OPTIMIZING WORKFORCE UTILIZATION AND LINE BALANCING IN SME TIE-DYE PRODUCTION: AN MPL-WP AND MPL-NWP MODELING APPROACH

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Received : April 2, 2025
Revised : July 26, 2025
Accepted : August 27, 2025

Abstract

This study proposed a mathematical model to optimize workforce utilization in Small and Medium-sized Enterprises (SMEs) operating multiple tie-dye production lines involving a total of 10 distinct jobs with processing times ranging from 15 to 60 minutes. Two assignment strategies were developed and compared: the Multiple Production Line with Worker Pool (MPL-WP) model, allowing workers to be flexibly assigned across production lines, and the Multiple Production Line without Worker Pool (MPL-NWP) model, restricting workers to specific lines. The models were formulated as binary integer programming problems incorporating processing time constraints, precedence relations, and takt time to ensure feasible production schedules. Using the Python-MIP optimization package, various scenarios with differing production demands and available times were solved to analyze the relationship among these factors and the required workforce size. Results were indicated that the MPL-WP model generally reduced the total number of workers needed by up to 25% compared to the MPL-NWP model, particularly under high-demand or time-constrained conditions. This has highlighted the operational benefits of worker flexibility in improving labor efficiency and reducing costs. Moreover, the findings were provided actionable insights for SMEs seeking to enhance productivity despite limited resources and fluctuating demands, reinforcing the practicality and relevance of flexible assignment models in real-world production planning.

Keywords: Assignment model, Binary integer programming, SME, Tie-dye production, Workforce optimization

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Introduction

In the vibrant world of Small and Medium-sized Enterprises (SMEs), particularly those involved in the textile industry, efficiency and resource utilization are paramount. This paper introduces a mathematical model that addresses these challenges through a job assignment approach, specifically designed for two similar production lines involved in the coloring process of tie-dye. The products of this SME are categorized into two color series: the multi-color series and the Signature Blue series, as shown in Figure 1.

(a) (b)

Figure 1 (a) Signature Blue series, (b) Multi-color series

To produce a tie-dye shirt in both series, the process begins with the tying of the fabric, a crucial step that determines the pattern and design of the final product. The fabric is tied in a specific manner to achieve a square pattern, a popular design in tie-dye textiles. Next, the dye is prepared. For the multi-color series, a mixture of blue, orange, yellow, and purple dyes is used—each in equal proportions (1 unit each)—to create a vibrant and balanced color palette. For the Signature Blue series, a single blue dye is used, resulting in a monochromatic yet striking design. The mixed dye is then injected into the fabric. This step requires precision and care to ensure that the dye penetrates the fabric evenly while maintaining the integrity of the square pattern. Finally, the tie-dye tools are removed, and the fabric is hung to dry. This step allows the dye to set and the pattern to emerge clearly.

Throughout this process, workers play a central role in each stage. From fabric tying and dye preparation to injection and drying, these tasks are performed manually and require skill, timing, and attention to detail. Any inefficiency in task allocation—such as assigning too many jobs to one worker or leaving others underutilized—can lead to production delays, reduced quality, and unnecessary labor costs. This is especially problematic for SMEs, where the workforce is limited and demand may vary across products. As such, effective worker assignment is not just a matter of efficiency—it is critical for the viability and sustainability of operations. Given these challenges, the development of an optimization model becomes essential. This study proposes mathematical models that minimize the number of workers required while ensuring all production tasks are completed accurately and on time. The models are structured to address key constraints such as takt time, task precedence, and job completeness. The uniqueness of our models lies in their adaptability to handle the complexities introduced by variations in pattern and color in the tie-dye process, despite the shirts undergoing the same set of production steps.

The assignment problem has been widely studied across various industries, evolving from classical models focused on minimizing cost or maximizing efficiency in task assignments (Silva et al., 2021; Zain & Akbar, 2022). Studies have expanded to address more complex scenarios such as the Balanced and Unbalanced Assignment Problems, where the number of tasks and agents differs (Liu et al., 2023). Further, the Prohibited Assignment Problem (PAP), which restricts certain assignments, has been explored to reflect real-world constraints in industries requiring flexible planning (Ibrahim et al., 2024; Song & Cheng, 2022). Similarly, the Bottleneck Assignment Problem (BAP) minimizes the maximum cost in an assignment, offering solutions for industries sensitive to production delays or bottlenecks (Michael et al., 2022).

