The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 2025

Volume 34, Pages 359-368

ICBASET 2025: International Conference on Basic Sciences, Engineering and Technology

Incorporating Worker Heterogeneity in Flexible Flow Shop Environment

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Abstract We study the flexible flow shop scheduling problem with the heterogeneous worker assignment. In many real-life manufacturing systems with flow shop environments, one of the fundamental scheduling challenges that needs to be addressed is job sequences across multiple workers. In addition, the manufacturing system may require workers to have different skills at various stages during their assignment. Therefore, worker availability at each stage may vary during the scheduling horizon. Unlike traditional flexible flow shop scheduling problem, where homogeneous workers are assumed, we consider workers with different skill levels, capabilities, and capacities. We present a mixed integer linear programming model to find the optimal sequence of job assignments, guaranteeing that jobs follow their predefined operation sequence while assigning workers with various skill sets in a flexible flow shop environment. The proposed model is tested at a battery manufacturing company. By analyzing the solution, we confirm its capability to represent the problem accurately. The proposed model offers a systematic scheduling approach for a flexible flow shop environment with a heterogeneous workforce and can be implemented in other industries.

Keywords: Production scheduling, Flexible workforce, Mixed integer linear programming, Sustainability

Introduction

In today's fast-paced business environments and fierce market conditions, companies try to enhance their competitiveness by meeting customer requirements, including product delivery times. Efficient delivery can be achieved through production scheduling. Production scheduling is the decision of timing and sequence of the tasks over available resources.

Production scheduling is a challenging task, especially considering complex manufacturing systems. Production systems often involve additional resources, including human- and robot-assisted operations, tools, and software (Benkalai et al., 2019; Mraihi et al., 2024). Many aspects need to be addressed while producing a schedule, such as human-related factors and varying processing times. Leaving out human factors and human-related operations notably limits the classical scheduling theory (Ostermeier, 2020). Even with Industry 4.0's significant role in production, human involvement will remain vital in operational systems (Neumann et al., 2021). The extent of an individual's involvement in a workspace depends on various factors, such as the capabilities and capacity of the worker. Workers' varying skills, qualifications, experience, and worker-specific characteristics affect where they can work and the speed at which they complete tasks. Multi-skilled workers or worker flexibility may decrease the bottlenecks in a production system and provide more efficient systems (Daniels et al., 2004). However, the heterogeneity of the skills makes the production scheduling problem difficult for the decision-makers. It brings about a "suboptimal" solution due to using worst-case scenarios or other measures

(Benavides et al., 2014). Therefore, the heterogeneity of the workers' qualifications must be considered when scheduling production.

The flexible flow shop problem (FFSP)(sometimes referred to as hybrid flow shop) is widely applicable to real-world systems and therefore got the attention of many researchers over the years (Burcin- Ozsoydan & Sagir, 2021; Naderi et al., 2009). FFSP can be considered a combination of parallel machine and flow shop scheduling. In FFSP, there are jobs that require sequential processing at stages, with at least one stage involving more than one machine providing a parallel machine environment (Pinedo, 2022; Tosun et al., 2020).

In this study, motivated by a battery production facility, we focus on an FFSP with the consideration of worker flexibility. It should be noted that worker/workforce flexibility terms cover flexible working hours, floaters, cross-training, teamwork, and temporary labor (Qin et al., 2015). In this context, we consider worker flexibility as cross-training and varying processing times. This study provides a mathematical model that explores the practical characteristics of labor multiskilling and heterogeneity of workers' processing times in a flexible flow shop environment, one of the commonly observed manufacturing environments, and helps managers to eliminate or decrease the bottlenecks in their systems through the optimal job assignments of multiskilled workers.

The remainder of the paper is organized as follows. First, we provide a background and related work on worker flexibility in flexible flow shop (FFS) environments. Second, we present the problem and a mixed integer linear programming model for the heterogeneous worker assignment problem in FFS environments. Thirdly, we introduce a real-life case representing the problem. Using real-world data from a battery manufacturing facility, we discuss the results in the Computational Experiments sections. Finally, we provide concluding remarks and highlight future directions.

