

A K-Means Clustering-Based Heuristic for Atypical Manpower Shift Planning in Manufacturing

Jui-Chuan Lin

College of Management
National Kaohsiung University of Science and Technology
Kaohsiung, Taiwan
I111123103@nkust.edu.tw

Cheng-Chih Chang

Department of Logistics Management
National Kaohsiung University of Science and Technology
Kaohsiung, Taiwan
sandy@e-cscc.com.tw

Jiun-Yan Shiau

Department of Logistics Management
National Kaohsiung University of Science and Technology
Kaohsiung, Taiwan
sho@nkust.edu.tw

Abstract

In the modern manufacturing and logistics landscape, balancing workforce costs with service quality remains a persistent challenge. Traditional integer programming (IP) approaches for manpower shift planning (MSP) often require advanced mathematical expertise and involve substantial computational effort, which limits their practical applicability in small and medium-sized enterprises. This study proposes a data-driven shift planning heuristic for a chemical logistics warehouse employing an atypical workforce. Instead of pursuing theoretically optimal but computationally intensive solutions, the proposed approach applies K-means clustering to identify representative demand patterns across work periods. These patterns are then used to guide the design of flexible shift start and end times. A real-world case study demonstrates that the clustering-based heuristic improves schedule flexibility, reduces overtime requirements, and supports compliance with labor regulation constraints. By aligning shift structures with demand density while accounting for practical workforce limitations, the proposed method generates feasible shift plans within short computational times. The results suggest that a simplified, clustering-driven heuristic provides a practical and efficient alternative to traditional optimization approaches in fast-paced manufacturing environments.

Keywords

Atypical Workforce, Manpower Shift Planning (MSP), K-means Clustering, Heuristic Algorithm.

1. Introduction

1.1 Challenges in Manufacturing Scheduling: From Rigid Structures to Atypical Demands

In today's dynamic manufacturing landscape, human resources are considered an organization's most critical asset, directly determining production capacity and delivery performance. However, traditional manufacturing scheduling

faces unprecedented challenges. Due to the high variability and unpredictability of production demand, compounded by stochastic factors such as absenteeism, sick leave, and high turnover rates, traditional static planning methods have become increasingly inadequate (Chen et al. 2023).

In this context, the introduction of an "Atypical Workforce" has become key to maintaining operational resilience. According to the Directorate-General of Personnel Administration (2024), an atypical workforce includes temporary employees, labor dispatchers, and contractors. While this workforce offers significant "temporal" and "numerical" flexibility, the precise scheduling of atypical workers within the strict constraints of manufacturing processes has emerged as a core challenge in modern Manpower Shift Planning (MSP) (Lagodimos and Leopoulos 2000).

1.2 Cross-Industry Comparison: Service-Driven Demand vs. Manufacturing-Led Planning

Abernethy et al. (1973) proposed a three-tier hierarchical structure for workforce management, consisting of planning, scheduling, and allocation. Within this framework, manufacturing and service industries exhibit fundamentally different capacity adjustment logics.

In service systems, production and consumption occur simultaneously, and labor functions as a buffer against stochastic customer arrivals. Service providers therefore rely on flexible shifts to dynamically adjust staffing levels over time (Brunner 2010). In contrast, manufacturing systems traditionally follow fixed and continuous shift rotations that are closely coupled with the master production schedule (MPS). As a result, workforce planning is often treated as secondary to equipment utilization and production sequencing (Chen et al. 2023; Van den Bergh et al. 2013).

This divergence highlights a structural limitation of traditional manufacturing scheduling when demand becomes volatile. It also motivates the exploration of service-style flexible shift concepts as a potential solution for modern manufacturing environments.

1.3 Paradigm Shift: Strategic Adjustment Indicators for Atypical Workers

With the transition toward Industry 4.0, manufacturing scheduling logic is shifting from "capacity-driven" to "demand-driven." This suggests that modern smart manufacturing should optimize around two core indicators:

1. **Dynamic Break Windows:** Breaking the traditional mode of simultaneous breaks for all staff by using atypical workers to "relay" positions, ensuring production continuity while complying with labor regulations.
2. **Ideal Waiting Time:** Minimizing the time gap between labor supply and task arrival through schedule optimization to reduce unproductive labor redundancy.