The Quadratic Assignment Problem (QAP), known for its application in facility layouts and manufacturing plant designs, has been recognized as NP-hard, with extensive research dedicated to its complexity and solution methods (Misevičius et al., 2024). The Generalized Assignment Problem (GAP) extends these principles by allowing agents to handle multiple tasks within capacity constraints, which is highly relevant to SMEs managing diverse production demands (Baldé et al., 2021). Multi-objective approaches further refine the assignment problem by balancing criteria such as cost, time, and worker satisfaction, as demonstrated in fuzzy and stochastic models (Beaula & Saravanan, 2022; Ulutaş et al., 2023). The incorporation of these models into transportation and routing problems, such as the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP), has expanded their applications to logistics and production scheduling (Alanzi & Menai, 2025; Bogyrbayeva et al., 2022). Additionally, the Air

Crew Assignment Problem showcases practical use in complex human resource scheduling (Kushwaha & Sen, 2025).

Despite this rich body of research, few studies specifically address the challenges faced by SMEs operating multiple production lines. While studies in scheduling (Pinedo, 2022; Jansen et al., 2022), flexible manufacturing systems (Weckenborg et al., 2024; Bouška et al., 2023), and supply chain management (Kumar et al., 2023; Schoenfelder et al., 2025) offer relevant insights, they often assume large-scale industrial settings. SMEs face distinct constraints, such as limited workforce, product variation, and fluctuating demand, which require specialized models. Recent research emphasizes the importance of sustainability and resource optimization in production systems (Jamwal et al. 2021), aligning with operational strategies discussed in production management (Rajeev et al., 2017).

However, while existing studies on the assignment problem touch on workforce optimization, line balancing, and pooling strategies, they haven't merged these techniques. Moreover, their application to Small and Medium-sized Enterprises (SMEs) or tie-dye production is unaddressed as illustrated in Table 1.

Table 1 The studies about the assignment problem related to this study

Model / Study	Optimization		Pooling Strategies	SME	Tie-dye Production
	Workforce	Line Balancing			
Zain & Akbar (2022)	✓				
Liu et al. (2023)	✓		✓		
Ibrahim et al. (2024)	✓				
Smith & Lee (2022)	✓		✓		
Michael et al. (2022)	✓	✓			
Beaula & Saravanan (2022)	✓				
Kushwaha & Sen (2025)	✓	✓			
Pinedo (2022)	✓	✓			
Jansen et al. (2022)	✓	✓			
Bouška et al. (2023)	✓	✓			
Schoenfelder et al. (2025)	✓		✓		
Proposed Models	✓	✓	✓	✓	✓

Objectives

This study proposes two versions of the model for multiple production lines: one that allows for worker pooling (MPL-WP) and another that does not (MPL-NWP). Implemented using Python-MIP and tested across multiple scenarios of time availability and demand, the models demonstrate how job assignment efficiency can be significantly improved even within the labor and operational limits of SMEs. These models fill this gap by comparing worker pool and non-worker pool strategies to optimize workforce utilization and line balancing in SMEs with multiple tie-dye production lines.

Materials and methods

1. Multiple Production Line with Worker Pool Model (MPL-WP)

This model is designed to minimize the size of the workforce under certain assumptions. These include: the number of workers must be equal to the number of tasks, each worker can be assigned more than one task, and each job must be performed by exactly one worker. The takt time is calculated based on the total demand. This model assumes a single pool of workers, implying that all jobs from all production lines are gathered into one set. In addition, the takt time should not less than the maximum production time of all job from all production line.

Indices

I = Number of job (i = 1, 2, …, N)

Parameter

TT = Takt time

PT_i = Processing time to produce a unit of job i

Pred = Precedence relations between jobs;

Decision variable

x_{ij} = Binary job assignment variable for worker j be assigned to job i

y_j = Binary variable to hire worker j

Objective function

$$MIN = \sum_{j=1}^{M} y_j \tag{1}$$

Constraint

$$\sum_{i=1}^{N} PT_i \times x_{ij} \leq TT \times y_j \qquad \forall\, j \text{ in } J \tag{2}$$

$$\sum_{j}^{N} x_{ij} = 1 \qquad \forall\, i \text{ in } I \tag{3}$$

$$\sum_{j}^{N} x_{sj} \times j \geq \sum_{j}^{N} x_{rj} \times j \qquad \forall\, s, r \text{ in } Pred \tag{4}$$

This model's main goal (1) is to minimize the workforce size, which in turn optimizes the use of resources. This is accomplished by a series of well-structured constraints. The first constraint (2) guarantees that the total processing time for all jobs doesn't surpass the cycle time or 100% utilization of one worker, preventing resource overuse. The second constraint (3) mandates that each job is performed only once, ensuring all tasks are finished within the production cycle. The third constraint (4) follows the predecessor constraint, preserving the order of the production sequence.