Related Literature

This section briefly reviews production scheduling in FFS environments with a focus on flexible workers. However, interested readers are referred to Maccarthy and Liu (1993) for a more general analysis of production scheduling. For different aspects of scheduling, readers are referred to Davis et al. (2016) for job priorities, Danping and Lee (2011), Kayisoglu et al. (2024) for re-entrant jobs, Schmidt (2000) for limited machine availability, and Madenoglu (2021) for solution methods in FFSP.

Here, we review the related literature on flexible workers in FFSP for multi-skilled workers and varying processing times. Daniels et al. (2004) presented a MILP model for a flow shop scheduling problem where processing times depend on how many workers are assigned to the same machine given the workers' skill matrix. The computational results show that a significant share of the potential benefits of labor flexibility can be achieved with a modest increment in the skill matrix. Benavides et al. (2014) also examined a flow shop environment where workers could be assigned to jobs based on their skills. Unlike Daniels et al. (2004), only one worker could be assigned to a machine. They proposed a MILP model to solve the worker assignment problem in the flow shop environment and provided a heuristic algorithm based on scatter search and path relinking. Fekri et al. (2024) worked in an FFS environment with multiple skilled workers. The proposed MILP model minimizes the total weighted completion time and total weighted idle time of the workers by assigning sets of workers to the machines required for the jobs. A genetic algorithm and a simulated annealing algorithm are provided as solution methods.

Next, we examine the related literature on varying processing time, including the learning (and forgetting effects) in FFS environments. Gong et al. (2020) explored a novel FFSP, considering factors such as machine/worker flexibility, varying processing times, and energy consumption. A MILP model and a hybrid evolutionary algorithm are proposed as solution algorithms. We should also mention learning effects when presenting studies with varying processing times. Several researchers examined the learning effects of mass production, suggesting that a worker might produce the same product in a shorter time when producing the same item/job consecutively (Biskup, 2008). Fichera et al. (2017), Pargar et al. (2018) and Seidgar et al. (2015) examined the learning effect in FFS environments, assuming that the learning effect occurs through the reduction of setup times. Seidgar et al. (2015) provided a mixed integer linear programming (MILP) model to solve the FFSP with the learning and forgetting effects of the workers setting up the machines.

Pargar et al. (2018) also investigated the effects of worker learning in a bi-objective FFSP environment. A MILP is provided for the bi-objective model, and two new hybrid metaheuristic algorithms, hybridizing water flow-like algorithms with non-dominated sorting and ranking concepts, are provided. Fichera et al. (2017) also provided a MILP model to minimize the makespan of a flow shop group scheduling problem with heterogeneous workers. For large-sized instances, an evolutionary algorithm was presented. Unlike the mentioned studies, Marichelvam et al. (2020) considered the learning effect over the processing times, setting the processing times of each worker to be equal to the multiplication of the skill factor, learning factor, forgetting factor, age factor of the worker, and processing time of the job. A MILP model and particle swarm optimization-based heuristic algorithms are proposed as solution algorithms.

Our study investigates FFSP with multiskilled workers as its primary focus. This problem is designed to represent a real-world scheduling challenge frequently encountered when different types of competencies are required for various operations in manufacturing. This study contributes to the literature by presenting a MILP model that considers multiskilled workers with various processing times in an FFSP setting.

Problem Definition and Proposed Mathematical Model

We focus on an extension of the traditional flexible flow shop scheduling problem (FFSSP). Unlike FFSSP, where worker capabilities are either ignored or assumed homogeneous, we consider workers with different skill levels, efficiencies, or processing speeds. Therefore, we study the flexible flow shop scheduling problem with heterogeneous worker assignment (FFSSP_HWA). Let J represent the set of jobs where $j, j' \in J$. Each job may have different order quantities that need to be processed. We define n_j as the number of orders of job j. Every job consists of a sequence of consecutive operations. Let I denote the set of operations, where $i, i' \in I$. There is a precedence relation between the operations ensuring that each job follows the specified sequence of operations in a predefined order as indicated by the operation numbers. In addition, if an operation of a job has started, the subsequent operations of that job cannot begin until the current operation is completed for the required order quantity of that job, denoted by n_j.

