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Research article

Two-sided disassembly line balancing problems with human–robot interaction: A triple bottom line approach

Dursun Emre Epcim[1], Zeynep Yüksel[2], Ibrahim Miraç Eligüzel[2] and Suleyman Mete[1,*]

[1] Department of Industrial Engineering, Gaziantep University, Gaziantep 27310, Turkey
[2] Department of Industrial Engineering, Gaziantep Islam Science and Technology University, Gaziantep 27310, Turkey

* **Correspondence:** Email: smete@gantep.edu.tr; Tel: +905436496757; Fax: +903423604383.

Abstract: The rise in consumption and technological advances has transformed the effective management of end-of-life (EOL) products into a critical sustainability problem. Insufficient handling of EOL items poses a significant risk to resource conservation as well as environmental, economic, and social dimensions. Consequently, sustainable approaches that incorporate economic, social, and environmental factors are essential in the recycling and reuse of EOL products. This paper examined the two-sided disassembly line balancing (TDLB) problem, a critical operational phase in the EOL recycling and reuse process, from a sustainability perspective. Additionally, the proposed novel mixed integer linear programming (MILP) model incorporates a human–robot interaction (HRI) structure that facilitates task execution by humans, robots, or through human–robot collaboration. The model's objective functions were structured in accordance with the Triple Bottom Line (TBL) approach, simultaneously addressing economic, environmental, and social dimensions. A lexicographic optimization method, incorporating the decision-maker's established priorities, was utilized to address the multi-objective problem context. For the solution and computational analysis of the proposed model, two small-scale (8 and 10 tasks) and two medium-scale (22 and 25 tasks) cases found in the literature were adapted to fit the model and used in the analysis. For the analyses, the results of the complete lexicographic solution approach were used to generate solutions for each case across six different priority orders and seven different cycle times for each order. Thus, the model was analyzed by running it in a total of 168 different scenarios. Optimal results were achieved in 99 of these cases. The results indicate that priority ranking is crucial for sustainability performance and that lexicographic optimization provides a feasible solution method in multi-criteria decision contexts with defined priorities.

Keywords: disassembly line balancing; two-sided line; human-robot interaction, triple bottom line; lexicographic optimization
Mathematics Subject Classification: 90B35, 90C11, 90C29

1. Introduction

Nowadays, satisfying increasing demand has been facilitated by technological advancements. This has augmented production rates and supply, but it has concurrently resulted in higher demand. Increasing consumption rates have generated an issue that requires resolution. The issue relates to the increasing amount of EOL products [1]. The inability to efficiently recycle the increasing volumes of EOL products, which are instead disposed of in the environment, represents a significant environmental threat and leads to resource waste. The proper recycling of EOL products and their preparation for reuse are significantly important in various respects. Currently, disassembly lines—characterized as a methodical process for separating a product into its constituent pieces, components, subassemblies, or other categories—are essential [2,3].

Traditional disassembly lines generally utilize human workers. Currently, numerous production lines have been assigned robot operators. Human operators are more economically efficient than robots for particular tasks, owing to their mobility and cognitive abilities. Nevertheless, when considering aspects such as fatigue and risk, robots possess a superior edge compared to humans. Hence, current disassembly line designs integrate human–robot interaction. This interaction mitigates the drawbacks associated with the separate utilization of humans and robots. Thus, human–robot interaction is a crucial factor of line performance [4,5].

Besides human–robot interaction on disassembly lines, the selection of line configuration is another issue that directly influences performance. In general, there are four distinct configurations: straight, U-shaped, two-sided, and parallel. While straight lines tend to be preferred in traditional applications, they are deemed inferior to other forms on various characteristics, including space efficiency and adaptability. In comparison to straight lines, two-sided lines provide superior benefits for the aforementioned characteristics.

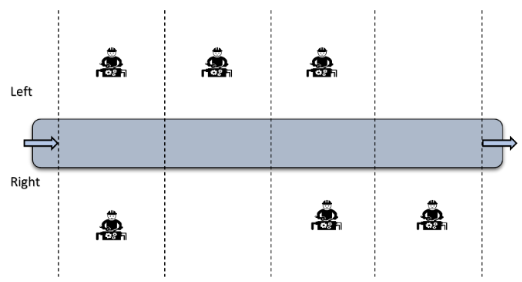

Figure 1. Schematic representation of a two-sided line.

Figure 1 illustrates how two-sided lines consist of paired station designs, facilitating concurrent operations on both sides. This structure is frequently utilized in the assembly and disassembly of large products, such as autos and buses, as mentioned by Baykasoğlu and Dereli [6]. The primary advantage of two-sided lines is the ability to perform tasks on both sides simultaneously, significantly reducing overall completion times. This advantage also mitigates the challenges associated with moving cumbersome components. In addition to concurrent work execution, the adaptability in task allocations is another advantage of two-sided lines. However, two-sided lines provide specific challenges. Ensuring jobs are performed according to precedence relations and addressing sequencing problems in mated stations with simultaneous operations are significant challenges identified by Kim et al. [7]. This context poses modeling difficulties for two-sided lines.

Regardless of the line type employed, a traditional disassembly line balancing model consists of three categories of objective functions: Type 1 minimizes the number of stations for a predetermined cycle time; Type 2 minimizes the cycle time for a predetermined number of stations; and Type E maximizes line efficiency with undetermined cycle time and number of stations [8]. These categories are predominantly composed of economic objective functions. Nonetheless, a sustainable balance cannot be attained just through economic objectives. At this point, the "triple bottom line" approach is proposed, as described by Elkington [9], which entails the integration of social, environmental, and economic aspects into decision-making processes. Incorporating environmental and social objective functions with economic ones guarantees that the final balance is sustainable.

The motivation behind this paper, as mentioned, is to propose a sustainable solution for the reuse and recycling processes of end-of-life (EOL) products, which represent a significant challenge. In this context, the focus is on disassembly lines, which are one of the key components of the relevant process. As is well known, disassembly lines consist of different types of lines. As noted by Baykasoglu and Dereli [6], two-sided lines are preferred for the disassembly of larger products. The reason for this is that, since operations can be performed on both sides of the line, there is no need to reorient the product for different tasks, which—particularly in the case of large products—leads to a waste of time and resources. In this regard, two-sided lines have been selected for this paper. Additionally, another classification criterion for disassembly lines is the type of operator. Some lines involve humans, robots, and human–robot interactions. Systems that rely solely on humans or robots have various disadvantages. For this reason, human–robot collaboration—which is frequently used nowadays—is addressed in this paper. The objective functions of the problem under consideration were formulated by evaluating them from a sustainability perspective. In this context, the TBL approach, which includes three types of objective functions—economic, social, and environmental—was used. The multi-objective model created with this approach was solved using lexicographic optimization. The most important reason for using this solution method is to ensure that the objective functions are optimized according to their different priority orders. Thus, the decision-maker will have the opportunity to view the results across all priority orders and select the most suitable option for their sector. The novelty of this paper lies in the proposal of a new MILP model specific to the problem at hand, as well as the use of the TBL approach and lexicographic optimization.

The remaining sections of the paper are as follows: Section 2 reviews the literature on line balancing involving two-sided human–robot interaction; Section 3 presents the problem statement and the proposed model; Section 4 presents and interprets the results obtained from case studies; managerial implications are given in Section 5, and Section 6 concludes the paper.

2. Literature review

A literature review was performed on research concerning two-sided disassembly line balancing issues that involve HRI. The results indicated a total of 8 studies, comprising 6 journal articles and 2 conference papers. An early study in this context is the conference paper by Liu et al. [10]. The study illustrates an instance of parallel cooperation, wherein hazardous tasks are assigned to robots, while non-hazardous tasks are assigned to humans or robots. In this form of HRI, people and robots share the same workplace while performing separate tasks. The research additionally examined the partial disassembly line balancing issue. A solution was proposed for scenarios including deterministic task durations and a single product. An enhanced Q-learning algorithm was devised and evaluated against SARSA, exhibiting superior solution quality and convergence efficacy, especially for large-scale cases.

Wu et al. [11] addressed the complete disassembly line balancing problem, in contrast to Liu et al. [10]. A mixed-integer programming approach was also proposed for the problem at hand. The proposed approach stipulates that hazardous activities be allocated to robots and complex tasks to humans. Additionally, the paper presents the notion of "interactive tasks" as a novel element of the research. Interactive tasks must be allocated to an operator on each side of the station and performed collaboratively by the operators. This model's structure guarantees the consideration of all four components of human–robot interaction. The paper proposes using MIP/Gurobi in small-scale cases and a Pareto-based discrete squirrel search algorithm in large-scale use cases.

Qin et al. [4] addressed the problem of partial disassembly line balancing. In this case, the process concludes when a specified disassembly revenue is reached in the objective function. The rationale for work allocation to human–robot operators mirrors that presented in Liu et al. [10]. The proposed model is solved using CPLEX for small instances, while the improved Q-learning method is proposed for large-scale scenarios. In contrast to Liu et al. [10], a mixed integer programming model is proposed.

The paper conducted by Al-fandi and Almasarwah [12] proposes the first stochastic approach in relevant literature. Uncertainty arises from variations in the competency of humans and robots, as well as the quality of end-of-life (EOL) products, and is based on task time. A MILP model was initially developed with deterministic average timings, aiming to minimize cycle times. Thereafter, discrete-event simulation was adopted to evaluate stochastic performance. To resolve the proposed multi-objective model, a composite desirability function was employed to merge multi-objective functions into a singular fitness score. Additionally, the proposed model incorporates a mixed-model structure that facilitates the simultaneous processing of two distinct EOL products on the same line. This study considered human–robot interaction as a type of cooperation.

Chu and Chen [13] considered a cooperative human–robot disassembly setting in which tasks were allocated between human and robot operators. Task assignments were made such that hazardous tasks were assigned to robots, high-demand tasks to humans, and other tasks to the appropriate operator. The partial disassembly line balancing problem was addressed for a single product. The model includes two distinct objective functions, and the solution employs NRL-MOEA/D—an approach enhanced with decomposition-based MOEA/D, SARSA, and Q-learning mechanisms.

The human–robot interaction and task assignment logic for operators in the paper by Wang et al. [14] are the same as those in Chu and Chen [13]. Although a single product is used in both papers, in Wang et al. [14], the complete disassembly line balancing problem is addressed. A model has been developed that allows a flexible human station to take over when the robot cannot complete a task due to a rusted joint or similar issue. This has been modeled as a human intervention/fallback mechanism. The model has been dynamically designed to perform replanning under disturbances such as increased task durations due to deformation or task durations dropping to zero due to missing parts. As the first dynamic modeling approach encountered in the relevant literature, this paper is considered a significant novelty. A preference-based MO-PPO algorithm was developed to solve the problem. A single policy was trained using preference vectors representing different objective priorities, with the aim of rapidly adapting to changing conditions.

