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BALANCING ASSEMBLY LINE WITH MOVING WORKERS AND WORKER-DEPENDENT TASK TIMES USING LINEAR PROGRAMMING FORMULATION

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ABSTRACT

This study addresses the moving heterogeneous worker assembly line balancing problem, a new variant of the classical problem that simultaneously considers worker-dependent task times and worker mobility between stations. In this setting, the processing time of each task differs according to the skills and efficiency of the assigned worker, while workers are allowed to move within a limited range to perform tasks at different stations. These features make the problem more realistic but also substantially more complex, as precedence relations, heterogeneous workloads, cycle time restrictions, and worker movements must all be satisfied simultaneously. To capture these interrelated aspects, mixed integer linear programming is proposed, which can provide exact solutions for small-sized instances. A dataset based on well-known precedence diagrams is generated to evaluate model performance across varying levels of task time variability and worker–station configurations.

The results show that the formulation optimally solves small-sized instances, whereas medium and large instances remain computationally demanding, with increasing gaps and longer solving times. The findings further reveal that adding an extra workstation can improve efficiency, especially in larger-sized problem instances. Overall, this study contributes to assembly line literature with a novel mathematical model that integrates worker heterogeneity and mobility, highlighting future research opportunities for heuristic and metaheuristic approaches.

1. INTRODUCTION

Assembly lines are fundamental elements of manufacturing systems, which are designed to organize tasks sequentially and support efficient mass production. They contribute to increased throughput, reduced production costs, and systematic task flow. Due to their significance, a wide range of studies have addressed issues such as line efficiency, balancing strategies, workforce utilization, design flexibility, and waste reduction. Over time, various configurations of assembly lines have been introduced, each creating unique optimization challenges.

The assembly line balancing problem (ALBP) is one of the most studied topics in this context. It involves the assignment of tasks to stations (or workers) in a manner that satisfies precedence relations for generally minimizing the number of stations (Type I) or the cycle time (Type II). As an NP-hard problem [1],[2], ALBP is central for efficiency, reducing idle time, and optimizing workforce performance. Traditional ALBP studies typically assume that workers are equally skilled and that task times are identical for each worker. However, in real-world applications, worker heterogeneity is inevitable, as task times vary depending on skills, experience, and qualifications [3],[4]. This has given rise to variants such as the assembly line worker assignment and balancing problem (ALWABP), hierarchical worker models, and worker-station assignment [5],[6].

Several assembly line configurations allow workers to move between stations, especially in systems with longer cycle times. These lines are studied under different terms, such as bucket brigades, walking workers, traveling workers, moving workers, or open-station systems [7]-[10]. Allowing workers to walk between stations enables them to perform tasks where they are most efficient, while still respecting precedence constraints and cycle time restrictions. Nevertheless, this flexibility increases problem complexity, as it requires simultaneous consideration of task allocation, worker-dependent task times, and station assignments. Modeling an assembly line with both walking workers and worker-dependent task times makes the problem more complicated, while offering many advantages. Allowing workers to walk to other stations enhances flexibility, as workers can perform tasks where they are most efficient, potentially improving line throughput. However, this flexibility also introduces additional complexity: models must consider task assignment, worker-specific task times, and precedence constraints simultaneously.

Due to their significance in production planning and efficiency improvement, these types of assembly lines have attracted substantial attention in literature. Within this research domain, two notable directions stand out: the walking worker assembly line balancing problem (WW-ALBP) and ALWABP. Studies on walking workers remain relatively limited, and their scope often varies depending on the degree of worker mobility between stations as well as the structural characteristics of the assembly line. Research on worker-dependent task times, generally studied under the ALWABP framework, has gained increasing prominence in recent years, as it captures the heterogeneity of worker skills and performance observed in real manufacturing systems. To provide a clearer perspective, the following sections review the literature on WW-ALs and ALWABPs separately, highlighting both their individual contributions and their potential complementarities.

Studies on walking worker assembly lines (WW-ALs) are as follows. Early attempts to address walking worker assembly lines can be traced back to Lassalle [11], who emphasized that process waiting times may create buffer stocks and prolong total production time. The study demonstrated that idle times resulting from the occupancy of subsequent stations could significantly impact system efficiency, and simulation experiments were conducted to predict waiting times under varying parameters. Following this, Wang et al. [7] investigated a straight-line ALBP in which workers move sequentially along the line to minimize the number of workers and stations required for a given production rate. Their results, obtained through simulation experiments under diverse configurations, demonstrated that walking worker systems could outperform fixed-worker lines in terms of productivity.