In this context, the atypical workforce plays a strategic role in enhancing scheduling flexibility. By allowing non-uniform shift start times, adjustable break windows, and shorter working-hour constraints, atypical workers enable firms to absorb demand fluctuations without excessive overtime or idle labor.

Rather than functioning as a fixed production resource, the atypical workforce provides a mechanism for fine-tuning labor supply in response to non-stationary demand distributions. This flexibility is particularly valuable in environments where demand peaks are irregular and difficult to predict.

1.4 Technical Path: Implementation of K-means Clustering-Based Heuristics

Given the complexity of atypical workforce scheduling, traditional optimization models often encounter computational bottlenecks due to the excessive number of variables. This study proposes a K-means Clustering-Based Heuristic Algorithm as the solution.

The K-means perspective treats complex demand fluctuations as "temporal feature points." By performing cluster analysis on demand intensity across different work periods, K-means identifies the natural centroids within the data, transforming chaotic task flows into representative "Shift Prototypes". This clustering-based preprocessing effect effectively restricts the search space by pre-establishing feasible earliest start times (st_i) and latest end times (et_i) for shifts, effectively shrinking the search space for Integer Programming (IP) models and enabling the generation of feasible solutions within a practical operational timeframe.

1.5 Research Motivation and Empirical Context

This study is motivated by the transformation of a 30-year-old chemical plant. Upon entering the electronic materials market, the company faced challenges characterized by "explosive growth" and "rapid decline" in order volumes. By implementing the integrated K-means scheduling framework proposed in this research, we aim to address the NP-hard computational challenges inherent in traditional IP models when processing large-scale logistics data (Alzghoul et al. 2014).

The research seeks to define and answer the following questions:

1. How should the objective function for atypical workforce scheduling be defined in a high-growth manufacturing environment?
2. How can clustering techniques identify multi-dimensional critical factors affecting shift design?
3. How much computational efficiency can be gained by the optimization model through K-means dimensionality reduction?
4. What is the empirical effectiveness of the resulting flexible start-and-end shifts in optimizing "Ideal Waiting Time"?

2. Literature Review

2.1 Theoretical Framework of Manpower Shift Planning (MSP)

Workforce resources are considered the most critical components of an organization's production capacity. Abernethy et al. (1973) proposed that workforce assignment should be viewed through a three-tier hierarchical structure: planning, scheduling, and allocation. Building upon this, Lagodimos and Leopoulos (2000) formally defined this challenge within the manufacturing context as the Manpower Shift Planning (MSP) problem.

The core objective of MSP is to synchronize "supply" and "demand" along a temporal axis. In a systematic review of the past decade's literature, Van den Bergh et al. (2013) noted that traditional MSP models predominantly rely on assumptions of "static demand" and "worker homogeneity," focusing on labor cost minimization. However, with increasing supply chain volatility, contemporary research has pivoted toward mathematical models capable of addressing uncertainty and stochastic elements.

2.2 Dialectics of Scheduling Logic: Manufacturing vs. Service Industries

The scholarly debate regarding scheduling patterns primarily centers on the dichotomy between "rigidity" and "flexibility":

1. **Manufacturing's Fixed Paradigm:** Traditionally, manufacturing schedules are tightly coupled with the Master Production Schedule (MPS), employing fixed and continuous cycles (Chen et al. 2023). Knuth (1993) observed that while manufacturing focuses on equipment utilization, it often overlooks the workforce's need for temporal autonomy, suggesting the limitations of rigid scheduling in modern management.
2. **Service Industry's Flexible Paradigm:** Conversely, service scheduling is driven by "customer contact," where labor acts as a buffer against stochastic arrivals. Brunner (2010) described how the service sector adjusts capacity by varying the number of service items/shifts at specific time points rather than maintaining fixed staffing levels.

This study contends that as manufacturing shifts toward "high-mix, low-volume" production, the boundaries between these sectors are blurring. Adopting flexible shift patterns from the service industry (e.g., airline scheduling; Shiao et al. 2020) has emerged as a novel trend for solving MSP in modern manufacturing.