Guo et al. [15] is an expanded version of the conference paper by Guo and Zhang [16]. For this reason, Guo and Zhang [16] was not included in the literature review. In contrast to the studies cited, Guo et al. [15] developed a model that addresses parallel two-sided lines formed by the merging of multiple two-sided lines. The model presented in the paper is structured as a multi-product framework capable of disassembling various goods. Additionally, the issue is referred to as complete disassembly, when all necessary disassembly tasks are allocated for every product. The model simultaneously employs a partial destructive disassembly method by integrating destructive procedures for components that are impossible to disassemble or where disassembly is impractical. Consistent with several studies in the context of human–robot interaction, the interaction is cooperative, with hazardous tasks allocated for robots and complex tasks allocated to humans. MILP is used for small-scale use cases, whereas the improved discrete water wave optimization algorithm is utilized for large-scale cases. An ε-constraint-based method is used to produce Pareto-optimal solutions for multi-objective optimization.

Table 1 presents a classification of the literature on human–robot interaction in two-sided disassembly line balancing. The table includes six journal articles and one conference paper obtained as a result of the literature review. As noted, the Guo and Zhang [16] paper—which is a conference paper—was not included in the table because Guo et al. [15] is an extended version of the Guo and Zhang [16].

The proposed model differs from the studies on disassembly lines—which were not included in the literature review—in that it addresses human–robot interaction and the two-sided line structure. In the studies listed in the table, no study has been found that simultaneously addresses all aspects of human–robot interaction, the three main components of sustainability—economic, social, and environmental objective functions (the TBL approach)—and the lexicographic optimization solution method. In this context, the proposed model fills this gap in the literature and makes a significant contribution by addressing these three elements collectively.

Upon examining the table, notable distinctions exist between the model presented in this paper and that of Wu et al. [11]. The most notable novel feature of the proposed model is the triple bottom line approach, which concurrently addresses economic, environmental, and social objective functions. Moreover, the proposed model is novel in its multi-objective solution methodology. A lexicographic optimization strategy has been utilized, in contrast to the other studies. The introduction of a new MILP also represents a contribution.

Table 1. Literature classification.

Papers	HRI/HRC Structure		Disassembly Mode					Number of Objectives		Product Type			Problem Characteristics				Multi Objective Optimization Approach	Solution Method
			Disassembly Extent		Disassembly Technique													
	Cooperation	Collaboration	Complete	Partial	Destructive	Partial Destructive	Non-destructive	Single	Multi	Single	Mixed	Multi	Deterministic	Stochastic	Fuzzy	Dynamic		
Guo et al. [15]		✓	✓			✓			✓			✓	✓				Improved Augmented ε-Constraint Method (AUGMECON-2)	MILP + Improved Multi-Objective Discrete Water Wave Optimization Algorithm (IDWWOA)
Wang et al. [14]	✓		✓				✓		✓	✓						✓	Preference-based Multi-Objective Reinforcement Learning	Multi-Objective Proximal Policy Optimization (MO-PPO)
Chu and Chen [13]	✓			✓			✓		✓	✓			✓				Decomposition-based Pareto Optimization (MOEA/D)	Reinforcement-Learning MOEA/D (NRL-MOEA/D)
Al-fandi and Almasarwah [12]	✓		✓				✓		✓		✓			✓			Composite Desirability Function	MILP + Discrete-Event Simulation + Response Optimizer
Qin et al. [4]	✓			✓			✓	✓		✓			✓				Not applicable	MIP + Improved Q-Learning Algorithm
Wu et al. [11]	✓	✓	✓				✓		✓	✓			✓				Pareto-based Fast Non-dominated Sorting	MIP + Discrete Squirrel Search Algorithm (DSSA)
Liu et al. [10]	✓			✓			✓	✓		✓			✓				Not applicable	Improved Q-Learning Algorithm
Proposed Model (TDLBP-HRC)	✓	✓	✓				✓		✓ (TBL)	✓			✓				**Lexicographic Optimization**	**MILP**

3. Problem definition and mathematical model

Figure 2. Conceptual illustration of a two-sided human–robot interaction disassembly line with mated stations. Source: Authors' illustration, developed using an AI-generated visual produced with OpenAI's ChatGPT image-generation model as an initial basis and subsequently modified by the authors.

The paper examines a two-sided disassembly line balancing problem that involves interaction between human and robotic operators. The line model has sequentially ordered mated stations. The workstations possess a right and a left side. Both robotic and human operators may be allocated to each side of the stations, either concurrently or independently. This indicates that all four essential models of human–robot interaction identified in the literature are taken into account. A novel mixed-integer mathematical model is developed for the TDLB-HRI problem. The rationale of the proposed model for the two-sided disassembly line balancing problem (TDLBP) is based on the framework established by Kucukkoc [17]. To incorporate human–robot interaction into the model, the process alternative index (d) utilized in the research of Li et al. [18] is utilized. This index denotes human, robot, and human–robot collaboration with values of 1, 2, and 3, respectively. Consequently, disassembly jobs are allocated to one of these three options. The model's objective functions were developed utilizing the triple bottom line approach. In this context, a structure containing three fundamental objectives—economic, environmental, and social—was formed. This structure was solved by lexicographic optimization. In this regard, six outcomes were achieved with varying priority sequences for the three primary objectives. This solution approach is appropriate when decision makers specify explicit priority relations.

The assumptions of the TDLBP-HRI model are as follows:

- The risks of tasks and the risk coefficients of different process alternatives are known.
- Humans and robots are homogeneous in terms of their working capabilities.
- The precedence relationships of tasks are known.
- The energy consumption of robots when they are working is known.
- The cycle time is known.
- The times for tasks to be performed by different process alternatives are known.
- Tasks are indivisible.

3.1. Notation and objectives

The TDLBP-HRI model, utilizing the notations specified in Table 2, is based on the two-sided disassembly line balancing model introduced by Kucukkoc [17]. A novel TDLBP-HRI model was developed by incorporating human–robot interaction into the existing framework. The proposed model has three distinct primary objective functions aligned with the TBL framework.

Table 2. Notations of the TDLBP-HRI model.

Symbol	Description
Sets and indices	
i, h, p	Task indices
j	Mated station index
k	Station side index (right, left)
d	Process alternative index
AR	The list of tasks to be performed on the right side of the station
AL	The list of tasks to be performed on the left side of the station
AE	The list of tasks that can be performed on both the right and left sides of the station
ANDPT	The list of tasks with AND precedence relationships
ORPT	The list of tasks with OR precedence relationships
$ANDP_i$	The list of AND predecessors for task i
ORP_i	The list of OR predecessors for task i
K_i	The list containing sub-lists that indicate on which side of the station task i can be performed
Parameters	
T_{id}	The processing time of task i with process alternative d
R_i	A list of 0s and 1s indicating whether task i is risky (1) or not (0)
A_{id}	A list containing the risk weights of tasks across different process alternatives
CT	Cycle time
GREC	Energy consumption for the working robot (kW/min)
M	A large number
Decision variables	
X_{ijd}	1 if task i is performed at mated station j with process alternative d; 0 otherwise
W_{ikd}	1 if task i is performed on side k with process alternative d; 0 otherwise
Z_{ih}	1 if task h is a predecessor of task i or if both tasks are assigned to the same station and task h is performed before task i; 0 otherwise
U_{jk}	1 if the station on side k of mated station j is opened; 0 otherwise
T_i^s	The start time of task i
F_j	1 if both sides of mated station j are opened; 0 otherwise
G_j	1 if only one side of mated station j is opened; 0 otherwise

Equation 3.3 aims to minimize the number of stations opened, while Equation 3.2 aims to minimize the station length. For example, if two stations need to be opened, and they are opened in pairs, the F variable will be 1, and the G variable will be 0. If the stations are not opened in pairs, F will be 0, and G will be 2. Therefore, when Equation 3.2 is applied, it forces the stations to be opened in pairs and results in a shorter station length. The economic objective of the model is Equation 3.1, which aims to minimize the sum of Equation 3.2 and Equation 3.3.

$$Min\ f_1 = f_{1.1} + f_{1.2} \tag{3.1}$$

$$f_{1.1} = Min \sum_j F_j + G_j \tag{3.2}$$

$$f_{1.2} = Min \sum_j \sum_k U_{jk} \tag{3.3}$$

Equation 3.4 is the social objective, aiming to minimize the total risk of the tasks. The variable X, which controls task assignment, is multiplied by the task risk parameter R and by the risk coefficient of the process alternatives in the range [0, 1]. Equation 3.4 ensures that risky tasks are performed by the operator with the lowest coefficient.

$$Min\ f_2 = \sum_d \sum_j \sum_i X_{ijd} * R_i * A_{id} \tag{3.4}$$

The model's environmental objective is achieved through Equation 3.5, which aims to minimize the total energy consumption resulting from the robots' operation. It is calculated by multiplying the energy consumed by the robot during operation (GREC) by the total operating time of the robots (all cases where the variable X equals 1 and the index d equals 2 or 3).

$$Min\ f_3 = GREC * \sum_j \sum_k \sum_{d \in [2,3]} T_{id} * X_{ijd} \tag{3.5}$$

3.2. Constraints

Constraints 3.6 and 3.7 are assignment constraints. Constraint 3.6 ensures that each task is assigned to a mated station and a process alternative, while Constraint 3.7 ensures that each task is assigned to a side of the station and a process alternative.

$$\sum_j \sum_d X_{ijd} = 1 \qquad \forall i \tag{3.6}$$

$$\sum_k \sum_d W_{ikd} = 1 \qquad \forall i \tag{3.7}$$

Constraints 3.8–3.13 are precedence constraints. Constraint 3.8 is used to calculate the start times of tasks considering their precedence relationships. According to this equality, if a task has a predecessor, the task's start time must be equal to or greater than the predecessor's finish time.

Constraints 3.9 and 3.10 work together: Constraint 3.10 sets Z_{hi} to 1 when task h is a predecessor of task i, while Constraint 3.9 ensures that Z_{ih}, which represents the opposite scenario, is 0 in this case. Constraint 3.11 regulates situations involving OR precedence relationships. Constraint 3.12 is a transitivity constraint. It regulates the precedence relationships among three different tasks. In this way, it ensures that the order of precedence continues logically. Constraint 3.13 ensures that Z_{hi} and Z_{ih} are not both 1 simultaneously.

$$T_i^s + M * (1 - Z_{hi}) \geq T_h^s + \sum_j \sum_d T_{hd} * X_{hjd} \qquad \forall i, h, i \neq h \qquad (3.8)$$

$$Z_{hi} + Z_{ih} = 1 \qquad \forall i \in ANDPT, h \in ANDP_i \qquad (3.9)$$

$$Z_{hi} = 1 \qquad \forall i \in ANDPT, h \in ANDP_i \qquad (3.10)$$

$$\sum_{h \in ORP_i} Z_{hi} \geq 1 \qquad \forall i \in ORPT \qquad (3.11)$$

$$Z_{ih} + Z_{hp} - 1 \leq Z_{ip} \qquad \forall i, h, p, i \neq h, h \neq p, i \neq p \qquad (3.12)$$

$$Z_{ih} + Z_{hi} \leq 1 \qquad \forall i, h, i \neq h \qquad (3.13)$$

Constraints 3.14–3.15 regulate task assignments. These constraints are used to prevent task overlap within the same station. Constraint 3.14 ensures that two tasks assigned to the same station or to a mated station are executed in a specific order of priority to prevent them from overlapping. Constraint 3.15 ensures that start times are determined for tasks for which a precedence relationship has been established in 3.14.