Research on alternative line structures also expanded over time. For instance, Shewchuk [12] studied U-shaped lines, focusing on the assignment of workers to machines with the dual objectives of minimizing the workforce and maximizing labor utilization. Similarly, Sirovetnukul and Chutima [13] examined U-line configurations, illustrating that worker allocation strategies significantly impact system efficiency. Another contribution came from Al-Zuheri et al. [14], who validated a stochastic worker assignment model through simulation, highlighting the impact of variability in task times on throughput. Building on this, Cevikcan [15] proposed a hierarchical modeling approach for worker-flexible ALs, while Al-Zuheri et al. [16] combined mathematical programming with genetic algorithms to jointly improve productivity and ergonomics.

Later studies extended these efforts into more specialized problem classes. Sikora et al. [8] formally introduced the traveling worker ALBP (TWALBP), proposing a mathematical model and testing it on both benchmark problems and industrial cases. Similarly, Deepak et al. [17] analyzed TWALBP through simulation, confirming the superiority of traveling worker lines over fixed-worker lines in terms of waiting time reduction and production rate improvement. More recently, Şahin and Kellegöz [9] investigated the multi-manned assembly line balancing problem with walking workers, presenting a mixed-integer linear programming formulation and an enhanced metaheuristic approach that outperformed traditional methods. Further contributions include the works of Liu et al. [10], who proposed a stochastic programming model with genetic algorithms under uncertainty in worker availability, and Petroodi et al. [18], who formulated a reconfigurable mixed-model line problem using Markov decision processes to optimize dynamic task assignments.

A second important research stream focuses on assembly lines where task durations vary between workers depending on their skills and qualifications. In such cases, the problem requires not only allocating tasks to workstations but also deciding which worker should execute each task, leading to the ALWABP. Most studies in this domain have concentrated on straight lines, although some contributions also address U-shaped [19],[20] and two-sided configurations [21].

ALWABP was first formally defined by Miralles et al. [22], who developed a model to minimize cycle time by simultaneously assigning tasks and workers. Subsequent studies extended this line of research. For instance, Blum and Miralles [23] proposed a beam search algorithm, while Araujo et al. [24] introduced collaborative worker variants to capture the effects of parallelization. Borba and Ritt [25] contributed new mathematical models and heuristics supported by lower bound techniques, while Ramezanian and Ezzatpanah [26] incorporated dual objectives of minimizing cycle time and worker-related costs. In addition, Oksuz et al. [19] addressed U-shaped lines using swarm intelligence algorithms, and Moreira et al. [27] emphasized the integration of heterogeneous workers into production systems. Janardhanan et al. [21] applied the migrating birds optimization algorithm to large-scale problems, and Akyol and Baykasoğlu [28] developed variants addressing ergonomic risks and disruption management. More recent contributions include Campana et al. [4], who proposed a hierarchical qualification system with both cycle time and cost objectives, Karas and Özçelik [29], who studied reassignments under disruptions, and Michels and Costa [30], who focused on integrating heterogeneous workers into multi-manned lines.

This study differs from previous ALBP research by simultaneously addressing worker mobility between stations and worker-dependent task times in a single, integrated mathematical formulation. While previous research has addressed these aspects separately under the WW-ALBP and ALWABP formulations, this article integrates both dimensions simultaneously, providing a more comprehensive and realistic representation of assembly lines with heterogeneous and mobile workers. Overall, the literature demonstrates significant progress in both WW-ALBP and ALWABP frameworks. However, the joint consideration of worker-dependent task times and worker mobility across stations has been rarely explored, despite its strong practical relevance to real industrial systems. This research gap motivates the present study, which unifies these two critical aspects within a single problem framework and proposes a mixed-integer linear programming formulation to capture their combined effects.

2. PROBLEM DEFINITION

This paper proposes the mobile heterogeneous worker (MHW) assembly line balancing problem (MHW-ALBP), a new formulation of the classical ALBP where task processing times vary according to the assigned worker and workers are allowed to move between stations within a predefined interval. By capturing both worker heterogeneity and mobility, the MHW-ALBP provides a more realistic representation of assembly line systems.

To illustrate the proposed problem more concretely, a precedence diagram is employed. Figure 1 illustrates the Bowman precedence diagram, where each node represents to a task and directed arcs denote precedence relations. The values in parentheses indicate the processing times of tasks for different workers, thus reflecting the worker-dependent nature of task durations. For instance, task 1 requires 3 units of time when performed by worker 1, whereas the same task takes 6 units of time for worker 2, clearly illustrating the heterogeneity in execution times.