In FFSSP_HWA, there are workers with different skills. Let W denote the set of workers. We define a binary parameter a_{iw}, which equals 1 if worker w is capable of performing operation i, and 0 otherwise. Furthermore, due to differences in experience and efficiency, workers may have varying processing speeds. To represent this, we define the parameter p_{ijw}, which denotes the processing time for a single order of job j at operation i when performed by worker w.

The objective of FFSSP_HWA is to minimize the makespan, which represents the total completion time of the schedule, i.e., the time at which the last job finishes processing. We denote the makespan as . We develop a mathematical model for FSSP_HWA. The model determines the start and completion time of each operation for each job, denoted by the decision variables and , respectively. is a binary decision variable that equals 1 if worker is assigned to operation of job , and 0 otherwise.

Sets, parameters, and decision variables for FFSSP_HWA

Sets

I	*Set of operations where* $i, i' \in I$
J	*Set of jobs* where $j, j' \in J$
W	*Set of workers*

Parameters

a_{iw}	1 *if worker w is capable of performing operation i*, 0 *otherwise*
p_{ijw}	*Processing time of job j for operation i done by worker w*
n_j	*Number of orders of job j*
M	*Arbitrary large number*

Decision Variables

C_{max}	*Makespan (the time at which the last job finishes processing)*
X_{ij}	*Start time of operation i for job j*
C_{ij}	*Completion time of operation i for job j*
P_{ij}	*Processing time of operation i for job j*
O_{ijw}	1, *if worker w is assigned to operation i of job j*, 0 *otherwise*.
$Y_{ii'jj'}$	1, *if operation i of job j starts before operation i' of job j'*, 0 *otherwise*.

Since assigned workers can influence the processing time of an operation, P_{ij} is introduced as a decision variable representing the processing time of operation i for job j. Lastly, the precedence decision variable $Y_{ii'jj'}$ takes the value 1 if operation i of job j starts before operation i' of job j', and 0 otherwise. With these definitions, the proposed model for FFSSP_HWA is given below:

Z = Min C_{max} (1)

s.t.

$C_{ij} \leq C_{max}$	$\forall i \in I, \forall j \in J$	(2)
$C_{ij} = X_{ij} + P_{ij}$	$\forall i \in I, \forall j \in J$	(3)
$\sum_w O_{ijw} = 1$	$\forall i \in I, \forall j \in J$	(4)
$X_{ij} + P_{ij} \leq X_{i+1,j}$	$\forall i \in I \; and \; i \neq \lvert I \rvert, \forall j \in J$	(5)
$X_{ij} + P_{ij} \leq X_{i'j} + M(1 - Y_{ii'jj})$	$\forall i, i' \in I, \forall j \in J$	(6)
$X_{ij} \leq X_{i'j'} + M(1 - Y_{ii'jj'})$	$\forall i, i' \in I, \forall j, j' \in J$	(7)
$X_{ij} + P_{ij} \leq X_{i'j'} + M(3 - Y_{ii'jj'} - O_{ijw} - O_{i'j'w})$	$\forall i, i' \in I, \forall j, j' \in J, \forall w \in W$	(8)
$O_{ijw} \leq a_{iw}$	$\forall i \in I, \forall j \in J, \forall w \in W$	(9)
$Y_{ii'jj'} + Y_{i'ij'j} = 1$	$\forall i, i' \in I \; and \; i \neq i', \forall j, j' \in J \; and \; j \neq j'$	(10)
$P_{ij} = \sum_w p_{ijw} n_j O_{ijw}$	$\forall i \in I, \forall j \in J$	(11)
$P_{ij}, X_{ij}, C_{ij} \geq 0$	$\forall i \in I, \forall j \in J$	(12)
$Y_{ii'jj'} \in \{0,1\}$	$\forall i, i' \in I, \forall j, j' \in J$	(13)
$O_{ijw} \in \{0,1\}$	$\forall i \in I, \forall j \in J, \forall w \in W$	(14)

