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Trade-offs in Robotic Assembly Line Balancing: Investigating Cycle Time, Energy Consumption, and Efficiency through Mathematical Optimization

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Abstract

Improving robotic assembly line balancing (RALBP) is key to increasing productivity, reducing cycle time (CT), and lowering energy consumption (EN). This study highlights the importance of optimizing robot deployment and workstation configuration to balance both objectives. A dual-objective model using a weighted sum approach evaluates different CT-to-EN priority ratios. Experiments across three problem sizes analyze the impact of station count and robot selection on CT, EN, and line efficiency. Results show that prioritizing CT increases energy use, while energy-focused configurations extend CT but enhance sustainability. ANOVA showed that robots count has a strong impact on efficiency in terms of WEST ratio, while adding more stations does not necessarily improve efficiency. The interaction effect (Robots × Stations) is insignificant as the two factors work independently rather than together. This research also introduces a benchmark dataset to support future studies in sustainable manufacturing.

Keywords
Assembly line balancing, Robotic, Optimization, Dual Objective, Integer linear programming

1.Introduction
Robotic assembly lines significantly boost productivity, product quality, and workplace safety, with technological

advancements broadening their industrial applications. The effectiveness of these systems hinges on factors including robot diversity, energy usage, and cycle time optimization. Research on robotic assembly line balancing (RALB) has prioritized refining critical variables such as cycle time, energy efficiency, and task assignment. Diverse mathematical frameworks and optimization strategies have emerged to improve performance while navigating compromises between operational speed and energy demands.

2. Literature Review

Robot Heterogeneity and Efficiency: The deployment of multiple robots with differing execution speeds and energy requirements shapes system efficiency. Zhou et al. (2017) demonstrated that expanding robot diversity enhances adaptability but complicates computational processes. Benavidez et al. (2021) observed that diverse robots shorten cycle times but elevate energy consumption due to peak power demands. However, no prior study comprehensively assesses whether robot variety sustains efficiency across varying problem scales.

Cycle Time-Energy Trade-offs: Balancing cycle time and energy remains pivotal in optimization. While weighted sum methods are common, the impact of adjusting weight ratios is under-researched. Nguyen et al. (2019) revealed that modifying weights in multi-objective integer linear programming (ILP) models shifts priority between cycle time and energy. Chen et al. (2022) noted that prioritizing cycle time alone spikes energy usage, whereas integrating energy constraints cuts consumption significantly.

Role of the WEST Ratio:
The Weighted Energy and Speed Trade-off (WEST) ratio is central to optimization, yet its direct effect on cycle time and energy is underexplored. Gonzalez et al. (2020) stressed the need to balance speed and energy for sustainability but omitted WEST-specific analyses. Patel et al. (2021) highlighted that the threshold where cycle time or energy dominates weighted models remains undefined.

Station Allocation Dynamics:
The number of stations influences cycle time, energy, and efficiency. Yin et al. (2016) found that increasing stations reduces cycle time until a saturation point, after which gains diminish. Zhang et al. (2020) reported that extra stations ease bottlenecks but may heighten idle periods and synchronization delays, raising energy use. Wu & Li (2021) underscored optimal station distribution as critical for maintaining efficiency.

Foundational Models and Advances:
Early research established mathematical frameworks for RALB optimization. Kara et al. (2011) pioneered a model for RALB, forming the basis for subsequent techniques. Joarder et al. (2018) later introduced multi-objective scheduling to enhance energy efficiency without compromising production rates. Li et al. (2020) advanced bi-objective methods to harmonize cycle time and energy consumption.

Weighted Sum Methodologies:
Weighted sum approaches are widely adopted in RALB. Nguyen et al. (2019) validated their utility in balancing objectives like cycle time and energy. Chen et al. (2022) integrated energy constraints into models, achieving notable consumption reductions. Gonzalez et al. (2020) analyzed speed-energy compromises, advocating equilibrium for sustainability. Patel et al. (2021) proposed dynamic weight adaptation for flexible optimization in industrial settings.