2.3 The Strategic Role of the Atypical Workforce

In the wake of globalization and labor market shifts, the atypical workforce (e.g., temporary and dispatched workers) has become an indispensable resource. Much like an adjustment valve, this workforce injects capacity during demand surges and curtails redundancy during troughs.

To further refine the optimization metrics in this context, this study highlights the role of atypical labor in covering dynamic break windows and reducing ideal waiting time. Such workers break the traditional 8-hour fixed constraint of full-time employees, allowing optimization models to seek superior solutions under complex regulatory constraints.

2.4 Data-Driven Techniques: Application of K-means Clustering in Scheduling

Traditional Integer Programming (IP) often struggles with combinatorial explosion in large-scale scheduling (Chen et al., 2023). Although advanced exact algorithms—such as those developed by Gérard et al. (2016)—offer theoretical

robustness, their prohibitive computational costs make them impractical for fast-paced enterprise operations. Consequently, data-driven preprocessing techniques have emerged as a practical alternative:

1. Pattern Recognition: K-means clustering can identify "task windows" and "demand prototypes" from chaotic historical order data, transforming raw data into structured decision references.
2. Integration of Dimensionality Reduction and Optimization: Alzghoul et al. (2014) argued that pre-establishing shift start (st_i) and end (et_i) points through clustering significantly reduces the search space for optimization models. This "two-stage" approach preserves the resilience required to handle uncertainty while ensuring the precision of the optimal solution.

Synthesizing existing literature, while flexible scheduling in services and fixed scheduling in manufacturing have been extensively discussed, there remains a notable research gap in integrating "service-style flexible shifts" into "atypical workforce management in manufacturing" via "K-means dimensionality reduction." Particularly in hybrid scenarios like chemical and electronic materials—where manufacturing continuity meets logistics stochasticity—balancing computational efficiency with scheduling quality remains an academic void. This study aims to bridge this gap through a two-stage heuristic algorithm.

2.5 Scheduling Human Capital with Kanban and Lean

Lean Management uses the kanban (pull) system to facilitate material flow and eliminate muda (waste) (Holweg, 2007). In such a pull system, resources are drawn into the process strictly based on known demand (Sugimori et al., 1977). Although the Kanban method is traditionally perceived as applicable only to inventory and parts management, the underlying collaborative philosophy of the Toyota Production System represents a highly adaptable framework (New, 2007). Consequently, its core principles and objectives are also highly appropriate for reducing "work in progress" (WIP) and preventing overproduction in Manpower Shift Planning (MSP).

Chemical companies, which were researched for this article, maintain rigid continuous shift schedules for their work forces using traditional (push) scheduling processes. Consequently, the push process results in too much idle time or overtime for their workers. In this volatile work environment, demand changes rapidly.

Applying the Kanban concept to human resources involves treating "atypical employees" as a flexible capacity pool that is "pulled" into action exactly when a specific need arises. Similar to how technology-enabled kanban systems facilitate real-time demand reporting and pull replenishment in logistics (Zeng et al. 2023), this HR approach relies on precise timing. To identify common peak demand times for these atypical employees, a K-means clustering heuristic is applied to generate a data-driven "kanban signal." The integration of such advanced data analytics with kanban principles exemplifies how modern technological adoption can amplify the impact of lean practices on operational performance (Tortorella et al. 2019). Ultimately, this collaborative approach significantly reduces surplus labor, resulting in a highly efficient and lean workforce (Lage Junior and Godinho Filho 2010).

While prior studies have examined manpower shift planning, flexible shift design, and heuristic scheduling approaches, fewer studies have focused on integrating clustering-based demand pattern extraction into atypical workforce planning in manufacturing settings. In particular, the existing literature has not sufficiently addressed hybrid environments such as chemical logistics warehouses, where production continuity, labor regulations, and stochastic workload peaks must be considered simultaneously. This study contributes by using K-means clustering as a preprocessing and shift-structuring tool to support fast and practical shift design.