The proposed model aims to minimize the time at which the last job completes processing, i.e., makespan, as defined in the objective function (1). Constraints (2) establish the makespan by ensuring that it is greater than or equal to all completion times. Constraints (3) define the completion time of each job as its starting time plus the processing duration. Constraints (4) guarantee that each operation is assigned to exactly one worker. Constraints (5) guarantee that, for the same job, the start time of an operation is greater than the completion time of the previous operation, as required by the precedence constraints. Constraints (6) establish the sequence of operations for the same job and accordingly define the values of the $Y_{ii'jj}$ variable. Constraints (7) ensure that operation i for job j must start before the operation i' for job j' if $Y_{ii'jj'}$ variable gets the value 1. Constraints (8) determine the sequence of operations for all jobs and ensure that workers are assigned accordingly, preventing them from being allocated to multiple jobs simultaneously. Constraints (9) ensure that workers are assigned to operations based on their capabilities. Constraints (10) guarantee that either operation i of job j starts before operation i' of job j' or vice versa. Constraints (11) determine the processing time of operation i of job j when executed by worker w. Finally, Constraints (12), (13), and (14) define the domains of the decision variables.

Case Study for FSSP_HWA

For the FFSSP_HWA, we consider a real-world case study from a manufacturing company specializing in the production of batteries. The production process involves four different types of batteries, each requiring the completion of sequential operations. There are a total of 19 operations. The precedence relationships among these operations are illustrated in Figure 1.

The workforce consists of eight workers, each possessing different skill sets and experience levels. As a result, processing times vary across workers, depending on their individual capabilities and familiarity with the specific operations. Out of the 19 operations, 18 require a worker, while Operation 1 (Cell Classification) is fully automated and performed by a machine. This operation does not require a worker. To incorporate this automated step into the model consistently, we introduce a dummy worker who is only assigned to Operation 1 and is not capable of performing any other task. This approach brings the total number of workers in the case to nine, including the dummy worker. Table 2 presents the worker skill matrix, which illustrates the operations each worker is capable of performing.