$$Z_{ih} + Z_{hi} + M * \left(2 - \sum_d X_{ijd} + X_{hjd}\right) + M * \left(2 - \sum_d W_{ikd} + W_{hkd}\right) \geq 1 \qquad \forall i, h, j, k \in K_i \cap K_h, i \neq h \qquad (3.14)$$

$$T_p^s + M * \left(2 - \sum_d X_{ijd} + X_{pjd}\right) + M * \left(2 - \sum_d W_{ikd} + W_{pkd}\right) + M * (1 - Z_{ip}) \geq T_i^s + \sum_{k \in K_i} \sum_d T_{id} * W_{ikd} \qquad \forall i, p, j, k \in K_i \cap K_p, i \neq p \qquad (3.15)$$

Constraints 3.16–3.17 relate to cycle time. Constraint 3.16 ensures that the start time of a task, when considered cumulatively, is greater than the cycle time of the previous station to which it is assigned. Constraint 3.17 ensures that the completion time of a task is less than the cycle time of the station to which it is assigned.

$$T_i^s \geq CT * \sum_d \sum_j (j-1) * X_{ijd} \qquad \forall i \qquad (3.16)$$

$$T_i^s + \sum_j \sum_d T_{id} * X_{ijd} \leq CT * \sum_d \sum_j j * X_{ijd} \qquad \forall i \qquad (3.17)$$

Constraints 3.18–3.20 regulate the opening of stations. Constraint 3.18 ensures that if a task is assigned to a mated station and side with any process alternative, the respective station side is opened. Constraint 3.19 manages the relationship between different station assignment variables. Constraint 3.20 is a sequencing constraint that ensures stations are opened in order.

$$U_{jk} \geq \left(\sum_d X_{ijd} + W_{ikd} \right) - 1 \qquad \forall i, j, k \qquad (3.18)$$

$$\sum_k U_{jk} - 2 * F_j - G_j = 0 \qquad \forall j \qquad (3.19)$$

$$F_j + G_j \geq F_{j+1} + G_{j+1} \qquad \forall j \qquad (3.20)$$

Constraint 3.21 ensures that tasks controlled by two different variables are assigned to the same process alternative in both variables.

$$\sum_j X_{ijd} = \sum_{k \in K_i} W_{ikd} \qquad \forall i, d \qquad (3.21)$$

The model was solved using the specified objective functions and constraints. During the solution process, it was observed that, particularly for the economic objective function, the LP relaxation produced a lower bound that was so low that the solver could not satisfy it, thereby increasing the optimality gap. Therefore, the economic objective was strengthened by calculating a valid lower bound based on the total minimum processing time and cycle time.

3.3. Lexicographic optimization approach

There are various approaches for solving multi-objective optimization models. One of these approaches is the weighted sum approach, which solves the problem by reducing it to a single objective function through the assignment of weights to the objective functions. This approach requires the normalization of objective functions, particularly when they differ in magnitude. This poses a significant challenge in cases where objective functions of different types and magnitudes are present, as in the proposed model. Furthermore, the weighted sum approach leads to problems in non-convex problems. Solutions for non-convex structures can also be obtained using the ε-constraint method. In this method, only one of the objective functions is solved, while the other objective functions are added as constraints. Determining the appropriate ε level to use when adding objective functions as constraints is a challenge and a disadvantage of this method. Another method is goal programming. The objective functions are treated with specific target values. The problem is optimized by solving it using a single objective function composed of target deviations [19–21].

In the problem addressed in this paper, the objectives differ in their managerial meaning, measurement scale, and unit of analysis. Furthermore, the objective functions do not have a specific target. For this reason, the weighted-sum and goal programming methods were not chosen. Although the ε-constraint method is an important alternative for solving objective functions that lack a weighting relationship among them, it involves the difficulty of determining target ranges and ε levels. Furthermore, the problem at hand involves obtaining results with different priority rankings among economic, social, and environmental objectives and evaluating these results from the perspective of different sectors. In this context, the lexicographic optimization approach has been used and is recommended as a suitable method.

4. Computational results and discussion

4.1. Experimental design and solution procedure

The solutions were generated using a computer equipped with an Intel® Core™ Ultra 7 255H processor (2.00 GHz), 32 GB RAM, and an Intel® Arc™ 140T integrated GPU with 128 MB dedicated graphics memory and up to 16 GB shared system memory. Additionally, Python's Gurobi library was used for the solution. The proposed model was solved using the 2P8-OR, 2P10-OR, 2P22-OR, and 2P25-OR cases presented in Kucukkoc [17]. Each case was modified by adding the necessary parameters to make it suitable for the problem at hand before all cases were solved. The newly added parameters were included randomly. All cases include six different lexicographic precedence orders. In addition, solutions were generated for each case and priority order using different CT values (27, 30, 33, 36, 39, 42, 45). The solutions were computed using a time limit of 300 s for each objective function. Consequently, each priority order scenario was solved within a total limit of 900 s.

4.2. Illustrative example: 10-task instance

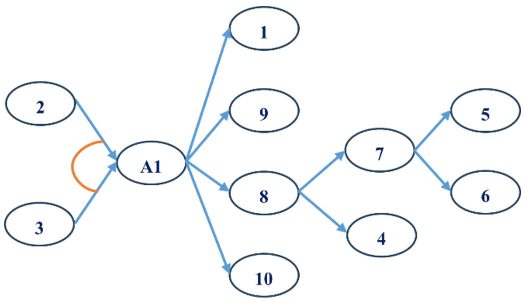

Figure 3. Precedence relationships diagram for the 2P10-OR case.

Figure 3 shows the precedence relationships in the 2P10-OR case. Tasks 2 and 3 are linked to tasks 1, 8, 9, and 10 via an OR precedence relationship. Task 8 is associated with tasks 7 and 4 by an AND precedence structure, and task 7 is linked to tasks 5 and 6 through an AND precedence structure.

In the 10-task scenario, the cycle time is established at 36 units, and the energy consumption of the robots during operations is considered to be 0.05 kW per unit. In addition to these two data points and the precedence connections, the supplementary data necessary for model resolution, including task risk, task suitability for specific station sides, risk coefficients for various process alternatives, and task completion times, are shown in Table 3. Except for task-side eligibility and human operator task-processing times, the remaining values reported in Table 3 were randomly generated and used as model parameters.

Table 3. The data used in solving the 10-task scenario.

Task	Task risk (0,1)	Tasks to suit which sides of the station	Risk coefficients for different process alternatives			Processing time for process alternatives		
			1	2	3	1	2	3
1	0	Left	0	0	0	14	36	12
2	1	Either	0.42	0.52	0.06	10	19	11
3	1	Right	0.13	0.53	0.34	12	16	29
4	1	Either	0.16	0.12	0.72	18	9	21
5	0	Left	0	0	0	23	15	14
6	1	Either	0.46	0.1	0.44	16	31	13
7	1	Right	0.15	0.65	0.2	20	15	36
8	0	Either	0	0	0	36	13	8
9	0	Either	0	0	0	14	10	17
10	0	Left	0	0	0	10	30	18

Table 4. Priorities of objective functions in different scenarios.

	A	B	C	D	E	F
Economic	1	1	2	2	3	3
Social	2	3	1	3	1	2
Environmental	3	2	3	1	2	1

The model includes three primary objectives: economic, social, and environmental, in accordance with the TBL framework. Varying prioritizations of these objectives during the model solution provide diverse outcomes. This condition yields six unique scenarios for the model, encompassing the three objectives. Table 4 delineates the six situations arising from varying prioritizations. In the table, objectives are designated priority numbers 1, 2, and 3, with the highest priority objective corresponding to the greatest number. In Scenario A, the hierarchy of priorities is environmental, social, and economic. In Scenario A, the solution commences with the environmental aim, subsequently addresses the social objective while maintaining previously acquired results to the greatest extent, and ultimately tackles the economic target to produce the final outcomes.

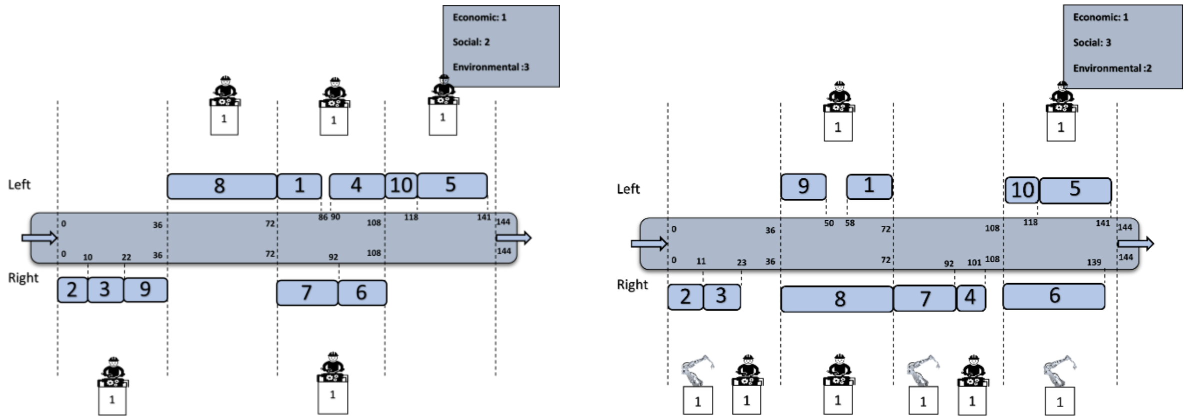

Figure 4. Task and operator assignments of scenarios A and B on a two-sided line.

Figure 4 shows the assignment results for Scenarios A and B. In Scenario A, four stations were set up; only one of these is a mated station, while the other three are unilateral. Three of the stations are on the left side, and two are on the right side. One human operator was assigned to each of the five stations, for a total of five human operators. All tasks were completed in 141 time units. In Scenario B, unlike Scenario A, six stations were opened, two of which are mated stations. Of the six stations opened, four are on the right side, and two are on the left side. Three robots and four human operators were assigned to these stations. All tasks were completed in 141 time units. In both Scenarios A and B, the economic objective has the lowest priority, while the environmental and social objectives have the highest priority. This demonstrates the trade-off between environmental and social objectives. When the environmental objective has the highest priority, all tasks are assigned to human operators to minimize energy consumption. Conversely, when the social objective has the highest priority, assignments are made in a way that minimizes risk.

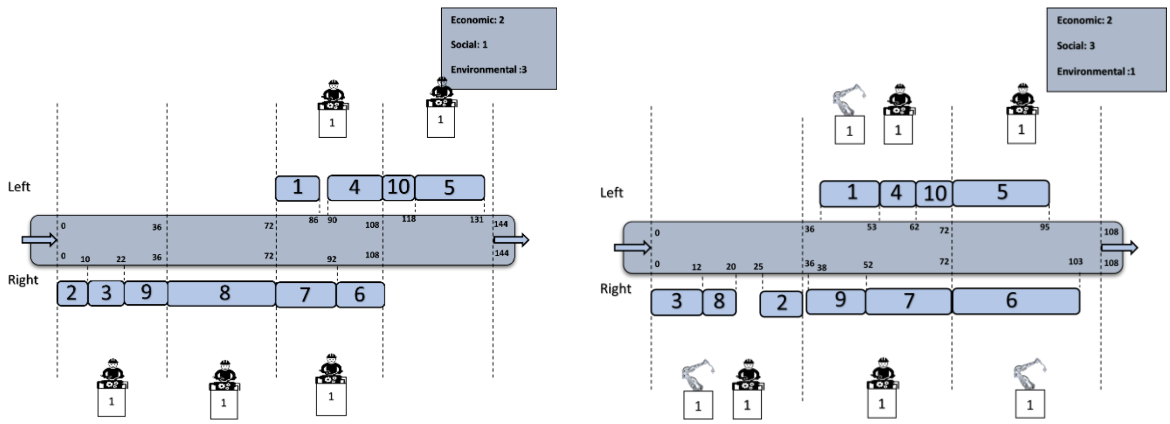

Figure 5. Task and operator assignments of scenarios C and D on a two-sided line.