3. Methodology: K-means Clustering-Based Heuristic

Although traditional Integer Linear Programming (ILP) models can theoretically guarantee a global optimum for shift planning, applying them to large-scale logistics data (e.g., 240 time intervals) often causes combinatorial explosion, making them impractical for fast-paced operations. To overcome this limitation, this study integrates K-means clustering with rule-based shift generation using data-driven heuristics. K-means was selected for three main reasons. First, because the case environment shows recurring yet irregular workload peaks, extracting patterns is more effective than relying on fixed shift templates. Second, K-means serves as a dimensionality reduction tool by grouping work periods with similar demand characteristics, thereby identifying representative demand windows that can be directly converted into candidate shift boundaries. Third, this clustering-based preprocessing approach avoids the computational bottlenecks of relying solely on exact optimization. As a result, it enables the rapid generation of

feasible, high-quality schedules within practical decision time, helping field managers schedule efficiently without advanced mathematical solvers.

The planning horizon is discretized into half-hour intervals, resulting in 240 time periods per week. Each period is treated as a clustering object and characterized by workload intensity and task requirements. The K-means algorithm is executed separately for $k = 3, 4, 5$, and 6 to identify representative demand patterns.

For each cluster, the earliest feasible start time (st_i) and latest feasible end time (et_i) are determined. These cluster boundaries are then used to generate candidate shifts subject to allowable working hours and break regulations. By pre-establishing feasible shift time windows through clustering, the proposed heuristic significantly restricts the search space and enables the rapid generation of practical shift schedules. The systematic logic of the proposed K-means clustering-based heuristic is summarized in Figure 1.

Detailed instructions are provided below for implementing the philosophy described above:

1. Gather periodic task plans (one week or one month). Based on the work time required for the task, the number of employees that need to be dispatched should be determined for each period.
2. Clustering the work periods in the periodic task plan into k clusters. The k-means algorithm was executed separately for $k = 3, 4, 5$, and 6.
3. Determine each cluster's start time(st_i) and end time(et_i).
4. For each cluster with full-time works, If the cluster duration ($et_i - st_i$) is less than or equal to the allowed working hours h , a single shift is generated. Otherwise, the cluster is divided into multiple shifts according to the maximum allowable working hours. And check if $st_i + 2h \leq et_i$; if $st_i + 2h \leq et_i$ create another shift from $st_i + h$ to $st_i + 2h$, and the other shift from $st_i + 2h$ to et_i ; else create another shift from $et_i - h$ to et_i . Where h is the allowed number of hours.
5. For each cluster with dispatched works, if $et_i - st_i \leq h + 2r$, create a shift; else create a shift from st_i to $st_i + h + 2r$, and another shift from $st_i + h$ to $et_i + 2r$. Where h is the allowed number of hours, and r is the break time.
6. Compare the costs based on numbers of workers among each case ($k=3$ to 6) to determine the final shift schedules.



Figure 1. K-means clustering heuristic for shift planning

4. Case Study: Chemical Logistics Warehouse

The case setting of this study is a warehouse whose storage and packaging area currently handles four core products. Accordingly, four work areas are established, each responsible for one product. After packaging, products are shipped via the warehouse's freight terminal. The four products differ substantially in operational characteristics. Product A requires 24-hour continuous production; the packaging area currently operates under a four-shift system with three rotations. Product B poses an odor-related pollution risk. To prevent impacts on other products and the surrounding environment, the company schedules its packaging activities in the evening and at night, and avoids packaging it simultaneously with other products as much as possible. Product C can be packaged during regular daytime working hours. Because the packaged goods are heavy, employees in this area must use a stacker to ensure safe material handling. Unlike the first three products, Product D is transferred directly to a storage tank through a pipeline after production. Employees must continuously monitor its storage condition and, when shipping is required, operate the pipeline to transfer the product to a tanker truck.

At present, workforce allocation follows a “product-wise independent” approach: each product's work area is staffed by dedicated personnel, leaving little room for mutual support across products. When production demand increases, the department typically relies on overtime. Such an operating mode is unfavorable for workforce cost control and flexible labor deployment.

In addition, there is an established agreement between the department and employees regarding working conditions. For example, employees are provided with rest time outside regular day-shift hours (08:00–17:00). During other working hours, breaks are generally not fixed; employees take short rests during available idle time. All current warehouse staff are full-time employees. Introducing short-term dispatched workers could improve scheduling flexibility. Considering the above operational characteristics and employment conditions, the planning reference factors proposed in this study can help the company enhance flexibility and efficiency in workforce scheduling.