2. Multiple Production Line with non-Worker Pool Model (MPL-NWP)

This model is designed to minimize the size of the workforce for each production line under certain assumptions. These include: the number of workers must be equal to the number of tasks, each worker can be assigned more than one task, and each job must be performed by exactly one worker. The takt time is calculated based on the total demand. This model assumes a pool of workers for each production line, implying that jobs from each production line are separated into k distinct sets. In addition, the takt time should not less than the maximum production time of all job from all production line.

Indices

I = Number of job (i = 1, 2, ..., N)

K = Number of production line (i = 1, 2, ..., M)

Parameter

CT^k = Takt time of Production line k

PT_i^k = Processing time to produce a unit of job i of Production line k

$Pred^k$ = Precedence relations between jobs;

Decision variable

x_{ij}^k = Binary assignment variable for worker j be assigned to job i of production line k

y_j^k = Binary variable to hire worker j of production line k

Objective function

$$MIN = \sum_{k=1}^{M}\sum_{j=1}^{N} y_j^k \tag{5}$$

Constraint

$$\sum_{i=1}^{N} PT_i^k \times x_{ij}^k \leq CT^k \times y_j^k \qquad \forall\, j \text{ in } J, k \text{ in } K \tag{6}$$

$$\sum_{j}^{N} x_{ij}^k = 1 \qquad \forall\, i \text{ in } I, k \text{ in } K \tag{7}$$

$$\sum_{j}^{N} x_{sj}^k \times j \geq \sum_{j}^{N} x_{rj}^k \times j \qquad \forall\, s, r \text{ in } Pred^k, k \text{ in } K \tag{8}$$

This model's main goal (5) is to minimize the workforce size of each production line. The first constraint (6) guarantees that the total processing time for all jobs doesn't surpass the cycle time of each production line. The second constraint (7) mandates that each job of each production line is performed only once. The third constraint (8) follows the predecessor constraint, preserving the order of the sequence of each production line

3. Production Line Data

The processing times were obtained through field observations conducted at a small-to-medium-sized enterprise (SME) located in Pathum Thani province, Thailand. This SME specializes in the production of tie-dye fabric products, including both the multi-color series and the signature blue series. As Table 2, the production process for the multi-color and Signature Blue tie-dye series consists of a series of jobs that vary in complexity and processing time. For the multi-color series, the process involves fabric tying, squaring, dye mixing (blue, orange, yellow, and purple), dye injection, and drying, with processing times ranging from 15 to 60 minutes. The Signature Blue series follows a similar process, but with fewer colors, including fabric tying, squaring, dye injection, and drying, with tasks taking between 15 and 50 minutes. Each task has defined successor steps, ensuring the proper sequence of operations across two separate production lines as Figure 2.

Figure 2. Precedence relations, (a) Multi-color series, (b) Signature blue series

Table 2 The information of multi-color and Signature blue production line

No. of job	Job description	Processing time	Successor	No. of Line
1	To tie the fabric (multi-color series)	25	2	1
2	To square pattern tie-dye (multi-color series)	15	3,4	1
3	To mix facbric dye of blue, orange, yellow and purple color (per 1 unit)	60	4	1
4	To inject the mixed dye to the fabric (multi-color series)	40	5	1
5	Remove the tie-dye tools and hang the fabric to dry again (multi-color series)	15	-	1
6	To tie the fabric (Signature blue)	50	7	2
7	To square pattern tie-dye (Signature blue)	30	8,9	2
8	To inject the mixed dye to the fabric (Signature blue)	20	9	2
9	To mix facbric dye of blue color (per 1 unit)	15	10	2
10	Remove the tie-dye tools and hang the fabric to dry again (Signature blue)	30	-	2

4. Scenario Experiments

These 9 scenario experiments were set to vary demand and available time on the worker size that also obtained through observations conducted at the same SME. The scenarios included variations in the demand in range of 100-200 units for Signature Blue and Multi-color products, and the available time in range of 2-6 hours as shown in Table 3. Moreover, the values of takt time are varied based on demand and available time.