Figure 5 shows the assignment results for Scenario C and Scenario D. In Scenario C, as in Scenario A, only one station is two-way, while the other three are one-way. Three of the opened stations are on the right side, and two are on the left side. Similar to Scenario A, one human operator is assigned to each of the five stations, for a total of five human operators. All tasks were completed within 131 time units. In Scenario D, two of the five opened stations are two-sided, and one is one-sided. Three of these stations are on the right side, and two are on the left. A total of four human and three robot operators were assigned. All tasks were completed within a total of 103 time units. In Scenarios C and D, the economic objective is the second priority, whereas it is assigned the lowest priority in Scenarios A and B. The trade-off between the environmental and social objectives is similar to that in Scenarios A and B. However, because the economic objective is the second priority, Scenario D differs from Scenario B in that five stations were opened.

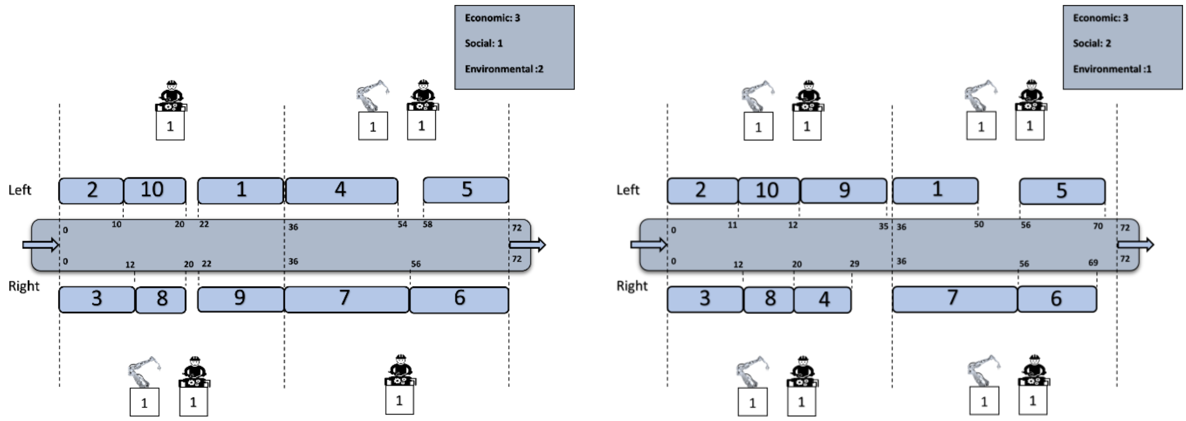

Figure 6. Task and operator assignments of scenarios E and F on a two-sided line.

In Scenarios E and F, where the economic objective is prioritized as the primary goal, both stations are fully bidirectional, as shown in Figure 6. The main reason for this is that the economic objective—aimed at shortening the line length and reducing the number of stations—is prioritized as the primary goal. In Scenario E, two robots and four human operators are assigned to these stations. All tasks were completed in 72 time units. In Scenario F, one robot and one human operator are assigned to each station, for a total of four human operators and four robot operators. All tasks were completed in 70 time units. The assignment of two robots in Scenario E and four robots in Scenario F stems from the trade-off between environmental and social objectives.

Figure 7 shows radar plots of six different priority states resulting from the lexicographic optimization approach to economic, environmental, and social objectives created using the triple bottom line approach. Radar maps A and B show high values for the economic objective due to the economic index having minimum priority. Furthermore, in scenario A, the environmental objective is seen to have a value of zero. The environmental objective has gained priority, and all tasks have been assigned to human operators to reduce energy consumption from robot operations. In scenario B, the social objective is observed to be almost negligible. This can be attributed to the priority of the social objective, leading to the allocation of tasks to alternatives with the lowest risk coefficients to mitigate the social objective. Scenarios C and D show cases where the economic objective has secondary importance. This prioritization does not lead to a decrease in the economic objective value for Scenario C, while a decrease in the economic objective value is observed for Scenario D. Moreover, similar to Scenario A, raising the environmental objective to the highest priority in Scenario C results in a zero environmental objective value. In Scenario D, similar to Scenario B, emphasizing the social objective as a primary priority results in a social objective value close to zero. Scenarios E and F represent situations where the economic objective is the highest priority. In these cases, a significant decrease in the value of the economic objective is observed due to prioritization. In Scenario E, the environmental objective is a secondary priority, leading to a reduced environmental objective value compared to Scenario F. In Scenario F, the social objective is a secondary priority, resulting in a reduced social objective value compared to Scenario E.

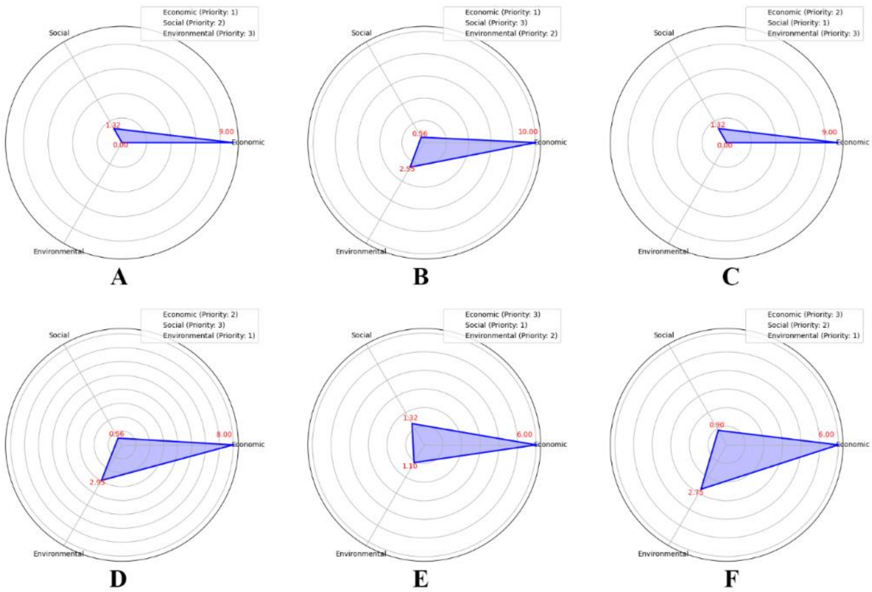

Figure 7. Radar graphs of the six different priority scenarios.

4.3. Sensitivity, computational performance, and scalability analysis

The proposed MILP model for the two-sided disassembly line balancing problem involving human–robot interaction was solved for four different scenarios from the literature. Results were obtained for six different priority sequences using the TBL approach. Additionally, each priority approach was solved using seven different CTs, and the results were analyzed.

Table 5. Size and computational performance of the proposed MILP formulation.

Instance	Tasks	Number of variables	Number of constraints	Number of nonzero coefficients	Overall computational outcome
2P8-OR	8	344	1625	19,369	All lexicographic stages solved to proven optimality
2P10-OR	10	442	2726	31,350	All lexicographic stages solved to proven optimality
2P22-OR	22	1198	20,545	199,933	Feasible time-limited sequential lexicographic solutions
2P25-OR	25	1432	28,462	265,026	Feasible time-limited sequential lexicographic solutions

As McGovern and Gupta [22] demonstrated in their work, the decision versions of disassembly line balancing problems belong to the NP-complete class. In this case, it can be said that the specific model addressed in this paper belongs to the NP-hard class. Table 5 provides information on the dimensions of the solved instances and their computational performance. As seen in the table, the time limit was reached in some stages for the 22 and 25 task scenarios (300 seconds per stage). Considering the number of variables, constraints, and nonzero coefficients in the table, this highlights the complexity of the problem. In particular, the high number of nonzero coefficients—which indicates the number of nonzero elements in the constraint matrix—demonstrates the model's density and computational difficulty [3].

Table 6 presents the computational analysis results of four cases solved under six lexicographic priority orders and seven different cycle times. For each priority order, each TBL objective was solved sequentially with a time limit of 300 seconds per objective. For example, when the 300-second limit was reached while solving an economic objective, the system moved on to solving the next priority objective. Thus, the total maximum time limit for each order is 900 seconds.

When examining the smaller case studies (2P8-OR and 2P10-OR), it is observed that optimum results are obtained quite quickly for all lexicographic priority rankings and cycle times. However, trade-offs between objective functions are observed in alternative priority rankings. Unlike small-scale cases, in medium-scale cases (2P22-OR, 2P25-OR), the time limit is reached for some objective functions. While the model solution encountered difficulties, particularly in the Eco-Soc-Env, Eco-Env-Soc, and Soc-Eco-Env priority sequences, faster and better results were obtained in the other three sequences. In general, the proposed formulation yields exact solutions for small samples and produces feasible sequential lexicographic solutions for medium-sized samples within the predicted computational time limit.

Table 6. Computational results for the test instances under different cycle times and lexicographic priority orders.