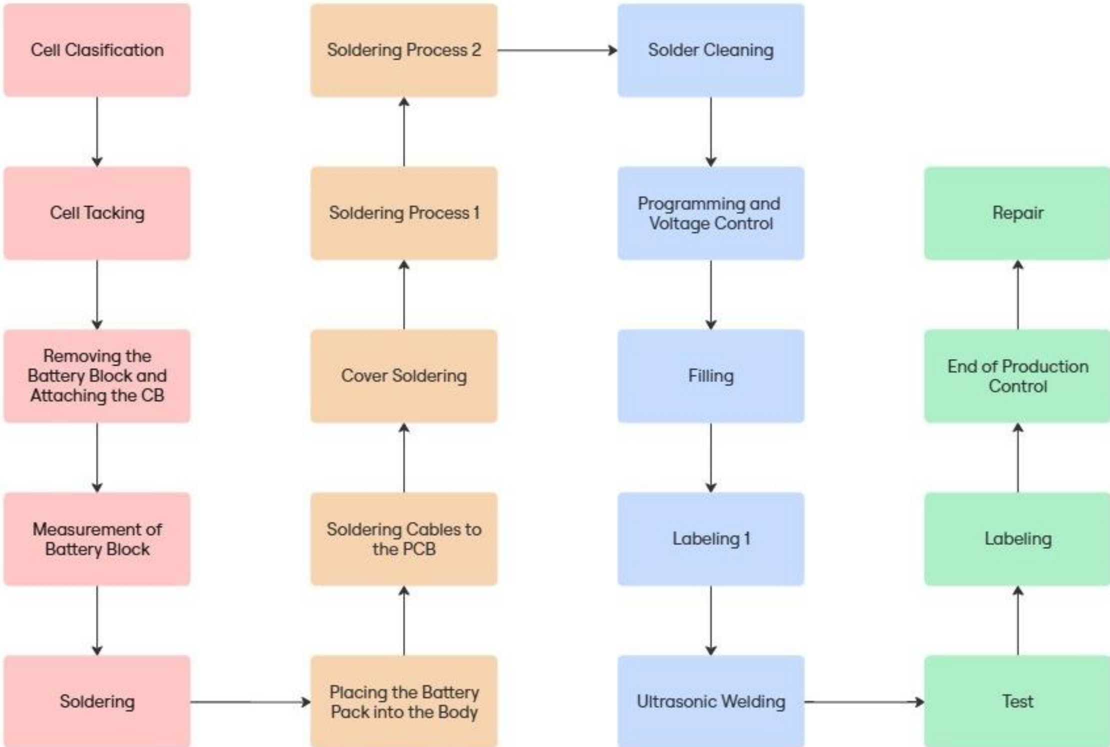

Figure 1. Precedence of operations

Table 2. Worker skill matrix

Operations	W1	W2	W3	W4	W5	W6	W7	W8	W9
1									✓
2				✓	✓	✓	✓	✓	
3	✓	✓	✓	✓	✓	✓	✓	✓	
4	✓	✓	✓	✓	✓	✓	✓	✓	
5					✓	✓	✓	✓	
6	✓	✓	✓	✓	✓	✓	✓	✓	
7					✓	✓	✓	✓	
8					✓	✓	✓	✓	
9					✓	✓	✓	✓	
10					✓	✓	✓	✓	
11	✓	✓	✓	✓	✓	✓	✓	✓	
12	✓	✓	✓	✓	✓	✓			
13	✓	✓	✓	✓	✓	✓	✓	✓	
14	✓	✓	✓	✓	✓	✓	✓	✓	
15	✓	✓	✓	✓					
16							✓	✓	
17	✓	✓	✓	✓	✓	✓	✓	✓	
18							✓	✓	
19	✓	✓	✓	✓	✓	✓	✓	✓	

In a single planning horizon, the company may receive varying order quantities for different jobs. A key scheduling constraint is that once an operation of a job has started, its subsequent operations cannot begin until the current operation is fully completed for the entire order quantity.

Computational Experiments with the Mathematical Model for FSSP_HWA

To test the proposed model for FFSSP_HWA through computational experiments, we utilized a production plan obtained from the company where we got our real-world case. The plan involves four different batteries, i.e., jobs, that will be scheduled within a single planning horizon. Specifically, it includes the production of 75 units of Job 1, 50 units of Job 2, 90 units of Job 3, and 100 units of Job 4. Our aim is to find the schedule that minimizes makespan while assigning workers to operations based on their skill sets. We solved this case using CPLEX and successfully obtained the optimal solution. The objective function value, representing the makespan, is 135,200 minutes. Our analysis of the solution confirms that the model accurately represents the problem and fulfills all predefined requirements.