Table 3 A summary of the scenario experiments

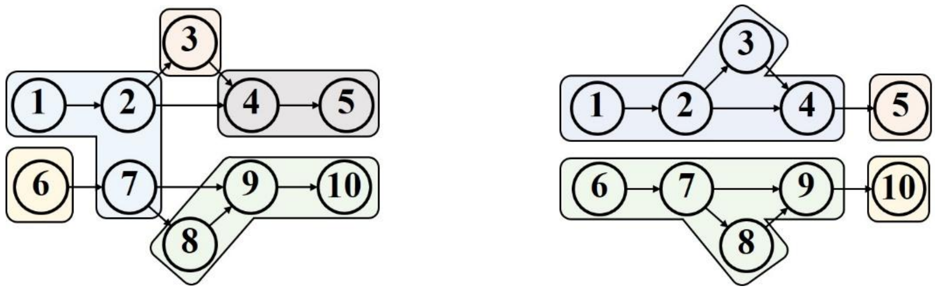
Scenarios	Demand (units)			Available time (Hours)	Takt time (sec)		
	Signature Blue	Multi-color	Total		MPL-WP	MPL-NWP	
						k=1	k=2
1	100	100	200	2	36*	72	72
2	100	100	200	4	72	144	144
3	150	100	250	4	57.6*	96	144
4	200	100	300	4	48*	72	144
5	200	150	350	4	41.14*	72	96
6	100	100	200	6	108	216	216
7	150	100	250	6	86.4	144	216
8	200	100	300	6	72	108	216
9	200	150	350	6	61.71	108	144

*These takt time less than the maximum processing time

Results and discussion

After using Python-MIP to optimize both models with the case study data, the results from the scenario experiments provided valuable insights into the relationship between demand, available time, and required worker size. Table 4 presents the optimal number of workers and their job assignments for Scenarios 2, 6, 7, 8, and 9 under two models: MPL-WP and MPL-NWP. Scenarios 1, 3, 4, and 5 are excluded, as optimal results for the MPL-WP model were not obtained in those cases.

In Scenario 2, the MPL-WP model required 5 workers: Worker A was assigned to Job 6; Worker B to Jobs 1, 2, and 7; Worker C to Job 3; Worker D to Jobs 4 and 5; and Worker E to Jobs 8, 9, and 10 as shown in Figure 3(a). In contrast, the MPL-NWP model achieved a more efficient solution with 4 workers, where Worker A handled Jobs 1 to 4, Worker B took Job 5, Worker C covered Jobs 6 to 9, and Worker D completed Job 10 as shown in Figure 3(b). In Scenario 6, MPL-WP needed 3 workers (A to Jobs 1 and 6–7, B to Jobs 2 and 8–9, and C to Jobs 3–5 and 10), while MPL-NWP used only 2 workers (A to Jobs 1–5 and B to Jobs 6–10). For Scenario 7, MPL-WP used 4 workers: Worker A handled Jobs 1, 6, and 7; Worker B took Jobs 2 and 8; Worker C was assigned Jobs 3 and 9; and Worker D took Jobs 4, 5, and 10. The MPL-NWP model used 3 workers, assigning Worker A to Jobs 1–4, Worker B to Job 5, and Worker C to Jobs 6–10. In Scenario 8, MPL-WP required 5 workers: Workers A to Job 6; B to Jobs 1, 2, and 7; C to Jobs 3 and 8; D to Jobs 4 and 5; and E to Jobs 9 and 10. MPL-NWP needed 3 workers, with Worker A assigned to Jobs 1–3, Worker B to Jobs 4–5, and Worker C to Jobs 6–10. In Scenario 9, MPL-WP required 6 workers and MPL-NWP achieved the solution with 4 workers, showing better efficiency under separate-line constraints.