		2P8 – OR							2P10 – OR							2P22 – OR							2P25 – OR						
Priority order	Cycle time		MIP gap (%)			Objective value				MIP gap (%)			Objective value				MIP gap (%)			Objective value				MIP gap (%)			Objective value		
		Solution time (s)	Eco	Soc	Env	Eco	Soc	Env	Solution time (s)	Eco	Soc	Env	Eco	Soc	Env	Solution time (s)	Eco	Soc	Env	Eco	Soc	Env	Solution time (s)	Eco	Soc	Env	Eco	Soc	Env
Eco – Soc – Env	27	<1	0	0	0	11	0,68	2,25	8,95	0	0	0	8	1,26	2,2	632,58	0	54,54	70,49	8	3,85	3,05	541,67	0	0	18,18	8	1,55	3,85
	30	<1	0	0	0	11	0,54	3,65	1,1	0	0	0	6	1,4	4	624,85	0	39,44	70,83	8	2,89	3,6	310,02	0	0	3,65	8	1,34	4,1
	33	<1	0	0	0	10	0,54	4,5	3,88	0	0	0	6	1,4	3,5	900	14,28	57,83	93,44	7	4,15	3,05	335,44	0	0	22,07	6	1,9	3,85
	36	<1	0	0	0	8	0,68	2,85	2,45	0	0	0	6	0,9	2,75	644,53	0	57,83	90,16	6	4,15	3,05	337,36	0	0	9,09	6	1,34	4,4
	39	<1	0	0	0	7	0,54	4,25	6,68	0	0	0	5	1,4	4	617,27	0	46,8	90,78	6	3,29	3,8	306,08	0	0	1,25	6	1,34	4
	42	<1	0	0	0	7	0,54	3,65	1,24	0	0	0	5	0,9	3,25	613,5	0	65	97,14	5	5	3,5	612,04	0	51,79	83,33	5	2,78	3,6
	45	<1	0	0	0	6	0,54	5,35	<1	0	0	0	5	0,9	2,55	605,57	0	54,54	98,36	5	3,85	3,05	604,9	0	13,54	20,77	5	1,55	3,85
Eco – Env – Soc	27	<1	0	0	0	11	0,8	1,35	5,15	0	0	0	8	1,78	2,1	644,66	0	54.76	42.33	8	4,37	2,1	359,53	0	0	47,61	8	2,65	1,05
	30	<1	0	0	0	11	0,8	1,35	<1	0	0	0	6	1,76	3,45	618,9	0	36,06	86,2	8	4,02	1,45	306,82	0	0	100	8	3,16	0,1
	33	<1	0	0	0	10	0,8	2,2	6,03	0	0	0	6	1,78	2,3	900	14,28	49,88	86,04	7	4,37	2,15	621,83	0	15,68	97,56	6	2,55	2,05
	36	<1	0	0	0	8	1,24	1,5	2,7	0	0	0	6	1,32	1,1	656,36	0	45,53	74,41	6	4,37	2,15	350,85	0	0	100	6	3,16	0,3
	39	<1	0	0	0	7	1,36	0	6,22	0	0	0	5	1,76	3,45	635,6	0	45,99	97,14	6	4,37	1,75	307,38	0	0	100	6	3,16	0,05
	42	<1	0	0	0	7	1,36	0	2,47	0	0	0	5	1,28	2,05	634,74	0	61,6	97,14	5	5	3,5	616,79	0	32,73	97,22	5	2,78	3,6
	45	<1	0	0	0	6	0,68	3,1	1,19	0	0	0	5	1,28	1,45	610,57	0	49,88	95,23	5	4,37	2,1	605,37	0	16,13	100	5	3,16	0,9
Soc – Eco – Env	27	<1	0	0	0	11	0,68	2,25	5,74	0	0	0	9	0,9	2,05	601	18.18	0	20.68	11	1,75	5,8	358,96	11,11	0	0	9	1,34	3,95
	30	<1	0	0	0	11	0,54	3,65	5	0	0	0	8	0,9	2,05	601,05	27,27	0	6,12	11	1,75	4,9	306,75	0	0	3,65	8	1,34	4,1
	33	<1	0	0	0	10	0,54	4,5	2,44	0	0	0	8	0,56	2,95	602,135	30	0	15,59	10	1,75	5,45	309,95	12,5	0	0	8	1,34	3,95
	36	<1	0	0	0	9	0,54	3,65	13,63	0	0	0	8	0,56	2,95	602,19	33,33	0	14,81	9	1,75	5,4	318,7	0	0	9,09	6	1,34	4,4
	39	<1	0	0	0	7	0,54	4,25	1,31	0	0	0	6	0,56	4,15	601,42	25	0	17,59	8	1,75	5,45	309,31	0	0	1,25	6	1,34	4
	42	<1	0	0	0	7	0,54	3,65	1,55	0	0	0	6	0,56	2,95	601,39	37,5	0	6,12	8	1,75	4,9	40,09	0	0	0	6	1,34	3,95
	45	<1	0	0	0	6	0,54	5,35	1,24	0	0	0	6	0,56	2,95	601,98	37,5	0	2,12	8	1,75	4,7	304,41	16,66	0	0	6	1,34	3,95
Soc – Env – Eco	27	<1	0	0	0	11	0,68	2,25	<1	0	0	0	9	0,9	2,05	302,74	18.75	0	0	16	1,75	4,6	39,7	0	0	0	9	1,34	3,95
	30	<1	0	0	0	11	0,54	3,65	<1	0	0	0	8	0,9	2,05	303,39	21,42	0	0	14	1,75	4,6	125,65	0	0	0	9	1,34	3,95
	33	<1	0	0	0	11	0,54	3,65	<1	0	0	0	8	0,56	2,95	303,14	23,07	0	0	13	1,75	4,6	24,57	0	0	0	8	1,34	3,95
	36	<1	0	0	0	9	0,54	3,65	1,2	0	0	0	10	0,56	2,55	310,76	27,27	0	0	11	1,75	4,6	124,42	0	0	0	8	1,34	3,95
	39	<1	0	0	0	9	0,54	3,65	<1	0	0	0	10	0,56	2,55	302,97	36,36	0	0	11	1,75	4,6	304,31	25	0	0	8	1,34	3,95
	42	<1	0	0	0	7	0,54	3,65	<1	0	0	0	9	0,56	2,55	304,31	30	0	0	10	1,75	4,6	15,32	0	0	0	6	1,34	3,95
	45	<1	0	0	0	7	0,54	3,65	<1	0	0	0	9	0,56	2,55	303,64	33,33	0	0	9	1,75	4,6	13,72	0	0	0	6	1,34	3,95
Env – Eco – Soc	27	<1	0	0	0	11	0,8	1,35	1,6	0	0	0	10	1,32	0,4	302,66	12,5	0	0	16	3,49	0	47,47	0	0	0	9	3,16	0
	30	<1	0	0	0	11	0,8	1,35	1,05	0	0	0	9	1,32	0,4	301,56	7,14	0	0	14	3,49	0	303,49	11,11	0	0	9	3,16	0
	33	<1	0	0	0	11	0,8	1,35	<1	0	0	0	8	1,32	0,4	302,58	23,07	0	0	13	3,49	0	42,92	0	0	0	8	3,16	0
	36	<1	0	0	0	10	1,36	0	1,13	0	0	0	9	1,32	0	303,03	27,27	0	0	11	3,49	0	302,133	25	0	0	8	3,16	0
	39	<1	0	0	0	7	1,36	0	<1	0	0	0	9	1,32	0	301,735	27,27	0	0	11	3,49	0	303,84	14,28	0	0	7	3,16	0
	42	<1	0	0	0	7	1,36	0	<1	0	0	0	9	1,32	0	302,9	30	0	0	10	3,49	0	6,1	0	0	0	6	3,16	0
	45	<1	0	0	0	7	1,36	0	<1	0	0	0	8	1,32	0	303,71	22,22	0	0	9	3,49	0	18,8	0	0	0	6	3,16	0
Env – Soc – Eco	27	<1	0	0	0	11	0,8	1,35	1,46	0	0	0	10	1,32	0,4	301,84	6,25	0	0	16	3,49	0	56,77	0	0	0	9	3,16	0
	30	<1	0	0	0	11	0,8	1,35	<1	0	0	0	9	1,32	0,4	302,17	7,14	0	0	14	3,49	0	303,5	11,11	0	0	9	3,16	0
	33	<1	0	0	0	11	0,8	1,35	<1	0	0	0	8	1,32	0,4	302,07	15,38	0	0	13	3,49	0	31,23	0	0	0	8	3,16	0
	36	<1	0	0	0	10	1,36	0	<1	0	0	0	9	1,32	0	303,16	27,27	0	0	11	3,49	0	302,01	25	0	0	8	3,16	0
	39	<1	0	0	0	7	1,36	0	<1	0	0	0	9	1,32	0	301,96	36,36	0	0	11	3,49	0	303,24	14,28	0	0	7	3,16	0
	42	<1	0	0	0	7	1,36	0	<1	0	0	0	9	1,32	0	302,94	20	0	0	10	3,49	0	11	0	0	0	6	3,16	0
	45	<1	0	0	0	7	1,36	0	<1	0	0	0	8	1,32	0	304,2	33,33	0	0	9	3,49	0	15,43	0	0	0	6	3,16	0

4.3.1. Cycle time sensitivity and structural changes

Cycle time sensitivity analyses were performed on the 2P10-OR case. In this context, solutions were obtained for a total of seven different cycle time values: 27, 30, 33, 36, 39, 42, and 45. Additionally, results were obtained for six different lexicographic priority orders in the problem. Thus, a total of 42 cycle time–priority scenarios were solved and analyzed. In the analyses, the results obtained with a cycle time of 36 were accepted as the baseline configuration. The cycle time of 36 was selected—not because it was better or worse than the other cycle time values, but to track changes in the solution structure, as visually explained in the results section. The purpose of this analysis is to observe the effects of cycle time on solution duration, active resources, task alternatives, and, consequently, the three TBL objectives.

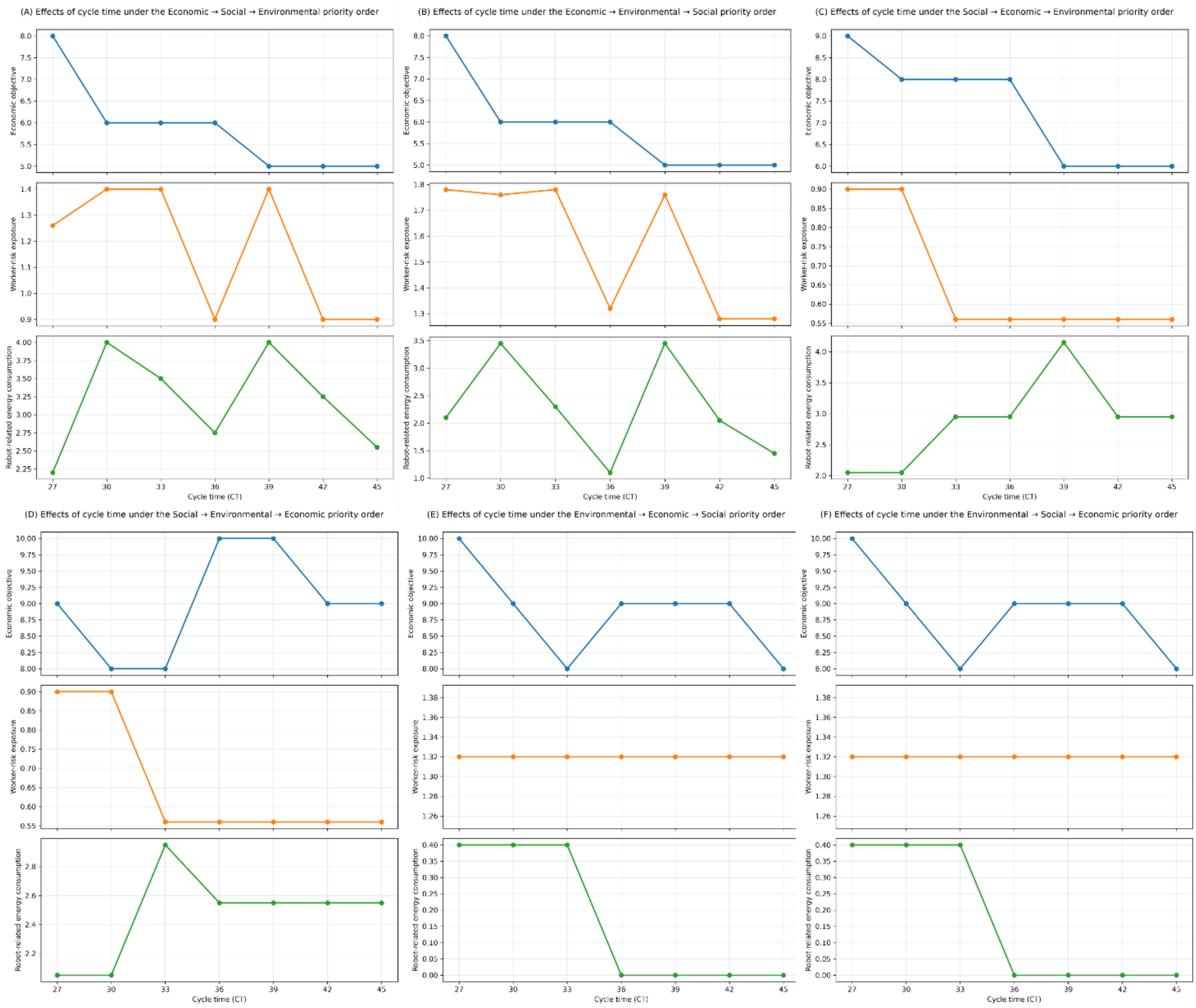

Figure 8. Effects of cycle time on the economic, social, and environmental objectives under six lexicographic priority orders.