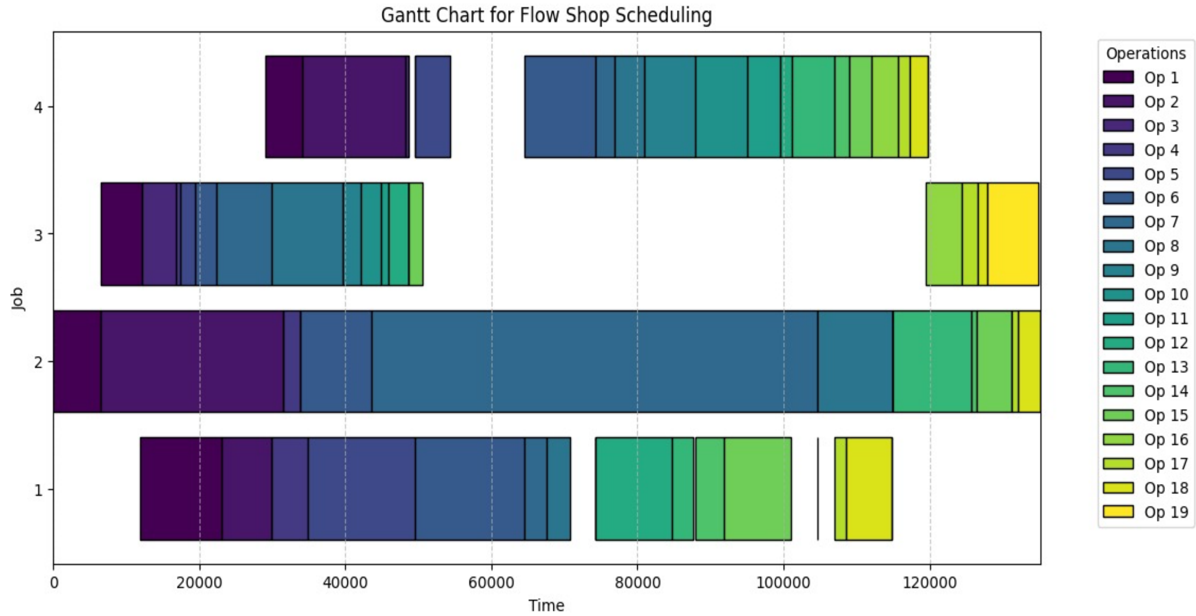

Figure 2. Gantt chart representing the schedule for each job

Figure 2 presents the Gantt chart illustrating the schedule for each job. Upon examining the chart, it is evident that the precedence constraints of the operations are satisfied. Makespan is equal to the completion time of the last operation of Job 2. In Job 2, each operation starts immediately after the preceding one, ensuring that no further improvement in makespan is possible for this production plan.

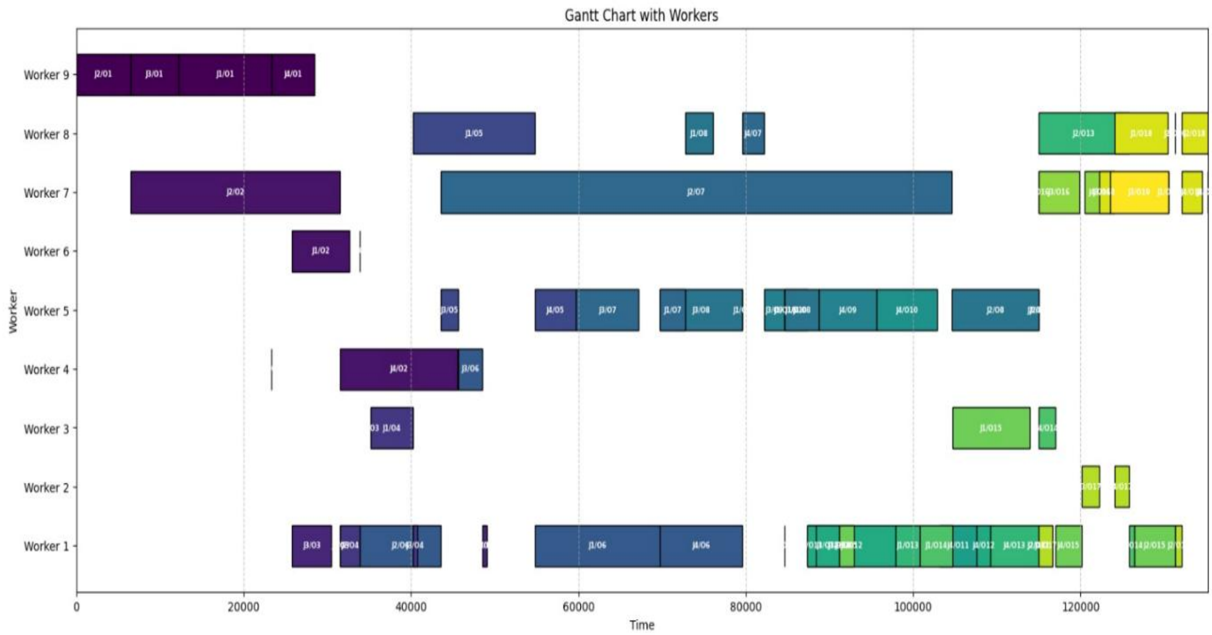

Figure 3. Gantt chart representing the schedule for each worker

Figure 3 presents the Gantt chart illustrating the schedule for each worker. As expected, workers are assigned to a new operation after completing their previous operation, as they cannot be assigned to multiple operations simultaneously. Upon analyzing the chart, we observed that some workers remain idle for a significant portion of the planning horizon. This observation prompted further analysis. To improve workforce utilization, we examined the possibility of assigning some workers to other tasks within the company instead of battery production. Specifically, we identified that Workers 2, 3, 4, and 6 had considerably lower workloads compared to others. To assess the impact of reducing the number of workers, we re-ran the proposed model, sequentially excluding Worker 2, then Worker 3, followed by Worker 4, and finally Worker 6. The results indicated that the objective function value remained unchanged, confirming that these four workers could be reallocated to other tasks without affecting the makespan value. Figure 4 presents the Gantt chart illustrating the job schedule with only four workers, while Figure 5 displays the corresponding worker schedule. Figure 4 also shows that the makespan remains unchanged in this revised schedule. A closer examination of Figure 5 reveals that Workers 1, 5, 7, and 8 are mostly utilized, with closely aligned working hours where Worker 9 serves as a dummy worker representing the first operation, which is performed automatically without a worker.