Figure 2 illustrates an assembly line with MHW, in which the line consists of three workstations and two workers who are assigned to perform the required tasks. Tasks 1, 2, 4 are allocated to the first workstation, tasks 3, 5, 6, 8 are assigned to the second workstation, and task 7 is placed in the third workstation. The graphical representation emphasizes that workers are not restricted to a single station but can move between stations to complete their assignments. The worker icons and arrows demonstrate possible worker movements along the line, showing how the interaction between task allocation, heterogeneous processing times, and worker mobility shapes the dynamics of the system. Compared to traditional fixed-worker ALBP models, this example captures a more realistic assembly line environment that considers both worker variability and flexibility jointly.

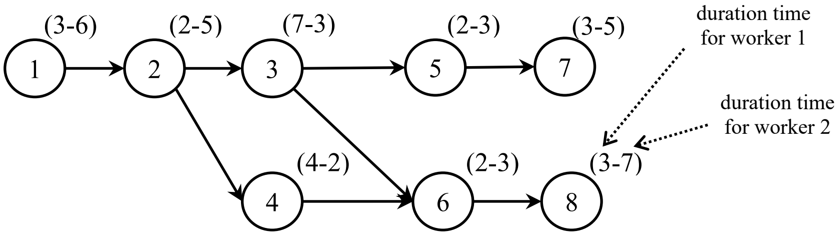

Figure 1. Bowman precedence diagram with worker-dependent task times.

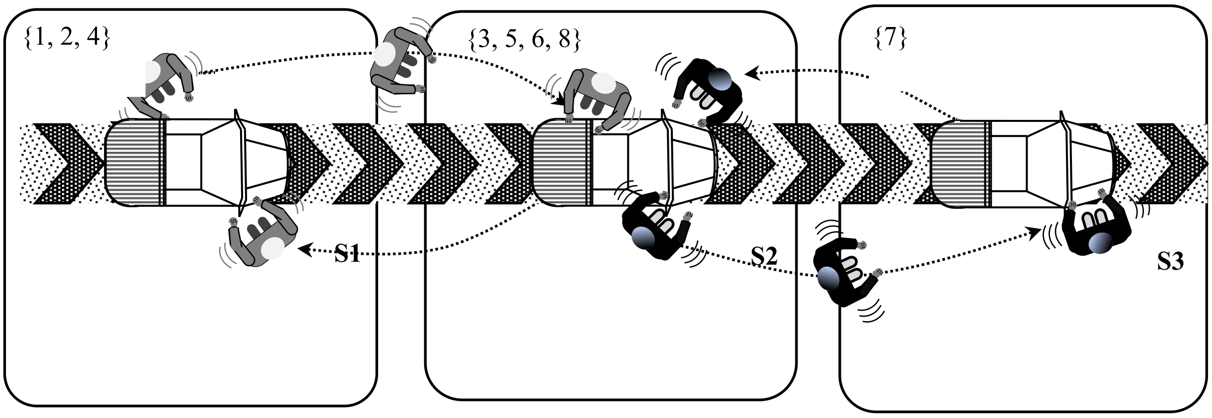

Figure 2. An illustration of an assembly line with mobile workers and worker-dependent task times.

The MHW-ALBP addresses the simultaneous assignment of tasks $i \in I$ to workers $k \in K$ and workstations $j \in J$, while ensuring that all tasks are scheduled under key operational restrictions such as precedence relations, cycle time constraint, and worker workload balance, with the primary objective of maximizing production rate. Each task i is characterized by a worker-dependent processing time t_{ik} , which varies according to the skills and efficiency of the assigned worker k. Workers are allowed to move between stations, but their mobility is restricted by a predefined interval limit ψ (set to 3 in this study). Walking times between stations are incorporated into the task start times; however, these walking times are assumed to be relatively small compared to the overall cycle time and therefore exert only a limited influence on system performance. At the beginning of each cycle, workers are at the station where their first task is located. Besides that, the problem is also defined under the following assumptions:

- The assembly line follows a straight-line configuration and produces a single product model.
- All precedence constraints among tasks must be satisfied.
- Each task is assigned to exactly one workstation and exactly one worker.
- Tasks are indivisible and non-preemptive once initiated.
- Task processing times are deterministic and depend on the assigned worker.
- Worker mobility is restricted by the station interval limit ψ.
- Walking times between stations are negligible compared to the cycle time.
- At any given moment, only one worker is allowed to operate on a specific semi-finished product.