5. Results and Discussion

5.1 Experimental Setting

The proposed data-driven heuristic was implemented using PolyAnalyst 6.5 as shown in Figure 2. The dataset consists of a one-week task plan from a chemical warehouse, where work periods (T_{xy}) are divided into 240 half-hour intervals. The workforce requirements are categorized by skills (J_1, J_2) and task types (W_1 to W_8). The k-means algorithm was executed for $k=3, 4, 5, 6$ to identify the most cost-effective shift configuration.

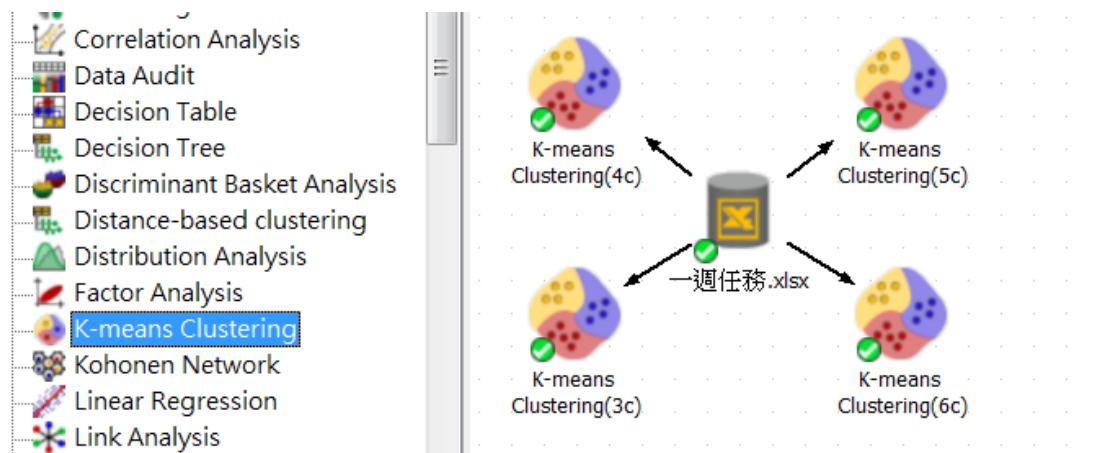


Figure 2. Screenshot of k-means clustering by using PolyAnalyst

5.2 Shift Planning Results ($k=3$ Case)

Shift planning procedures based on results from k-means clustering with $k=3$. Table 1 presents the condensed results for the $k=3$ scenario. This configuration generated five distinct shifts: three for full-time workers (Shifts A, B, C) to

ensure 24-hour baseline operation, and two for atypical (dispatching) workers (Shifts D, E) to handle daytime demand surges.

Table 1. Workers based on results of k-means clustering with k=3

Time	Period	Workers Required (Often)	Max Workers	Insuff. (Avg.)	Insuff. (Max)	Shift A	Shift B	Shift C	Shift D	Shift E
23:00–06:30	0–15	5	5	0	0	5	-	-	-	-
07:00	16	3	3	0	0	-	-	3	-	-
08:30	19	11	16	2	-3	-	-	3	10	-
09:00	20	12	16	5	1	-	-	3	10	4
...	...	...	...	...	...	...	...	...	...	...
12:30	27	8	13	5	0	-	-	3	10	-
15:00	32	18	19	1	0	-	5	-	10	4
16:30	35	7	13	2	-4	-	5	-	-	4
18:00	38	5	7	0	-2	-	5	-	-	-
19:00–22:30	40–47	5	5	0	0	-	5	-	-	-
Total				50	-19					

5.3 Analysis of Cluster Size (*k*)

According to Table 2, different cluster sizes are compared in terms of shift structure and workforce utilization. Shift configuration can be more flexible as *k* increases, since demand patterns are captured with finer granularity.