(a) (b)

Figure 3 Optimal solution of scenario 2 (a) MPL-WP, (b) MPL-NWP

Table 4 Optimal job assignment plans

Sce.	MPL-WP Worker size	No. of job 1	2	3	4	5	6	7	8	9	10	MPL-NWP Worker size	No. of job 1	2	3	4	5	6	7	8	9	10
1												6	A	A	B	C	C	D	E	E	E	F
2	5	B	B	C	D	D	A	B	E	E	E	4	A	A	A	A	B	C	C	C	C	D
3												5	A	A	B	C	C	D	E	E	E	E
4												5	A	A	B	C	C	D	D	D	D	E
5												5	A	A	B	C	C	D	D	E	E	E
6	3	A	B	B	C	C	A	A	B	C	C	2	A	A	A	A	A	B	B	B	B	B
7	4	A	B	B	D	D	A	C	C	C	D	3	A	A	A	A	B	C	C	C	C	C
8	5	B	B	C	D	D	A	B	E	E	E	3	A	A	A	B	B	C	C	C	C	C
9	6	B	B	C	D	D	A	E	E	F	F	4	A	A	A	B	B	C	C	C	C	D

After obtaining the optimal solutions from all scenarios, a comparison of worker size and labor cost was conducted across four levels of total demand: 200, 250, 300, and 350 units, as presented in Tables 5 to 8. Each table shows how different models (MPL-WP and MPL-NWP), available time, and takt time affect the efficiency of workforce utilization and overall labor cost. In addition, the labor cost was calculated based on the new minimum wage rate (July 1, 2025). For Pathum Thani province, the applicable wage rate is 372 Baht per day.

Table 5 compares the optimal worker size and labor cost for a total demand of 200 units under different available time conditions and model applications (MPL-WP and MPL-NWP).

In Case 1, using MPL-WP with only 2 hours available and a takt time of 36 seconds (which is less than the maximum processing time), the model fails to find a feasible solution due to time constraints. Case 2 applies MPL-WP with 4 hours available, requiring 5 workers and resulting in a labor cost of 1,860 Baht. In Case 3, when the available time increases to 6 hours, the same model requires only 3 workers, reducing labor cost to 1,116 Baht, demonstrating the benefit of extended production time. Cases 4 to 6 apply the MPL-NWP model. Case 4, with 2 hours available, requires 6 workers and results in the highest labor cost of 2,232 Baht. In Case 5, with 4 hours, the labor cost drops to 1,488 Baht with 4 workers. The most cost-effective result appears in Case 6, where 6 hours of available time allow the model to operate with only 2 workers, achieving the lowest labor cost of 744 Baht which is the best choice for the 200 units of total demand.

Table 6 presents the optimal worker size and labor cost for a total demand of 250 units under different available time conditions and model applications. In Case 1, using the MPL-WP model with only 4 hours of available time and a takt time of 57.6 seconds, the model could not find a feasible solution, as the takt time was less than the maximum processing time. In Case 2, still using MPL-WP but with 6 hours of available time and a takt time of 86.4 seconds, the model achieved a feasible solution with 4 workers, resulting in a labor cost of 1,488 Baht. Switching to the MPL-NWP model, Case 3 (4-hour scenario) required 5 workers, leading to a higher labor cost of 1,860 Baht, while Case 4 (6-hour scenario) reduced the required workforce to 3 workers, achieving the lowest labor cost of 1,116 Baht which is the best choice for the 200 units of total demand.

Table 7 presents the optimal worker size and labor cost for a total demand of 300 units, with different time constraints and model applications (MPL-WP and MPL-NWP). In Case 1, the MPL-WP model with only 4 hours of available time (takt time = 48 seconds) could not generate a feasible solution, as the takt time was less than the maximum processing time. In Case 2, increasing the available time to 6 hours (takt time = 72 seconds) allowed MPL-WP to produce a feasible solution with 5 workers and a labor cost of 1,860 Baht. For the MPL-NWP model, both Case 3 and Case 4 produced feasible solutions. In Case 3, with 4 hours available (takt time = 72 and 144 seconds), the model required 5 workers, matching MPL-WP in cost at

1,860 Baht. However, in Case 4, extending the available time to 6 hours (takt time = 108 and 216 seconds) reduced the workforce requirement to just 3 workers, resulting in the lowest labor cost of 1,116 Baht which is the best choice for the 200 units of total demand.

Table 8 presents the optimal worker size and labor cost for a total demand of 350 units, considering different time constraints and two model types: MPL-WP and MPL-NWP. In Case 1, the MPL-WP model with 4 hours of available time (takt time = 41.14 seconds) failed to produce a feasible solution because the takt time was shorter than the maximum processing time. However, in Case 2, increasing the available time to 6 hours (takt time = 61.71 seconds) enabled the MPL-WP model to generate a feasible solution, requiring 6 workers and resulting in a labor cost of 2,232 Baht. Under the MPL-NWP model, both Case 3 and Case 4 produced feasible solutions. In Case 3, with 4 hours available (takt times = 72 and 96 seconds), the model required 5 workers at a labor cost of 1,860 Baht. In Case 4, when the available time increased to 6 hours (takt times = 108 and 144 seconds), the optimal worker size dropped to 4, and labor cost was minimized to 1,488 Baht which is the best choice for the 200 units of total demand.