Based on these assumptions, a mixed-integer linear programming (MILP) model is developed in the following section to formally describe the problem structure and decision-making framework.

3. SOLUTION METHODS

The information regarding the notations used in the MILP is presented below.

Sets and Parameters:

n	total number of tasks
m	total number of workstations
wn	total number of workers
I	set of tasks $\{1, 2, \ldots, n\}$
J	set of workstations $\{1, 2, \ldots, m\}$
K	set of workers $\{1, 2, \ldots, wn\}$
P_i	set of immediate predecessors of task i
t_{ik}	processing time of task i when it is performed by worker k
ψ	maximum station range within which a worker can travel
M	sufficiently big number

Variables:

x_{ij}	Binary variable with value 1 if task i is assigned to station j.
w_{ik}	Binary variable with value 1 if task i is assigned to worker k.
C	Cycle time
t_i^{actual}	Positive variable which shows the required duration time of *task i* according to the assigned worker
l_i	Positive variable which shows the starting time of task i with interval 0 and cycle time.
r_{ih}	Auxiliary binary variable, used to perform one task before the other if tasks i and h are assigned to the same worker.
rr_{ih}	Auxiliary binary variable, used to perform one task before the other if tasks i and h are assigned to the same workstation.

Objective functions and constraints are as follows:

$$minimizing\ C \tag{1}$$

$$\sum_{j\in J} x_{ij} = 1 \qquad \forall\, i \in I \tag{2}$$

$$\sum_{k\in K} w_{ik} = 1 \qquad \forall\, i \in I \tag{3}$$

$$\sum_{k\in K} t_{\mathrm{ik}} \cdot w_{ik} \le t_i^{actual} \qquad \forall\, i \in I \tag{4}$$

$$l_i + t_i^{actual} \le C \qquad \forall\, i \in I \tag{5}$$

$$l_h + t_h^{actual} \le l_i \quad + \mathrm{M} \cdot (2 - x_{ij} - x_{hj}) \qquad \forall\, j \in J;\ \forall\, i \in I;\quad \forall\, h \in P_i \tag{6}$$

$$\sum_{j\in J} j \cdot x_{hj} \le \sum_{j\in J} j \cdot x_{ij} \qquad \forall\, i \in I;\quad \forall\, h \in P_i \tag{7}$$

$$t_i^{actual} \le l_h - l_i + \mathrm{M} \cdot (3 - w_{hk} - w_{ik} - r_{ih})$$
$$\forall\, i \in I;\ \forall\, h \in \{\, s \mid s \in I \text{and } i < s \,\};\ \forall\, k \in K \tag{8}$$

$$t_h^{actual} \le l_i - l_h + \mathrm{M} \cdot (2 - w_{hk} - w_{ik} + r_{ih})$$
$$\forall\, i \in I;\ \forall\, h \in \{\, s \mid s \in I \text{ and } i < s \,\};\ \forall\, k \in K \tag{9}$$

$$t_i^{actual} \le l_h - l_i + \mathrm{M} \cdot \left(3 - x_{hj} - x_{ij} - rr_{ih}\right)$$
$$\forall\, i \in I;\ \forall\, h \in \{\, s \mid s \in I \text{ and } i < s \,\};\quad \forall\, j \in J \tag{10}$$

$$t_h^{actual} \leq l_i - l_h + \mathrm{M} \cdot (2 - x_{hj} - x_{ij} + rr_{ih})$$

$$\forall\, i \in I;\ \forall\, h \in \{\, s \mid s \in \mathrm{I} \text{ and } i < s \,\};\quad \forall\, j \in J \tag{11}$$

$$\textstyle\sum_{j \in J} j \cdot (x_{hj} - x_{ij}) \leq \psi + m \cdot (2 - w_{hk} - w_{ik}) \qquad \forall (i,\, h) \in I;\ \forall\, k \in K \tag{12}$$

$$\textstyle\sum_{j \in J} j \cdot (x_{ij} - x_{hj}) \leq \psi + m \cdot (2 - w_{hk} - w_{ik}) \qquad \forall (i,\, h) \in I;\ \forall\, k \in K \tag{13}$$