Figure 8 shows the changes in TBL objectives across six different lexicographic priority orders as cycle time varies. It is evident that no objective remains completely stable, with the exception of two cases. This indicates that CT has a sensitivity effect on the results that depends on the priority order. When we examine the graphs for the cases where TBL objectives are prioritized first, it appears that as cycle time increases, the economic objective decreases stepwise, particularly at 30 and 39. In particular, a decline in the economic objective was observed when the cycle time was 30 and 39. Since an increase in cycle time allows for more tasks to be performed on a single line, it can be said that the economic objective, which represents operational resource requirements associated with activated station sides and mated stations, is directly affected by cycle time. Although the graphs show a similar pattern for social and environmental objectives, it would be incorrect to state that, as with the economic objective, social and environmental objectives are directly affected by an increase in cycle time. Although an increase in cycle time creates flexibility in task assignments, allowing social and environmental objectives to yield the desired low values, this is an indirect effect. Another point worth noting is that, in situations where the environmental objective is the top priority, the social objective is not affected by cycle time in any way. This situation stems from the fact that, rather than cycle time, the environmental objective assigns tasks to humans as much as possible to reduce energy consumption. This is the primary reason why the social objective remains constant at 1.32. The findings indicate that the effect of cycle time depends on the lexicographic priority order.

Table 7. Cycle time–induced changes in line configuration and task assignments under the Eco–Soc–Env priority.

CT	Economic objective	Active station sides	Mated workstations	Single-sided workstations	Total used workstations	Total idle time	Bottleneck station side(s)	Bottleneck load	No. of tasks differing from CT=36	Task(s) differing from CT=36
27	8	5	2	1	3	11	WS1-L; WS3-L	27	7	T2, T4, T5, T6, T8, T9, T10
30	6	4	2	0	2	4	WS1-R; WS1-L	30	3	T4, T7, T9
33	6	4	2	0	2	12	WS1-L; WS2-L	33	6	T1, T4, T7, T8, T9, T10
36	6	4	2	0	2	19	WS1-L	35	0	Baseline configuration
39	5	3	1	1	2	1	WS1-R; WS2-R	39	4	T2, T7, T9, T10
42	5	3	1	1	2	5	WS2-L	41	4	T4, T6, T7, T9
45	5	3	1	1	2	5	WS1-L; WS2-L	45	6	T1, T4, T5, T6, T7, T9

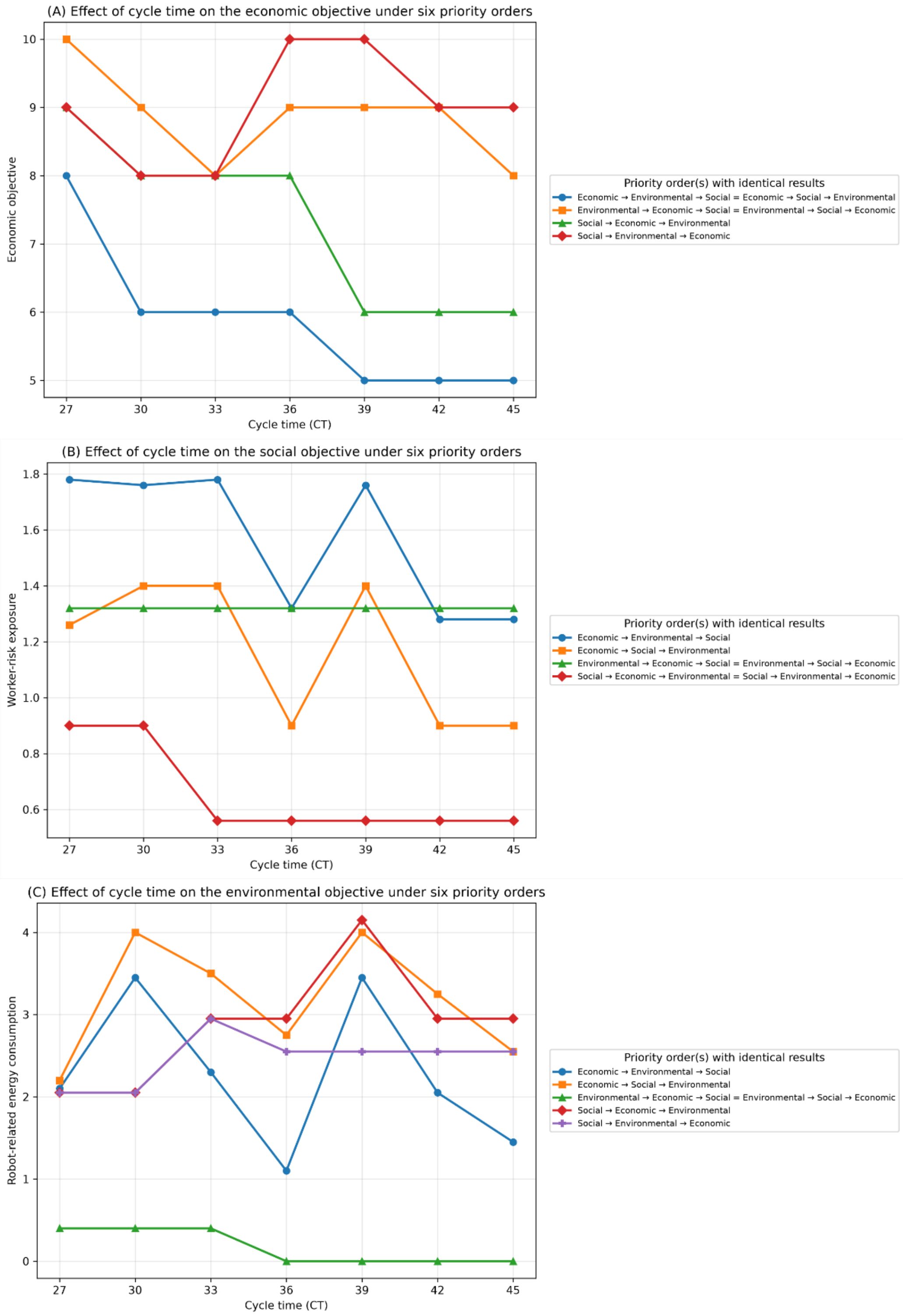

Figure 9. Cycle-time sensitivity of the economic, social, and environmental objectives across six lexicographic priority orders.

Table 7 shows how cycle-time changes under the Eco–Soc–Env priority order affect the physical resource structure and task assignments in the 2P10-OR case. In this problem, a station consists of two sides, and depending on the assignment, either both sides or just one side may be active. In the table, the "Active Station Sides" column reports the number of active left or right workstation sides. A "mated" station represents a station with task assignments on both sides, while a "single-sided" station represents a station with only one side active. In the table, the case with a cycle time of 36 is considered the baseline configuration. As can be seen from the table, the values related to the station tend to decrease as the cycle time increases. Changes in the station structure were observed when the cycle time was 30 and 39. Although changes were observed in the total idle time and bottleneck values, these changes were not proportional to the increase in cycle time. In cases where resource configuration remained unchanged and the cycle time was 33 and 36, differences in assignments were observed. This indicates that cycle time affects not only the number of stations but also the selection of task sides and processing modes.

Figure 9 shows the changes in values across six lexicographic priority orders for the TBL objectives at different cycle times. As can be seen from the graphs, each objective function achieved the lowest values, as expected, in the orders where it had the highest priority. Changes in cycle time caused irregular variations in all cases except two. This highlights the sensitivity of cycle time. At the same time, it is evident that cycle time sensitivity is not consistent across lexicographic orders. While cycle time provides flexibility in scheduling, the selected priority order determines how this flexibility is utilized to improve economic performance, worker risk, or environmental performance.

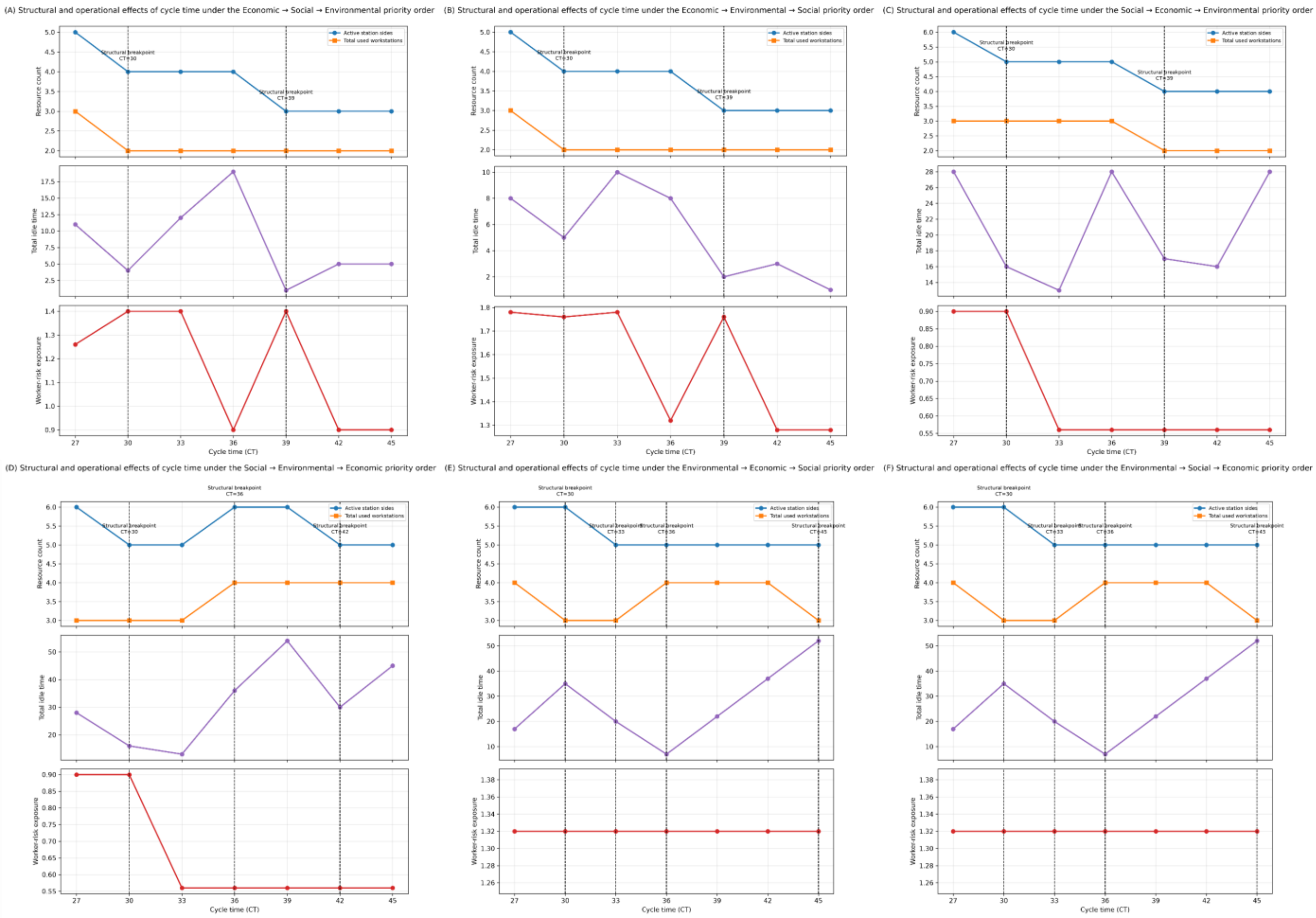

Figure 10. Structural and operational effects of cycle time under six lexicographic priority orders.