Table 5 The optimal worker size and labor cost based on 200 units of total demand

Case	Applied model	Demand (units)			Available time (Hours)	Takt time (sec)			Optimal worker size	Labor cost (Baht)
		Signature Blue	Multi-color	Total		MPL-WP	MPL-NWP			
							k=1	k=2		
1	MPL-WP	100	100	200	2	36*			None	None
2					4	72			5	1,860
3					6	108			3	1,116
4	MPL-NWP				2		72	72	6	2,232
5					4		144	144	4	1,488
6					6		216	216	2	744

*These takt time less than the maximum processing time

Table 6 The optimal worker size and labor cost based on 250 units of total demand

Case	Applied model	Demand (units)			Available time (Hours)	Takt time (sec)			Optimal worker size	Labor cost (Baht)
		Signature Blue	Multi-color	Total		MPL-WP	MPL-NWP			
							k=1	k=2		
1	MPL-WP	150	100	250	4	57.6*			None	None
2					6	86.4			4	1,488
3	MPL-NWP				4		96	144	5	1,860
4					6		144	216	3	1,116

*These takt time less than the maximum processing time

Table 7 The optimal worker size and labor cost based on 300 units of total demand

Case	Applied model	Demand (units)			Available time (Hours)	Takt time (sec)			Optimal worker size	Labor cost (Baht)
		Signature Blue	Multi-color	Total		MPL-WP	MPL-NWP			
							k=1	k=2		
1	MPL-WP	200	100	300	4	48*			None	None
2					6	72			5	1,860
3	MPL-NWP				4		72	144	5	1,860
4					6		108	216	3	1,116

*These takt time less than the maximum processing time

Table 8 The optimal worker size and labor cost based on 350 units of total demand

Case	Applied model	Demand (units)			Available time (Hours)	Takt time (sec)			Optimal worker size	Labor cost (Baht)
		Signature Blue	Multi-color	Total		MPL-WP	MPL-NWP			
							k=1	k=2		
1	MPL-WP	200	150	350	4	41.14*			None	None
2					6	61.71			6	2,232
3	MPL-NWP				4		72	96	5	1,860
4					6		108	144	4	1,488

*These takt time less than the maximum processing time

In comparison to existing research, our study provides new insights into the application of assignment models tailored for small and medium-sized enterprises (SMEs) with multiple production lines—an area that remains underrepresented in current literature. Traditional assignment models, such as those discussed by Silva et al. (2021) and Zain & Akbar (2022), typically focus on optimizing cost or task efficiency under fixed and idealized conditions. However, our research extends these foundational principles by addressing the real-world challenges SMEs face, including workforce limitations, fluctuating demand, and production flexibility requirements. In particular, the integration of worker pool (MPL-WP) and non-worker pool (MPL-NWP) strategies in our study builds on the direction set by Liu et al. (2023), who introduced historical data to improve adaptability in generalized assignment contexts.

Moreover, our study contributes to the evolving literature on the Generalized Assignment Problem (GAP), particularly regarding its application in complex and capacity-constrained environments like SMEs. Smith & Lee (2022) demonstrated the potential of Lagrangian relaxation for solving reliability-oriented GAP, and our research complements this by offering a production-line-specific application using MILP. Similar to the foundational work by

Ibrahim et al. (2024) on GAP, we show that workforce allocation across tasks—within the bounds of available time and labor capacity—can lead to significant cost savings. Importantly, while much of the existing research, such as that by Baldé et al. (2021), emphasizes large-scale networks or industrial applications, our focus on SMEs addresses a clear research gap where resource optimization is more constrained yet critically important.

Additionally, this study draws a parallel between our model structure and the Quadratic Assignment Problem (QAP), a well-established model in facility layout and manufacturing optimization, as reviewed by Misevičius et al. (2024) and Baldé et al. (2021) While QAP is traditionally applied to spatial planning and layout configurations, the mathematical similarities allow us to adapt its principles to worker assignment across parallel production lines. Our approach also resonates with the flexibility frameworks proposed by Weckenborg et al. (2024), where decision models for flexible manufacturing systems (FMS) stress the importance of dynamic scheduling, line balancing, and multi-line coordination. By evaluating MPL-WP and MPL-NWP, we emphasize the operational trade-offs between resource sharing and independence—mirroring key considerations in flexible system design.