Table 2. The performance of different cluster sizes in terms of shift structure and workforce utilization

k-value	k=2	k=3	k=4	Meaning of the value
Workers	27	27	27	
Shifts	4	5	6	The larger the value, the more shifts
Idle workers (avg.)	62	50	50	The lower the value, the more severe the workforce shortage.
Insufficient workers (avg.)	-12	0	0	The negative value means that a task must work overtime
Insufficient workers (max.)	-34	-19	-18	The smaller the negative value is, the smaller the workforce gap will be when the peak period, urgent orders, large orders, or other tasks with random change are completed.
Overtime workers	17	9.5	9	The smaller the value is, the less overtime labor is required and the lower the labor cost.

Compared with the coarser clustering setting (*k*=2), the proposed approach with *k*=3 reduces weekly overtime from 17 to 9.5 hours while maintaining the same workforce size (27 workers). The *k*=3 configuration reduces overtime by approximately 44.1% relative to the *k*=2 case. Although increasing to *k*=4 further reduces overtime slightly to 9 hours, the improvement is marginal relative to the increase in shift complexity. These results quantitatively indicate that a moderate cluster size (*k*=3) provides the optimal balance between labor cost reduction and operational manageability.

Furthermore, it is important to emphasize that the variables presented in Table 2—specifically the average and maximum number of "insufficient workers" and "overtime workers"—serve as the core quantitative performance metrics for this study. By accurately quantifying the idle workforce and overtime requirements, these metrics directly evaluate the operational trade-off between labor cost efficiency and service level fulfillment.

5.4 Discussion

The data-driven approach demonstrates a clear advantage in handling the variability of atypical workforce requirements. Unlike traditional fixed-shift systems, the clustering-based heuristic aligns shift boundaries with actual demand density. This is particularly evident in Clusters 2 and 3, which accurately captured the daytime "packaging" and "emergency activity" peaks that are common in warehouse operations. For the case company, $k=3$ or $k=4$ provides the optimal balance between operational flexibility and administrative simplicity.

5.5 Visualized Pull-Scheduling and Internal Benchmarking

Using both full-time and atypical workers (Figure 3 and Figure 4), the clustered results are transformed into visualized schedules (Gantt charts) to demonstrate their practical value and integration with Lean techniques. As shown in Figure 4, atypical workers are deployed precisely during peak demand hours in a stair-step structure (e.g., 08:00–16:00), acting as a "pull-based" Kanban resource to absorb demand shocks. Due to the proposed heuristic, idle labor is minimized and overtime is reduced (from 17 hours to 9.5 hours for $k=3$) compared to the previous "product-wise independent" schedule. For field managers, an alternative to traditional IP is demonstrating the ability to generate a highly flexible, visual, and legally compliant schedule in a short period of time.

Fulltime	Time Zone	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
	Workforce	8	8	8	8	8	8	8	12	12	12	12	12	12	12	16	16	12	10	10	10	10	8	8	8		
Shift	Work Period																								Workers	Hours	
I01	00:00~08:00																									1	9
I02	02:00~10:00																									3	9
I03	04:00~12:00																									2	9
I04	06:00~14:00																									2	9
I05	08:00~16:00																									4	8
I07	12:00~20:00																									3	9
I08	14:00~22:00																									2	8
I09	16:00~24:00																									1	8
I10	18:00~02:00																									3	8
I11	20:00~04:00																									2	8
I12	22:00~06:00																									2	9

Figure 3. Shifts of the result for full-time workers

Dispatching	Time Zone	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
	Workforce	8	8	8	8	8	8	8	12	12	12	12	12	12	16	16	12	10	10	10	10	8	8	8			
Shift	Work Period																								Workers	Hours	
J01	08:00~12:00																									2	4
J05	12:00~16:00																									1	4
J06	13:00~17:00																									1	4
J07	14:00~18:00																									1	4
J08	15:00~19:00																									1	4
J11	18:00~22:00																									1	4
Shift	Work Period																								Workers	Hours	
K01	08:00~14:00																									2	6
K04	11:00~17:00																									1	6
K05	12:00~18:00																									1	6
K06	13:00~19:00																									1	6
K07	14:00~20:00																									1	6
K08	15:00~21:00																									1	6

Figure 4. Shifts of the result for atypical workers

6. Conclusion

The results directly address the proposed research questions by clarifying the objective structure, identifying key shift design factors through clustering, and demonstrating computational efficiency gains. Hiring and scheduling personnel have long been challenging tasks for operators. Adequate staffing is essential for maintaining service quality; however, overstaffing increases labor costs. Conversely, reducing headcount to cut costs may lead to labor shortages and delayed service, ultimately failing to meet customer needs. Therefore, balancing service performance and workforce cost is the central challenge that personnel scheduling aims to address. A well-designed shift planning and personnel scheduling system helps allocate labor more efficiently and ensures that tasks can be completed within each planning period.