Figure 10 illustrates the effects of cycle-time variation on resource configuration, total idle time, and worker-risk exposure across six lexicographic priority orders. A cycle time of 30 is the first observed structural breakpoint across the tested priority orders. However, when the economic objective is ranked first, structural breakpoints are observed at cycle times of 30 and 39. Upon examining total idle times, no monotonic pattern is observed. These changes are not proportional to the increase in cycle time. Therefore, it cannot be stated that total idle time increases or decreases in tandem with changes in cycle time. The same applies to worker-risk exposure.

As the findings indicate, cycle time affects the solution structure and objective values; however, its effects on total idle time, bottleneck locations, and worker-risk exposure are priority-order dependent and non-monotonic. Therefore, it cannot be said that there is an "ideal" value for cycle time. The selection of an appropriate cycle time varies depending on the lexicographic priority order.

4.3.2. Task-risk weight sensitivity and robustness

In the previous section, it was observed that cycle time can indirectly influence the social objective by reflecting worker-risk exposure values. In this section, the effects of changes in the risk weights of risky tasks are examined. Whether a task is risky is represented by the task-risk parameter R provided to the model, and a task is either risky or not. Within the established analytical framework, it was observed how the model is affected in situations where the risk status is not clearly defined by sharp boundaries. In the 2P10-OR scenario, the task-risk weight of each risky task was individually decreased and increased by 20% and 50%, respectively.

Table 8. Design of the task-risk-weight sensitivity analysis.

Item	Specification
Fixed cycle time	36
Risky tasks (baseline R_i= 1)	T2, T3, T4, T6, T7
Adjustment method	One risky task is varied at a time
Risk multipliers	0.50, 0.80, 1.00, 1.20, 1.50
Fixed parameters	All A_{id} coefficients and all non-adjusted R_i values
Priority orders	All six lexicographic priority orders
Reported outcomes	TBL objectives, resource configuration, and task assignments

Table 8 lists the elements of the designed analysis. As can be seen from the table, all parameters were held constant except for the risky tasks, for which the R values were set to 1. The risky tasks were solved using multipliers of 0.50, 0.80, 1.00, 1.20, and 1.50, and the results were analyzed. For each priority order, 20 risk-weight variation scenarios were evaluated by changing each of the five risky tasks using the four non-baseline multipliers (0.50, 0.80, 1.20, and 1.50). The multiplier 1.00 represents the baseline configuration.

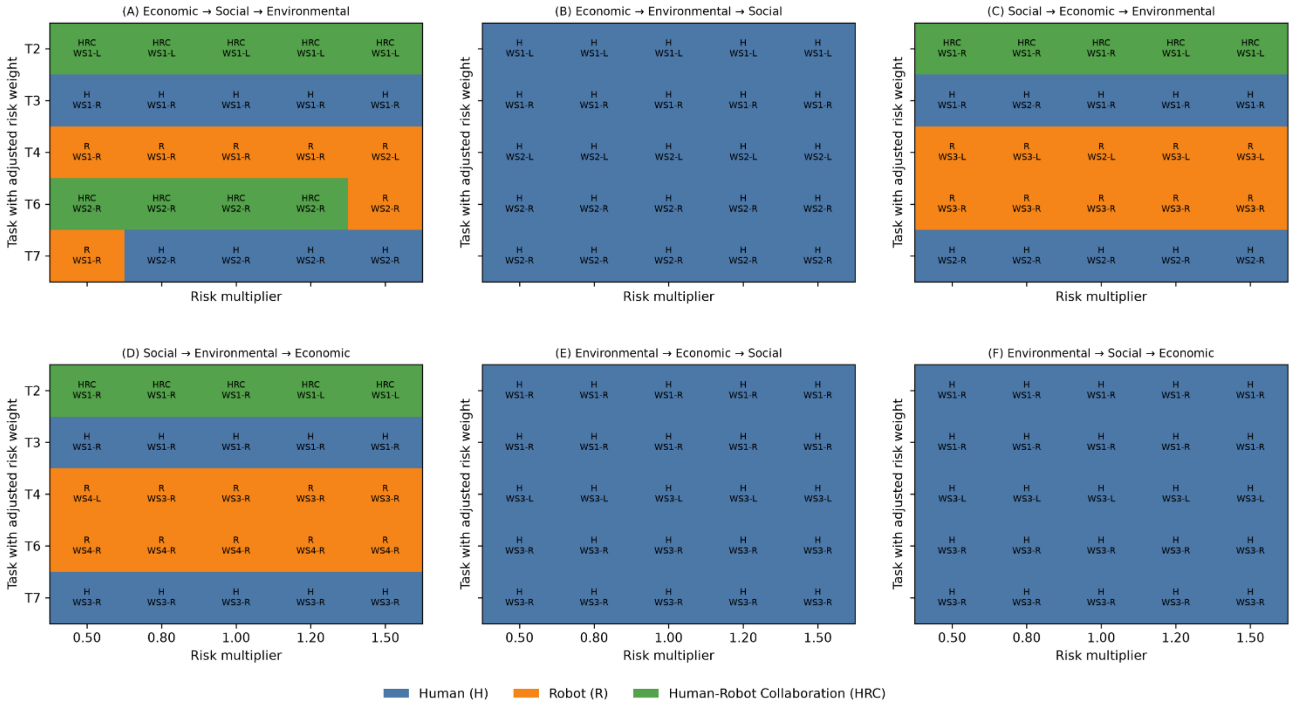

Figure 11. Stability of high-risk task assignments under task-risk-weight variations.

Figure 11 shows, for six lexicographic priority orders, the selected execution mode and workstation side for each high-risk task when the risk weight changes. It also visually illustrates the relation to the baseline multiplier of 1.00. In the graphs, high-risk tasks assigned to human, robot, and human–robot collaboration process modes are represented by different colors. Therefore, when examined by column, it is evident that the process mode changes in columns with distinct color patterns. The cells within the graphs contain information on the process mode and station side to which the high-risk tasks are assigned. Consequently, when examined by row, it becomes clear that assignment differences arise at this point for tasks where the station-side information varies.

Table 9 shows the robustness assessment for six lexicographic priority orders at a cycle time of 36. As mentioned, there are 20 scenarios for each priority order. The "Scenarios with assignment changes" column indicates in how many of these 20 scenarios at least one task's station or operation mode differs from the baseline. "Maximum no. of changed tasks" refers to the highest number of tasks assigned differently from the baseline in a single scenario. "Scenarios with high-risk task mode changes" refers to the number of scenarios in which the task mode of a task whose weight was changed shifted between human, robot, or HRC. If only the station side has changed, it is not included in this column. It was observed that changes in the risk coefficient did not affect the number of active stations or the economic objective in any of the priority rankings. This is a significant finding and demonstrates that the economic objective is resilient to changes in the risk coefficient. In contrast, a high rate of task assignment changes was observed for all three priority rankings. This indicates assignment-level sensitivity to task-risk-weight variations under these priority orders.

Table 9. Assignment robustness under task-risk-weight variations at CT = 36 across lexicographic priority orders.

Priority order	Scenarios with assignment changes (out of 20)	Maximum no. of changed tasks	Scenarios with high-risk task mode changes (out of 20)	Maximum change in active station sides	Maximum change in economic objective	Largest assignment-change scenario	Robustness assessment
Economic → Social → Environmental	15	6	2	0	0	T7 (x0.50)	Sensitive
Economic → Environmental → Social	0	0	0	0	0	–	Stable
Social → Economic → Environmental	17	6	0	0	0	T2 (x1.50)	Sensitive
Social → Environmental → Economic	10	7	0	0	0	T4 (x0.50)	Sensitive
Environmental → Economic → Social	0	0	0	0	0	–	Stable
Environmental → Social → Economic	0	0	0	0	0	–	Stable

Figure 12 shows the number of task assignment changes relative to the baseline for each scenario across six lexicographic priority orders. The presence of an asterisk (*) in a cell indicates that the assignment of the risky task itself has changed relative to the baseline. An asterisk indicates that the task whose risk weight was adjusted also has a different assignment from the baseline. Without an asterisk, the adjusted task retains its baseline assignment, although other task assignments may differ. As can be seen from the graphs, scenarios where environmental objectives are the top priority and those with an economic–environmental–social priority order are not sensitive to changes in the risk coefficient, whereas other scenarios are sensitive.

The results of the cycle time and risk factor sensitivity analyses revealed that the cycle time parameter is a strategic parameter that influences both structural and operational design, while the task-risk weighting parameter was found to influence task-assignment decisions under specific priority sequences rather than the resource structure.

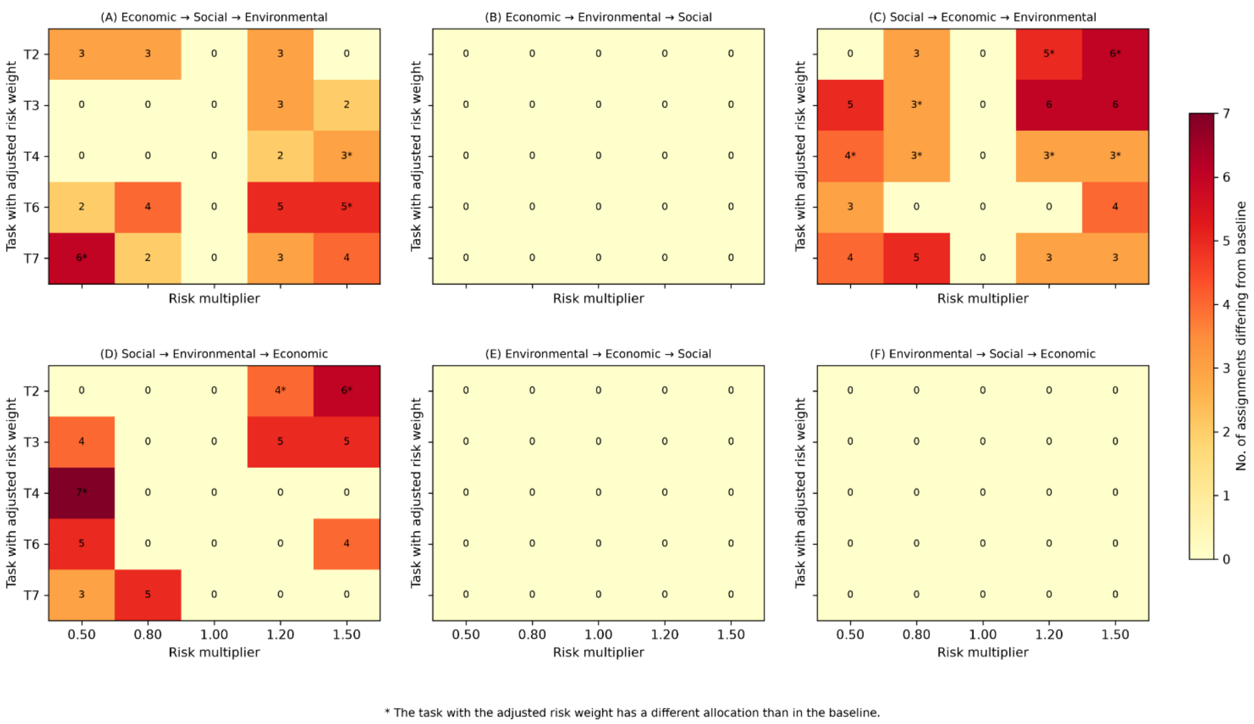

Figure 12. Assignment changes relative to the baseline under task-risk-weight variations.