Lastly, our work addresses a persistent gap in the literature concerning the unique needs of SMEs in production scheduling and workforce planning. As Kumar et al. (2023) and Schoenfelder et al. (2025) have observed, existing research tends to emphasize large organizations or public-sector scheduling, often overlooking SMEs. By formulating a model specifically for tie-dye production lines in SMEs, we reflect the call for more sustainable and context-specific optimization strategies as emphasized by Jamwal et al. (2021) and Rajeev et al. (2017). The integration of real-world labor rates, production constraints, and the dual-model comparison provides a practical framework that supports decision-making in resource-limited SME settings.

Despite offering valuable insights, this research has several limitations that should be acknowledged. First, the optimization models (MPL-WP and MPL-NWP) were developed and tested under controlled conditions with predefined production times, demand levels, and limited variability in worker skills. This may not fully capture the dynamic and uncertain nature of real-world SME production environments, where disruptions, machine breakdowns, or lastminute order changes can significantly affect operations. Second, the study assumes consistent worker productivity and does not account for learning curves, fatigue, or differences in individual performance, which can influence the accuracy of workforce planning. Additionally, the models were applied to a specific case involving tie-dye production lines in a single province, which may limit the generalizability of the findings to other industries or regions with different labor policies, product types, or manufacturing processes. Lastly, while the labor cost was calculated using the new minimum wage for Pathum Thani in 2025 (372 Baht/day), future changes in wage policies, labor laws, or economic conditions may impact cost-effectiveness and model applicability over time.

Conclusions

This study demonstrates the application of assignment models to optimize workforce utilization in SMEs with multiple tie-dye production lines. By comparing the worker pool (MPL-WP) and non-worker pool (MPL-NWP) strategies, the results clearly show that these models can minimize labor costs and reduce the number of required workers without compromising production goals. For example, under a demand of 300 units and 6 hours of available time, the MPL-NWP model required only 3 workers with a total labor cost of 1,116 Baht—the lowest among all scenarios. This emphasizes how properly structured assignments and sufficient available time can yield highly cost-efficient outcomes. The analysis further reveals that MPL-NWP consistently outperforms MPL-WP in scenarios where worker sharing is limited or infeasible, which is common in many SMEs. These findings offer concrete evidence that assignment models tailored to SME constraints can significantly improve labor planning. The results benefit SME managers by providing a practical decision-support tool that enhances workforce flexibility, reduces unnecessary labor costs, and aligns production capacity with fluctuating demand. This research also contributes to the growing emphasis on sustainable and resource-optimized operations in small and medium enterprises, bridging a gap in current literature that often overlooks this sector's operational complexity.

Recommendation

While this study provides valuable insights into optimizing workforce utilization in SMEs with multiple tie-dye production lines, incorporating broader perspectives into the research itself could further enrich its contributions. One limitation is the reliance on a specific case study and a fixed production structure, which may limit the generalizability of the findings across different industries or operational environments. For instance, the assumption in the MPL-NWP model that workers cannot be shared across production lines may not reflect more flexible or hybrid systems used in other contexts. Additionally, this study focused on predefined job tasks and constant worker availability, which may not capture real-world dynamics such as fluctuating demand, varying task durations, or unforeseen workforce constraints.

To address these limitations and bring new dimensions to this research, future extensions could be embedded within the current framework. For example, integrating real-time data analytics into the assignment model—such as dynamic demand updates or worker attendance—could enhance responsiveness and decision-making accuracy. Moreover, applying the proposed models to different types of SMEs, such as those in food processing or textiles, would provide a richer comparative analysis and demonstrate wider applicability. The research could also be expanded to include sustainability considerations. Incorporating green manufacturing practices, energy efficiency, or environmental impacts into workforce planning could align labor optimization with broader social and ecological goals. Additionally, the use of AI and machine learning for predictive scheduling and adaptive worker assignments would introduce an innovative layer, positioning this research at the forefront of smart manufacturing practices tailored for SMEs. These enhancements would not only strengthen the model's robustness but also open up new, interdisciplinary perspectives that make the research more relevant and impactful.