To reduce labor expenses, some companies extend employees' working hours. Although this may appear to lower total labor cost, excessive workloads can trigger higher turnover and more operational errors, which in turn generate additional costs. Moreover, as labor laws and regulations become increasingly stringent, overly rigid or intensive schedules may even expose firms to penalties. In practice, many small and micro enterprises still rely on manual shift planning and personnel scheduling, which is time-consuming, labor-intensive, and often unable to accurately estimate workforce requirements. While integer programming can produce rigorous shift plans, it requires mathematical expertise to formulate and implement, and the solving process can be computationally burdensome making it impractical for most companies. In many cases, a simple and implementable approach is more valuable.

Accordingly, this study applies k-means clustering to group the data for analysis. The characteristics of each cluster are then used as planning principles, thereby avoiding the need to construct a complex mathematical optimization model.

This study introduces an innovative shift planning principle for a warehouse management unit in the chemical industry. The proposed approach replaces the previous method that fixed the same starting time point across shifts, improves scheduling flexibility, and remains compliant with labor laws and regulations. One key finding is that combining an appropriate set of starting-time points in a multi-shift plan with the handling of peak periods or randomly varying tasks can substantially reduce overtime and overall labor cost.

Shift planning and personnel scheduling are designed to ensure smooth resource allocation, yet real-world operations involve uncertainty. From a practical perspective, pursuing a theoretically optimal solution may be less meaningful than obtaining a feasible plan quickly. Generating a workable schedule in a short time allows managers to deploy resources earlier and keep operations moving in the right direction. The k-means clustering approach proposed in this study can significantly shorten the time required for planning and calculation.

Overall, the proposed approach addresses the research questions by clarifying the objective structure of atypical workforce scheduling, identifying critical shift design factors through clustering, and demonstrating that substantial computational efficiency gains can be achieved without sacrificing solution feasibility. This confirms the practical value of data-driven heuristics for manpower shift planning in modern manufacturing environments.

While this study presents a practical contribution with a strong emphasis on field applicability, certain limitations inherent to heuristics must be acknowledged. From a strict mathematical perspective, k-means clustering does not guarantee a global optimum for cost minimization because it groups demand patterns to find an approximate solution. This study prioritized fast and feasible alternatives, since deriving mathematically perfect optimal solutions via traditional integer programming is complex and computationally prohibitive for field managers.

The current approach simplifies operational requirements as well. In actual chemical facilities, manpower shift planning involves highly complex constraints regarding safety certifications and operational proficiency levels. As opposed to this, the proposed model categorizes these factors primarily according to skill types and task types. These multidimensional constraints should be integrated into the algorithm in future research, such as certifications for hazardous materials handling and advanced machinery proficiency. Additionally, incorporating Lean manufacturing techniques, particularly the Kanban system, could be explored as a collaborative approach to further optimize the "Ideal Waiting Time" and enhance real-time responsiveness in atypical workforce scheduling.