$$x_{ij} \in \{0,1\} \qquad \forall\, i \in I;\ \forall\, j \in J \tag{14}$$

$$w_{ik} \in \{0,1\} \qquad \forall\, i \in I;\ \forall\, k \in K \tag{15}$$

$$r_{hi} \in \{0,1\};\ rr_{hi} \in \{0,1\} \qquad \forall\, h \in I;\ \forall\, i \in I \tag{16}$$

$$l_i \geq 0 \qquad \forall\, i \in I \tag{17}$$

$$C \geq 0 \tag{18}$$

The objective function of the mathematical model (1) is to minimize the cycle time, which is equivalent to maximizing the production rate. Equation (2) assigns each task to a workstation, while Equation (3) assigns each task to a worker. Constraint (4) adjusts the actual processing time of a task according to the assigned worker. According to constraint (5), the finishing time of a task cannot be greater than the cycle time. According to constraint (6), if task i and h are assigned to the same workstation and have precedence relations among them ($h \rightarrow i$), the predecessor task must be performed earlier. Constraint (7) adjusts the precedence relations according to station assignments. When tasks i and h are assigned to the same worker, only one of the constraints (8) or (9) becomes active, enforcing their sequential execution. Similarly, when tasks i and h are assigned to the same workstation, only one of the constraints (10) or (11) becomes active, ensuring their sequential execution. The movement range between workstations is regulated by constraints (12) and (13). Finally, constraints 14-18 are the sign and binary restrictions.

4. COMPUTATIONAL EXPERIMENTS

To assess the effectiveness of the proposed MILP and to determine the problem sizes up to which the model can be solved optimally, a dataset of 63 test instances was employed. Details of the dataset are presented in the subsequent subsection. The models were solved using the Cplex 22.1 solver on a web-based server platform, with a computation time limit of 18,000 seconds per instance.

4.1. Data Set

A dataset consisting of 63 test instances was generated based on well-known precedence diagrams. The instances differ in terms of the number of workers, the number of workstations, and the degree of task time variability among workers (low, medium, and high). The general characteristics of the dataset are summarized in Table 1.

Table 1. General information about the dataset.

Precedence Diagram	***#Tasks***	***# Instances***	***Worker–Station Configurations***	μ_{avg}	σ_{avg}		
					Low	***Medium***	***High***
Bowman	8	6	2–2, 2–3	9.09	0.80	1.50	2.03
Mansoor	9	6	2–2, 2–3	12.07	1.09	1.48	2.38
Jackson	11	6	2–2, 2–3	4.18	0.45	0.64	0.96
Roszieg	25	9	5–5, 5–6, 6–6, 6–7	6.41	2.25	3.87	4.95
Buxey	29	9	5–5, 5–6, 6–6, 6–7	10.7	1.10	2.32	4.12
Gunther	35	9	5–6, 6–6, 6–7	13.35	1.81	2.61	6.13
Kilbrid	45	9	6–7, 7–7, 7–8	11.90	1.47	2.66	9.12
Warnecke	58	9	7–7, 7–8, 8–9, 9–9, 9–10	27.30	3.51	5.23	5.88

As shown in Table 1, the dataset covers a wide range of precedence diagrams, ranging from small-sized (Bowman, 8 tasks) to large-sized problems (Warnecke, 58 tasks). Each diagram was tested under different worker–station configurations, ensuring diversity across problem sizes and structures. The mean processing times (μ_{avg}) computed as Equation (19) and the average standard deviations ($\sigma_{avg} = \frac{1}{n} \cdot \sum_{i \in I} \sigma_i$) by taking the values computed using Equation (20) corresponding to the three variability levels illustrate the heterogeneity within the dataset.

$$\mu_{avg} = \frac{1}{n} \cdot \frac{1}{wn} \cdot \sum_{i \in I} \sum_{k \in K} t_{ik} \tag{19}$$

$$\sigma_i = \sqrt{\sum_{k \in K} \left(t_{ik} - t_i^{avg}\right)^2 \Big/ wn} \tag{20}$$

4.2. Experimental Results

The computational results are summarized in Table 2, which reports the number of optimally solved instances (#OS), average percentage gap ($gap\% = 100 \cdot (obj - LBC)/obj$) from the lower bound computed using Equation (21), and average CPU times for each precedence diagram.

$$LBC = max\left\lceil t_{min}^{max}, \quad T_{sum}^{min} \big/ wn \right\rceil \tag{21}$$

In Equation (21), T_{sum}^{min} indicates the summation of the minimum processing times for each task, *wn* is the number of workers, and t_{min}^{max} corresponds to the maximum task duration within this set of minimum values. For small-sized diagrams (Bowman, Mansoor, Jackson), all instances were solved optimally within very short CPU times. Bowman instances were solved almost instantly, while Mansoor and Jackson required slightly more computational effort, though still negligible compared to the time limit.