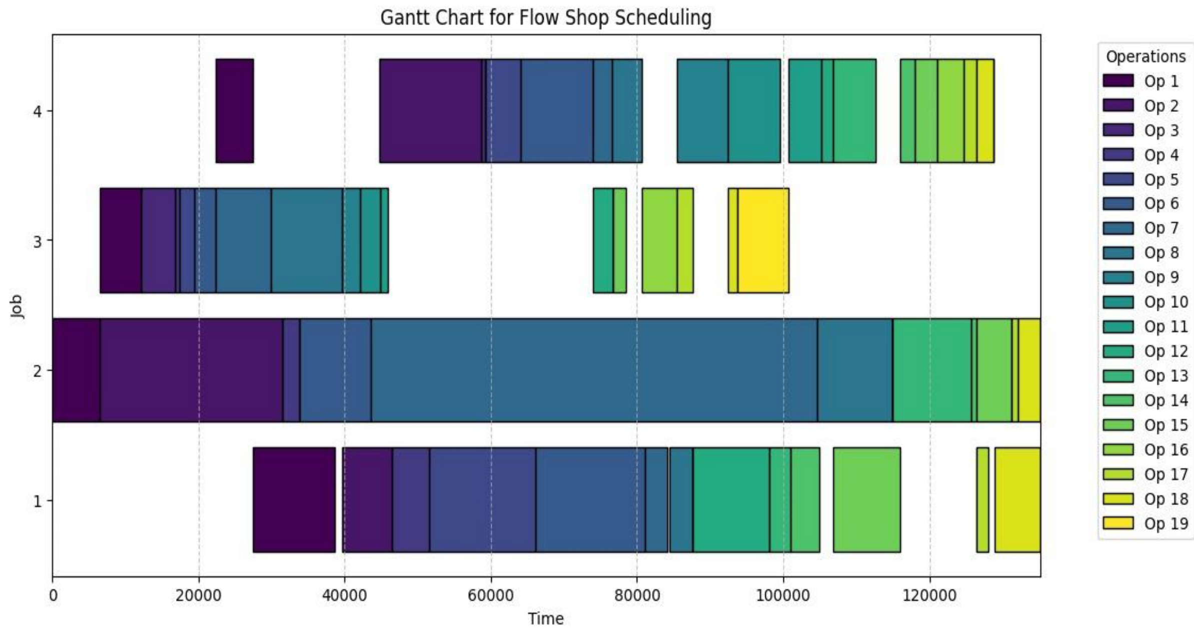

Figure 4. Gantt chart representing the schedule for each job with workers 1, 5, 7, 8 and 9

