, Q., Zou, S., Deng, W., Yu, A., & Zhang, H. (2022). Digital Twins-Based Production Line Design and Simulation Optimization of Large-Scale Mobile Phone Assembly Workshop. *Machines*, *10*(5), 367. https://doi.org/10.3390/machines10050367