For medium-sized instances such as Roszieg, only a single instance could be solved optimally, with the remaining instances yielding an average % gap of approximately 9.6% and an average CPU time close to the imposed limit. For larger precedence diagrams (Buxey, Gunther, Kilbrid, and Warnecke), none of the instances were solved optimally within the given time limit. The average % gap increases consistently with problem size, rising from 6.0% for Buxey to over 20.0% for Warnecke. The computational results also provide insights into the time and resource requirements of the proposed MILP formulation. For small instances, the model was solved within seconds using standard computational resources. For the largest dataset (Warnecke, 58 tasks), the solver reached the 18,000-second limit without achieving optimality, requiring high memory usage.

Table 2. Experimental results according to the precedence diagram.

Precedence Diagram	***#Tasks***	***#Instances***	***# OS***	***Avg. %gap***	***Avg. CPU (s)***
Bowman	8	6	6	0.00	0
Mansoor	9	6	6	0.00	1
Jackson	11	6	6	0.00	51
Roszieg	25	9	1	9.59	16451
Buxey	29	9	0	6.00	18000
Gunther	35	9	0	8.99	18000
Kilbrid	45	9	0	14.97	18000
Warnecke	58	9	0	20.08	18000

#OS: number of optimal solutions

The computational complexity of the proposed mathematical formulation increases exponentially with the problem size. As the number of tasks, workers, and stations increases, the number of binary decision variables and precedence-related constraints expands combinatorially, resulting in a rapid escalation of the solution space. This makes the problem computationally intractable for large instances, as each additional task or worker introduces multiple new assignments and sequencing possibilities. Given that the problem is NP-hard, the MILP solver must explore an exponentially increasing number of feasible combinations, which explains the sharp rise in CPU time and optimality gaps observed in Table 2. These findings indicate that while the MILP model is feasible for small-sized instances, it becomes computationally intensive for larger ones, suggesting the need for more scalable heuristic or hybrid approaches in future research.

4.3. Effect of Adding an Extra Workstation

The impact of opening an additional workstation is presented in Table 3. The table compares the average objective values obtained when the number of stations equals the number of workers ($m = wn$) with the case where one additional station is opened ($m = wn+1$).

For small-sized precedence diagrams (Bowman, Mansoor, and Jackson), optimal solutions were obtained in all instances, and adding an extra station resulted in slight improvements in the objective values. For example, in the Bowman instances, the average objective decreased from 35.0 to 34.3 when an extra station was added. Similar improvements were observed for Mansoor and Jackson, where the average objectives decreased from 64.7 to 63.0 and from 21.3 to 21.0, respectively.

Table 3. Showing the effect of opening an extra workstation.

Diagram	***#Instance***	***Avg. Obj* ($m = wn$)**	***Avg. Obj* ($m = wn+1$)**
Bowman	3	35.0*	34.3*
Mansoor	3	64.7*	63.0*
Jackson	3	21.3*	21.0*
Roszieg	3	21.7	21.0
Buxey	3	52.7	52.2
Gunther	3	78.7	74.0
Kilbrid	3	77.7	69.7
Warnecke	3	229.3	213.8

**Optimal solutions are found for each instance*
m: the number of stations
wn: the number of workers

For medium and large-sized instances (Roszieg, Buxey, Gunther, Kilbrid, and Warnecke), the average objectives also show reductions when an extra workstation is introduced. However, it should be emphasized that these results were not obtained from optimal solutions, as indicated by the absence of stars in Table 3. Therefore, the observed improvements in such cases cannot be interpreted as definitive effects of opening an extra station, but rather as indicative trends based on the best solutions found within the time limit. Notably, in the largest diagrams, such as Warnecke, the reduction from 229.3 to 213.8 suggests that additional stations may provide substantial improvements in large-scale systems, although further verification with exact solutions would be required.

5. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This study introduced the heterogeneous worker assembly line balancing problem with workers' mobility, a new variant that jointly considers worker-dependent task times and worker mobility between stations. When task times vary according to the skills and efficiency of the assigned worker, the allocation of tasks becomes substantially more complex, as it requires balancing heterogeneous workloads while still respecting precedence relations and cycle time restrictions. Allowing workers to move between stations further increases this complexity, since the model must simultaneously determine task assignments, worker allocations, and feasible movement ranges. This dual consideration of heterogeneity and mobility introduces additional constraints and interdependencies, but it also creates opportunities to increase flexibility and line efficiency. Unlike previous studies that consider only worker mobility or worker heterogeneity, this study integrates both factors within a single MILP model. This combined approach increases the realism of the proposed formulation and introduces a new problem type. The proposed model extends existing ALBP frameworks and provides a foundation for future research on more flexible and realistic assembly line systems.

The suggested MILP can serve as a decision-support tool for production planners and line managers, optimizing workforce allocation and workstation design across heterogeneous skill levels. It enables decision-makers to assess the trade-offs between worker flexibility and line efficiency, providing insight into when additional workstations or reassignments may enhance throughput. Moreover, the model can be adapted to dynamic production settings by incorporating time-dependent worker availability or stochastic task times, enabling its application in environments with fluctuating demand, shift schedules, or operator learning effects. These extensions would further enhance the model's practical value in real industrial systems.

Due to the increased number of tasks and workers in real-world applications, the MILP model may face computational challenges when solving large-scale instances. Future research may focus on designing efficient heuristic algorithms or a hybrid MILP–metaheuristic to provide high quality solutions for large-sized instances. Moreover, integrating the proposed model into digital manufacturing or decision-support platforms would enhance its practical relevance and facilitate real-time implementation in industrial environments. Another promising direction is the integration of additional real-world characteristics such as stochastic or dynamic task times, learning and deterioration effects, or ergonomic considerations, which would extend the model's applicability to industrial environments. In addition, multi objective approaches that simultaneously address production rate, cost efficiency, and worker well-being could align this research with emerging trends in the literature. Finally, applying the proposed formulation and solution approaches to industrial case studies would provide further validation and highlight managerial insights into the role of worker heterogeneity and mobility in assembly line systems.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

Murat Şahin: Development of mathematical model, data processing, data analysis, manuscript preparation.

İsmet Söylemez: Data analysis, literature review, data analysis, manuscript preparation.

All authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] A. Yoosefelahi, M. Aminnayeri, H. Mosadegh, and H. D. Ardakani. Type II robotic assembly line balancing problem: An evolution strategies algorithm for a multi-objective model. *Journal of Manufacturing Systems*, *31*(2), 2012, 139-151.

[2] Y. Delice, E. K. Aydoğan, İ. Söylemez, and U. Özcan. An ant colony optimisation algorithm for balancing two-sided U-type assembly lines with sequence-dependent set-up times. *Sādhanā, 43*(12), 2018, 199.

[3] M. C. O. Moreira, J. F. Cordeau, A. M. Costa, and G. Laporte. Robust assembly line balancing with heterogeneous workers. *Computers and Industrial Engineering*, *88*, 2015, 254-263.

[4] N. P. B. Campana, M. Iori, and M. C. O. Moreira. Mathematical models and heuristic methods for the assembly line balancing problem with hierarchical worker assignment. *International Journal of Production Research, 60*(7), 2022, 2193-2211.

[5] B. Sungur, and Y. Yavuz. Assembly line balancing with hierarchical worker assignment. *Journal of Manufacturing Systems, 37*, 2015, 290-298.

[6] O. Polat, C. B. Kalayci, Ö. Mutlu and S. M. Gupta. A two-phase variable neighbourhood search algorithm for assembly line worker assignment and balancing problem type-II: an industrial case study. *International Journal of Production Research*, *54*(3), 2016, 722-741.

[7] Q. Wang, G. W. Owen, and A. R. Mileham. Determining numbers of workstations and operators for a linear walking-worker assembly line. *International Journal of Computer Integrated Manufacturing, 20*(1), 2007, 1-10.

[8] C. G. S. Sikora, T. C. Lopes, and L. Magatão. Traveling worker assembly line (re) balancing problem: Model, reduction techniques, and real case studies. *European Journal of Operational Research, 259*(3), 2017, 949-971.

[9] M. Şahin, and T. Kellegöz. Balancing multi-manned assembly lines with walking workers: problem definition, mathematical formulation, and an electromagnetic field optimization algorithm. *International Journal of Production Research*, *57*(20), 2019, 6487-6505.