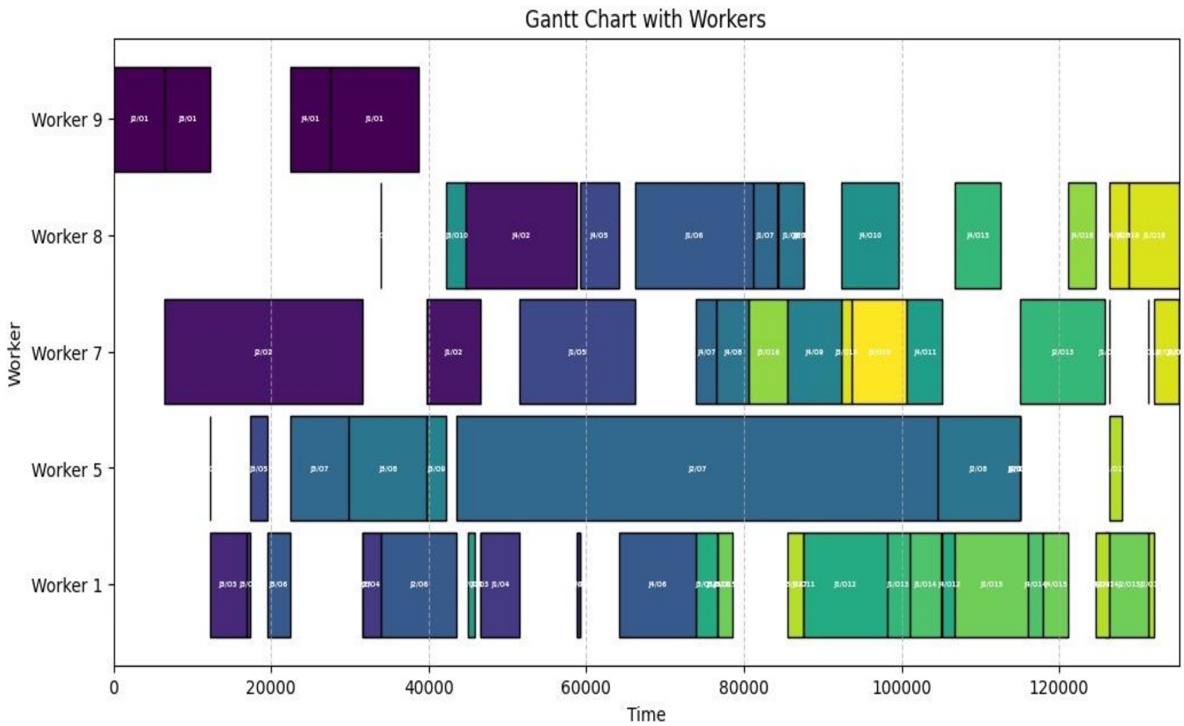

Figure 5. Gantt chart representing the revised schedule for each worker

Concluding Remarks and Future Research Directions

This study focuses on FFSSP_HWA, a flexible flow shop scheduling problem with heterogeneous worker assignment, inspired by a real-world company manufacturing batteries. Traditional flow shop scheduling models often ignore worker-related factors, assuming the processing capabilities of workers are the same. However, in real-life settings, workers possess different skills and experience levels that influence their suitability for specific operations and their processing speeds. To address this gap, our study incorporates both worker skills and worker efficiency variations in the scheduling process. By considering worker flexibility through cross-training and heterogeneous processing times, our model represents a more realistic production environment.

An integer programming model is developed for FFSSP_HWA. This model takes into account the precedence of the operations for the jobs, assigns workers to operations according to their skills, and minimizes the makespan. To test the proposed model, we conducted computational experiments using real-world production data. This case involves scheduling four different batteries, i.e., jobs with varying quantities, aiming to minimize the makespan while assigning workers based on their skill sets. The model was solved optimally using CPLEX. Examing the solution confirms its capability to represent the problem accurately. Additionally, we performed a sensitivity analysis on workforce utilization by analyzing worker assignments and identifying underutilized workers. Through iterative reduction of workers, we re-ran the model to assess its impact. The results proved that the makespan remained unchanged despite reducing the number of workers, indicating that some workers could be reassigned to other tasks. This analysis emphasizes the model's ability to support workforce planning decisions besides scheduling the jobs to minimize makespan in a flexible flow shop environment with heterogeneous workers.

To sum up, this study addresses the flexible flow shop scheduling problem with heterogeneous worker assignments, incorporating worker skills and varying processing speeds. By incorporating real-world constraints and solving the problem optimally using CPLEX, we show the model's effectiveness in accurately representing workforce flexibility in production scheduling. A case study from a company manufacturing battery validates the applicability of the proposed model. Moreover, sensitivity analyses on workforce utilization provide opportunities for optimizing labor allocation. While we were able to solve our case optimally using CPLEX, larger real-life problems with more jobs, operations, and workers may create computational challenges, making it difficult to reach optimality. As a future direction, we plan to test the model on larger instances. In cases where optimal solutions cannot be obtained, we aim to develop heuristic solution algorithms to solve the problem efficiently. Future studies could also extend this model by integrating additional constraints required for different industrial areas.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

Funding

* This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors

Acknowledgments or Notes

* This article was presented as an oral presentation at the International Conference on Basic Sciences, Engineering, and Technology (www.icbaset.net) held in Trabzon/Türkiye on May 01-04, 2025.

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To cite this article:

Ozpacaci, K., Bekli, S. & Kayisoglu, B., (2025). Incorporating worker heterogeneity in flexible flow shop environment. *The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 34,* 359-368.