References

- Abernethy, W. J., Baloff, N., Hershey, J. C. and Wandel, S., A three-stage workforce planning and scheduling model: A service-sector example, *Operations Research*, vol. 21, no. 3, pp. 693-711, 1973.
- Alzghoul, A., Backlund, A. and Lofstrand, M., Comparing a knowledge-based and a data-driven method in querying data streams for system fault detection: A hydraulic drive system application, *Computers in Industry*, vol. 65, no. 8, pp. 1126-1135, 2014.
- Brunner, J. O., *Flexible Shift Planning in the Service Industry: The Case of Physicians in Hospitals*, Lecture Notes in Economics and Mathematical Systems, vol. 640, Springer, 2010.
- Directorate-General of Personnel Administration, Human resources statistics, Executive Yuan, Taiwan, Available: <https://www.dgpa.gov.tw/en/information?uid=354&pid=12304>, Accessed on January 12, 2026.
- Holweg, M., The genealogy of lean production, *Journal of Operations Management*, vol. 25, no. 2, pp. 420-437, 2007.
- Knuth, P., The design of shift systems, *Ergonomics*, vol. 36, no. 1-3, pp. 15-28, 1993.
- Lage Junior, M. and Godinho Filho, M., Variations of the kanban system: Literature review and classification, *International Journal of Production Economics*, vol. 125, no. 1, pp. 13-21, 2010.
- Lagodimos, A. G. and Leopoulos, V., Greedy heuristic algorithms for manpower shift planning, *International Journal of Production Economics*, vol. 68, no. 1, pp. 95-106, 2000.
- New, S. J., Celebrating the enigma: the continuing puzzle of the Toyota Production System, *International Journal of Production Research*, vol. 45, no. 16, pp. 3545-3554, 2007.
- Chen, C., Lee Kong, T. and Kan, W., Identifying the promising production planning and scheduling method for manufacturing in Industry 4.0: A literature review, *Production and Manufacturing Research*, vol. 11, no. 1, Article 2279329, 2023, <https://doi.org/10.1080/21693277.2023.2279329>
- Shiau, J. Y., Lin, J. C. and Huang, W. C., A hybrid personnel scheduling model for staff rostering problems, *Mathematics*, vol. 8, no. 10, pp. 1702, 2020.
- Sugimori, Y., Kusunoki, K., Cho, F. and Uchikawa, S., Toyota production system and Kanban system Materialization of just-in-time and respect-for-human system, *International Journal of Production Research*, vol. 15, no. 6, pp. 553-564, 1977.
- Gérard, M., Clautiaux, F. and Sadykov, R., Column generation based approaches for a tour scheduling problem with a multi-skill heterogeneous workforce, *European Journal of Operational Research*, vol. 252, pp. 1019-1030, 2016.
- Tortorella, G. L., Giglio, R. and van Dun, D. H., Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement, *International Journal of Operations & Production Management*, vol. 39, no. 6/7/8, pp. 860-886, 2019.
- Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E. and De Boeck, L., Personnel scheduling: A literature review, *European Journal of Operational Research*, vol. 226, no. 3, pp. 367-385, 2013.
- Zeng, N., Ye, X., Liu, Y. and König, M., BIM-enabled Kanban system in construction logistics for real-time demand reporting and pull replenishment, *Engineering, Construction and Architectural Management*, vol. 30, no. 8, pp. 3069-3096, 2023.

Biographies

Jui-Chuan Lin is a Ph.D. candidate at the College of Management, National Kaohsiung University of Science and Technology. His research interests include production planning management, big data analytics, and enterprise resource planning. He is currently serving as a manager in a group enterprise.

Cheng-Chih Chang graduated from the master's program in Logistics Management at the National Kaohsiung University of Science and Technology. Her research interests include production planning management, big data analytics, and enterprise resource planning. She currently serves as the general manager of a large chemical corporation.

Jiun-Yan Shiau is a Professor in the Department of Logistics Management at National Kaohsiung University of Science and Technology (NKUST), Taiwan. He currently teaches courses in computer programming, database systems, big data analytics, enterprise resource planning (ERP), and electronic commerce. In addition to his academic appointment, he also serves as the Associate Dean of the College of Management at NKUST, contributing to both academic leadership and administrative governance. Professor Shiau received his master's and Ph.D. degrees in Industrial Engineering from Arizona State University, USA. His primary research interests encompass the applications of information systems, cross-border e-commerce, operations management, and business models. His scholarly works

have been published in a wide range of reputable international journals, including Computers in Industry, Computers & Industrial Engineering, International Journal of Production Research, International Journal of Production Economics, International Journal of Manufacturing Technology and Management, International Journal of Systems Science: Operations & Logistics, Journal of Information and Optimization Sciences, Internet Research, International Journal of Logistics Systems and Management, and International Journal of Industrial Engineering, among others. Moreover, Professor Shiau has actively presented his research findings at numerous prestigious international conferences, such as the IEOM, ICNSC, IEEE SOLI, CIE, and the IISE Annual Conference and Expo, as well as other major international academic forums.