[10] M. Liu, Z. Liu, F. Chu, R. Liu, F. Zheng, and C. Chu. Risk-averse assembly line worker assignment and balancing problem with limited temporary workers and moving workers. *International Journal of Production Research,* 60(23), 2022, 7074-7092.

[11] S. Lassalle, Q. Wang, G. W. Owen, and A. R. Mileham. A study of in-process waiting time on a linear walking worker assembly line. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *221*(12), 2007, 1763-1770.

[12] J. P. Shewchuk. Worker allocation in lean U-shaped production lines. *International Journal of Production Research*, *46*(13), 2008, 3485-3502.

[13] R. Sirovetnukul and P. Chutima. The impact of walking time on U-shaped assembly line worker allocation problems. *Engineering Journal*, *14*(2), 2010, 53.

[14] A. Al-Zuheri, L. Luong, and K. Xing. The role of randomness of a manual assembly line with walking workers on model validation. *Procedia CIRP*, *3*, 2012, 233-238.

[15] E. Cevikcan. A mathematical programming approach for walking-worker assembly systems. *Assembly Automation*, *34*(1), 2014, 56-68.

[16] A. Al-Zuheri, L. Luong, and K. Xing. A framework supporting the design of walking worker assembly line towards improving productivity and ergonomics performance, *Int. Journal of Engineering Research and Application 4*(3), 2014, 514-523.

[17] A. Deepak, R. Srivatsan, and V. Samsingh. A case study on implementation of walking worker assembly line to improve productivity and utilisation of resources in a heavy duty manufacturing industry. *FME Transactions*, *45*(4), 2017, 497.

[18] S. E. H. Petroodi, S. Thevenin, S. Kovalev, and A. Dolgui. Markov decision process for multi-manned mixed-model assembly lines with walking workers. *International Journal of Production Economics*, *255*, 2023, 108661.

[19] M. K. Oksuz, K. Buyukozkan, and S. I. Satoglu. U-shaped assembly line worker assignment and balancing problem: A mathematical model and two meta-heuristics. *Computers and Industrial Engineering*, *112*, 2017, 246-263.

[20] Z. Zhang, Q. Tang, D. Han, and Z. Li. Enhanced migrating birds optimization algorithm for U-shaped assembly line balancing problems with workers assignment. *Neural Computing and Applications, 31*, 2019, 7501-7515.

[21] M. N. Janardhanan, Z. Li, and P. Nielsen. Model and migrating birds optimization algorithm for two-sided assembly line worker assignment and balancing problem. *Soft Computing, 23*, 2019, 11263-11276.

[22] C. Miralles, J. B. Garcia-Sabater, C. Andres, and M. Cardos. Branch and bound procedures for solving the Assembly Line Worker Assignment and Balancing Problem: Application to Sheltered Work Centres for Disabled. *Discrete Applied Mathematics*, *156*(3), 2008, 352–367.

[23] C. Blum, and C. Miralles. On solving the assembly line worker assignment and balancing problem via beam search. *Computers and Operations Research*, *38*(1), 2011, 328-339.

[24] F. F. Araujo, A. M. Costa, and C. Miralles. Two extensions for the ALWABP: Parallel stations and collaborative approach. *International Journal of Production Economics*, *140*(1), 2012, 483-495.

[25] L. Borba and M. Ritt. A heuristic and a branch-and-bound algorithm for the assembly line worker assignment and balancing problem. *Computers and Operations Research*, *45*, 2014, 87-96.

[26] R. Ramezanian and A. Ezzatpanah. Modeling and solving multi-objective mixed-model assembly line balancing and worker assignment problem. *Computers and Industrial Engineering*, *87*, 2015, 74-80.

[27] M. C. O. Moreira, R. Pastor, A. M. Costa and C. Miralles. The multi-objective assembly line worker integration and balancing problem of type-2. *Computers and Operations Research*, *82*, 2017, 114-125.

[28] S. D. Akyol and A. Baykasoğlu. ErgoALWABP: A multiple-rule based constructive randomized search algorithm for solving assembly line worker assignment and balancing problem under ergonomic risk factors. *Journal of Intelligent Manufacturing, 30*, 2019, 291-302.

[29] A. Karas and F. Ozcelik. Assembly line worker assignment and rebalancing problem: A mathematical model and an artificial bee colony algorithm. *Computers and Industrial Engineering, 156*, 2021, 107195.

[30] A. S. Michels and A. M. Costa. Model and heuristics for the multi-manned assembly line worker integration and balancing problem, *International Journal of Production Research, 62*(24), 2024, 8719-8744