5. Managerial implications

As mentioned, the lexicographic approach produces six different outcomes when three different objective functions are used. This provides an advantage by allowing decision-makers to see the trade-offs between objective functions for all priority orders. In this context, the TBL approach—which involves optimizing economic, social, and environmental objectives in a specific order—is particularly advantageous when decision-makers have a clear idea of their priority order.

In sectors with high-cost pressures, such as high-volume white goods, electronics refurbishment, and remanufacturing facilities, the Eco–Soc–Env and Eco–Env–Soc rankings are likely to be preferred. Depending on the sector and business environment, social or environmental factors may be selected as the second priority.

In sectors with hazardous waste, chemical exposure, or high risks of cutting and explosive hazards, the Soc–Eco–Env and Soc–Env–Eco sequences are expected to be selected. Depending on the sector's cost pressures and energy consumption needs, the second priority may be selected as either economic or environmental.

In sectors with carbon/energy reduction targets and pressures, it is likely that one of the Env–Eco–Soc or Env–Soc–Eco sequences will be selected. For the second priority, either economic or social may be chosen depending on cost pressures and the job's risk factors.

6. Conclusion

This paper proposes a mixed-integer linear programming model for the two-sided disassembly line balancing problem with human–robot interaction. In the proposed model, human–robot interaction is controlled using the process alternative index. Consequently, the model provides the allocation of humans, robots, or a combination of both to various sides of the workstation (mated stations) in accordance with the objective function. The objective functions of the proposed model were developed in accordance with the triple bottom line (TBL) approach. This ensures the accomplishment of integrated results across the three fundamental components of sustainability: economic, environmental, and social dimensions. A lexicographic optimization method was employed to address the model's multi-objective structure. This methodology facilitated the resolution and examination of TBL objectives based on varying priority rankings.

Cases consisting of 8, 10, 22, and 25 tasks, taken from the literature, were adapted to the model and solved. As a result of the lexicographic approach, six different outcomes were obtained for different TBL objective priority rankings across all solved models. Furthermore, for each priority ranking, the solution was computed with seven different cycle times, and the results were analyzed. For the small-scale cases (8 and 10 tasks), the optimal result was achieved for every cycle time and priority ranking. For medium-sized scenarios with 22 and 25 tasks, however, optimal results could not be guaranteed in some stages. In these stages, the 300-second limit for each TBL objective was reached. As can be seen from these analyses, the results underscore the necessity of using heuristic approaches for medium- and large-scale instances of the problem at hand, which is classified as NP-hard. Furthermore, the findings demonstrate that the priority order significantly affects the selected resources, task allocations, and sustainability outcomes, and that trade-offs exist among the objectives. This result underscores the need to evaluate sustainability factors in disassembly line design collectively, taking into account the trade-offs among them. Furthermore, the potential for using the proposed approach in situations where decision-makers can establish a priority order has been demonstrated.

This study's primary novel contribution, alongside the proposal of a MILP model for the TDLB-HRC problem, is the implementation of the TBL approach, which concurrently models economic, environmental, and social objectives, incorporating the decision-maker's explicit priorities into the solution via a lexicographic approach. The proposed method provides a pragmatic decision-support framework, especially for disassembly-line design with an established priority hierarchy among sustainability objectives.

Future research may expand the model to incorporate stochastic task durations, robotic faults, other product categories, dynamic rebalancing strategies, and meta-heuristic approaches for large-scale scenarios. Moreover, applications utilizing real industrial data will enhance the evaluation of the operational viability of TBL metrics.

Author contributions

Dursun Emre Epcim: Conceptualization, methodology, software, formal analysis, investigation, data curation, visualization, writing—original draft preparation, and writing—review and editing; Zeynep Yüksel: Methodology, formal analysis, validation and writing—review and editing; Ibrahim Miraç Eligüzel: Methodology, software, validation and writing—review and editing; Suleyman Mete: Supervision, technical validation, and writing—review and editing. All authors reviewed and approved the final version of the manuscript and accept responsibility for its content.

Use of Generative-AI tools declaration

The authors declare that OpenAI's ChatGPT image-generation model was used to create the initial visual basis for Figure 2, which was subsequently modified by the authors. OpenAI's ChatGPT was also used for linguistic editing of the manuscript.

Conflict of interest

The authors declare that they have no conflict of interest.

References

1. M. E. Asif, A. Rastegarpanah, R. Stolkin, Robotic disassembly for end-of-life products focusing on task and motion planning: A comprehensive survey, *J. Manuf. Syst.*, **77** (2024), 483–524. https://doi.org/10.1016/j.jmsy.2024.09.010
2. E. Özceylan, C. B. Kalayci, A. Güngör, S. M. Gupta, Disassembly line balancing problem: a review of the state of the art and future directions, *Int. J. Prod. Res*, **57** (2019), 4805–4827. https://doi.org/10.1080/00207543.2018.1428775
3. S. Mete, F. Serin, A reinforcement learning approach for disassembly line balancing problem, In: *2021 International Conference on Information Technology (ICIT)*, 2021, 424–427. https://doi.org/10.1109/ICIT52682.2021.9491689

4. S. Qin, C. Xiang, J. Wang, S. Liu, X. Guo, L. Qi, Multiple product hybrid disassembly line balancing problem with human-robot collaboration, *IEEE Trans. Automat. Sci. Eng.*, **22** (2024), 712–723. https://doi.org/10.1109/TASE.2024.3418898
5. Z. A. Çil, S. Mete, F. Serin, Robotic disassembly line balancing problem: A mathematical model and ant colony optimization approach, *Appl. Math. Model.*, **86** (2020), 335–348. https://doi.org/10.1016/j.apm.2020.05.006
6. A. Baykasoglu, T. Dereli, Two-sided assembly line balancing using an ant-colony-based heuristic, *Int. J. Adv. Manuf. Technol.*, **36** (2008), 582–588. https://doi.org/10.1007/s00170-006-0861-3
7. Y. K. Kim, Y. Kim, Y. J. Kim, Two-sided assembly line balancing: A genetic algorithm approach, *Prod. Plan. Control*, 11 (2000), 44–53. https://doi.org/10.1080/095372800232478
8. T. Yin, Y. Wang, S. Cai, Y. Zhang, J. Long, Unified modeling and multi-objective optimization for disassembly line balancing with distinct station configurations, *Mathematics*, **12** (2024), 2734. https://doi.org/10.3390/math12172734
9. J. Elkington, Partnerships from cannibals with forks: The triple bottom line of 21st-century business, *Environ. Qual. Manag.*, **8** (1998), 37–51. https://doi.org/10.1002/tqem.3310080106
10. Y. Liu, M. Zhou, X. Guo, An improved Q-learning algorithm for human-robot collaboration two-sided disassembly line balancing problems, In: *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, IEEE, Prague, Czech Republic, 2022, 568–573. https://doi.org/10.1109/SMC53654.2022.9945263
11. T. Wu, Z. Zhang, Y. Zhang, Y. Zeng, Modelling and optimisation of two-sided disassembly line balancing problem with human–robot interaction constraints, *Expert Syst. Appl.*, **230** (2023), 120589. https://doi.org/10.1016/j.eswa.2023.120589
12. L. Al-fandi, N. Almasarwah, Optimising and modeling the mixed-model two-sided disassembly line balancing problem with human-robot cooperation restrictions, *Int. J. Prod. Res.*, **63** (2025), 4389–4412. https://doi.org/10.1080/00207543.2024.2449241
13. M. Chu, W. Chen, Human-robot cooperation two-sided partial disassembly line balancing problem, *Int. J. Prod. Res.*, **63** (2025), 4478–4503. https://doi.org/10.1080/00207543.2025.2452385
14. J. Wang, M. Li, F. Meng, H. Zhao, X. Sun, Multi-objective reinforcement learning for dynamic balancing of two-sided human–robot collaborative disassembly lines, *Comput. Ind. Eng.*, **212** (2026), 111703. https://doi.org/10.1016/j.cie.2025.111703
15. L. Guo, Z. Zhang, H. Song, Y. Li, Industrial application of a human-robot collaborative parallel two-sided destructive disassembly line balancing problem in multi-product, multi-line layouts, *Robot. Comput. Integr. Manuf.*, **99** (2026), 103209. https://doi.org/10.1016/j.rcim.2025.103209
16. L. Guo, Z. Zhang, Parallel two-sided destructive disassembly line balancing problem for human-robot collaboration in the context of multitype EOL products, In: *Fifth International Conference on Electronic Information Engineering and Data Processing (EIEDP 2026)*, SPIE, 2026, 1084. https://doi.org/10.1117/12.3115033
17. I. Kucukkoc, Balancing of two-sided disassembly lines: Problem definition, MILP model and genetic algorithm approach, *Comput. Oper. Res.*, **124** (2020), 105064. https://doi.org/10.1016/j.cor.2020.105064
18. Z. Li, M. Janardhanan, Q. Tang, Z. Zhang, Models and algorithms for U-shaped assembly line balancing problem with collaborative robots, *Soft Comput*, **27** (2023), 9639–9659. https://doi.org/10.1007/s00500-023-08130-y

19. N. Gunantara, A review of multi-objective optimization: Methods and its applications, *Cogent Eng.*, **5** (2018), 1502242. https://doi.org/10.1080/23311916.2018.1502242
20. G. Mavrotas, Effective implementation of the ε-constraint method in Multi-Objective Mathematical Programming problems, *Appl. Math. Comput.*, **213** (2009), 455–465. https://doi.org/10.1016/j.amc.2009.03.037
21. C. Romero, A general structure of achievement function for a goal programming model, *Eur. J. Oper. Res.*, **153** (2004), 675–686. https://doi.org/10.1016/S0377-2217(02)00793-2
22. S. M. McGovern, S. M. Gupta, A balancing method and genetic algorithm for disassembly line balancing, *Eur. J. Oper. Res.*, **179** (2007), 692–708. https://doi.org/10.1016/j.ejor.2005.03.055