References

Alanzi, E., & Menai, M. E. B. (2025). Solving the traveling salesman problem with machine learning: A review of recent advances and challenges. **Artificial Intelligence Review**, 58(9), 267.

Baldé, M. A. M. T., Gueye, S., & Ndiaye, B. M. (2021). A greedy evolutionary hybridization algorithm for the optimal network and quadratic assignment problem. **Operational Research International Journal**, 21(3), 1663–1690.

Beaula, T., & Saravanan, S. (2022). Solution to fuzzy multi-objective assignment problems using diagonal optimal method. **Communications in Mathematics and Applications**, 13(4), 1277–1285.

Bogyrbayeva, A., Meraliyev, M., Mustakhov, T., & Dauletbayev, B. (2022). Learning to solve Vehicle Routing Problems: A survey. **arXiv**.

Bouška, M., Šucha, P., Novák, A., & Hanzálek, Z. (2023). Deep learning-driven scheduling algorithm for a single machine problem minimizing the total tardiness. **European Journal of Operational Research**, 308(3), 990–1006.

Ibrahim, N. S., Shuib, A., & Zaharudin, Z. A. (2024). Modified Hungarian model for lecturer-to-course assignment. In **AIP Conference Proceedings**, 2850(1), 080001.

Jansen, K., Klein, K. M., Maack, M., & Rau, M. (2022). Empowering the configuration-IP: New PTAS results for scheduling with setup times. **Mathematical Programming**, 195(1), 367–401.

Kumar, A., Shrivastav, S. K., Shrivastava, A. K., Panigrahi, R. R., Mardani, A., & Cavallaro, F. (2023). Sustainable supply chain management, performance measurement, and management: A review. **Sustainability**, 15(6), 5290.

Kushwaha, D. K., & Sen, G. (2025). An integrated modeling approach for multi-class individual crew scheduling in demand channels. **Computers & Industrial Engineering**, 205, 111168.

Liu, H., Zhang, H., Luo, K., Xu, Y., Xu, Y., & Tong, W. (2023). Online generalized assignment problem with historical information. **Computers & Operations Research**, 149, 106047.

Michael, E., Wood, T. A., Manzie, C., & Shames, I. (2022). Sensitivity analysis for bottleneck assignment problems. **European Journal of Operational Research**, 303(1), 159–167.

Misevičius, A., Andrejevas, A., Ostreika, A., Verene, D., & Žekiene, G. (2024). An Improved Hybrid Genetic-Hierarchical Algorithm for the Quadratic Assignment Problem. **Mathematics**, 12(23), 3726.

Jamwal, A., Agrawal, R., Sharma, M., & Giallanza, A. (2021). Industry 4.0 Technologies for Manufacturing Sustainability: A Systematic Review and Future Research Directions. **Applied Sciences**, 11(12), 5725.

Pinedo, M. L. (2022). **Scheduling: Theory, algorithms, and systems (6th ed.)**. Springer.

Rajeev, A., Pati, R. K., Padhi, S. S., & Govindan, K. (2017). Evolution of sustainability in supply chain management: A literature review. **Journal of Cleaner Production**, 162, 299-314.

Schoenfelder, J., Heins, J., & Brunner, J. O. (2025). Task assignments with rotations and flexible shift starts to improve demand coverage and staff satisfaction in healthcare. **Journal of Scheduling**, 28(3), 329–353.

Silva, A., Coelho, L. C., & Darvish, M. (2021). Quadratic assignment problem variants: A survey and an effective parallel memetic iterated tabu search. **European Journal of Operational Research**, 292(3), 1066–1084.

Smith, A., & Lee, B. (2022). Solving the reliability-oriented generalized assignment problem by Lagrangian relaxation and Alternating Direction Method of Multipliers. **Expert Systems with Applications**, 205, 117644.

Ulutaş, A., Kiridena, S., Shukla, N., & Topal, A. (2023). A new fuzzy stochastic integrated model for evaluation and selection of suppliers. **Axioms**, 12(12), 1070.

Weckenborg, C., Schumacher, P., Thies, C., & Spengler, T. S. (2024). Flexibility in manufacturing system design: A review of recent approaches from operations research. **European Journal of Operational Research**, 315(2), 413–441.

Zain, I., & Akbar, Y. R. (2022). Division of tasks using the Hungarian method. **Journal of Business and Management Review**, 3(8), 502–514.