Robotic assemble line is classified into two types:
type 1, where robots are the only resource for doing tasks. While in type 2, collaboration between human operators and robots takes place. Gokcen, H., & Agpak, K. (2006) and Soysal-Kurt, H., & İşleyen, S. K. (2022). optimized the cycle time and energy efficiency by effective task allocation in both types of RALB

Types of Robotic Assembly Lines Regarding Layout:
configuration of RAL is classified in to varios layouts as Straight Line, U-Shaped Line, Parallel Lines and Serpentine & Circular Layouts. Research by Kara and Ozguven (2011) and Zhang et al. (2020) emphasizes the benefits of U-shaped layout in improving productivity, especially when optimized using evolutionary algorithms.

Solution Techniques for RALB:

there are two main methods for solving RALB which are exact solution methods and metaheuristic approaches. Battaïa and Dolgui (2013) and Janardhanan et al. (2019) proved that hybrid metaheuristics can significantly improve solution quality and computational efficiency.

Cycle Time and Energy consumption Relationship in Terms of PARETO Charts:
A key in RALB is the trade-off between cycle time (CT) and energy consumption (EN), which can be analyzed using Pareto front. Sun, Z., & Wang, L. (2020), Sun et al. (2020) and Zhang, J., et al. (2022) proposed multi-objective optimization approach for optimizing both objectives. They revealed that minimizing energy consumption while maintaining efficiency can be achieved by careful optimization.

RALB and Sustainability:
Sustainability in RALB has recently gained attention to avoid human worming. Dolgui and Proth (2010) and Beier et al. (2018) discuss different ways to integrate sustainability into robotic assembly line, emphasizing the importance of Industry 4.0 in improving efficiency while reducing energy consumption and waste.

Robot Types and Count: Effect on Cycle Time (CT), Energy (EN), and Performance
The number and types of robots used in an assembly line has a great effect on line performance. increasing robot count reduces cycle time, it may also lead to increase energy consumption and costs. Studies by Haris Aziz et al. (2021) and Kathryn E. Stecke and Mahdi Mokhtarzadeh (2022) highlight the importance of balancing robot count and task complexity to obtain higher efficiency.

Collaborative robotic assembly line balancing (c-RALB) introduces human-robot interaction (HRI) to enhance efficiency and flexibility. Marta Lagomarsino et al. (2022) and Elena Merlo et al. (2023) discuss frameworks for real collaboration, show that optimal task-sharing technics lead to higher productivity and ergonomic benefits.

Key Research Objectives:

- Formulating a dual-objective ILP model that directly incorporates the cycle time-to-energy ratio.
- Assessing the influence of robot diversity on cycle time, energy, and efficiency across varying problem scales.
- Analyzing the effect of problem parameters on WEST ratio (Workstation Efficiency & Synchronization Tradeoff).
- Identifying the critical weight ratio threshold where cycle time or energy becomes the dominant optimization factor.

3. Problem Definition

This research addresses the *straight robotic one-sided assembly line balancing problem (RALB-II)*, where a product's assembly involves a set of tasks with predefined precedence relationships and task durations. The primary objective is to minimize cycle time (CT) and energy consumption (EN) through optimal tasks and robot allocation across workstations. Each task can be performed by any robot within predefined precedence constraints, with task execution times varying by robot type. A single robot is assigned to each station to execute its allocated tasks, ensuring the cumulative task time per station does not exceed the cycle time and precedence rules are strictly followed.

Assumptions for Dual-Objective Optimization
The following assumptions underpin the optimization model, ensuring practical feasibility and consistency across experimental scenarios: The number of workstations is predetermined for each case.

- A finite set of robot types is available, each with distinct task execution times and energy consumption rates.
- Robots can be assigned to multiple stations, but each station operates with only one dedicated robot.
- Task execution times are robot-dependent and predetermined.
- Precedence constraints between tasks are fixed and vary with problem size.
- Tasks may be assigned to any station, provided precedence relationships are maintained.
- Tasks are non-repetitive (no duplication) within the assembly line.
- A robot's energy consumption scales linearly with cycle time, governed by a type-specific coefficient.
- Robots consume energy at a constant rate during idle periods.
- A weighted sum method optimizes CT and EN, with varying weight ratios analyzed to evaluate trade-offs.
- Cycle time equals the maximum task execution time across all stations.

- Total energy consumption aggregates energy used by all robots over the cycle time.
- All tasks must be completed within the predefined number of stations.
- Sufficient robots are available to complete all tasks within the allowable cycle time.

4. Mathematical model and solution method

Nomenclature

Decision variables:

X_{is}=$\{ 1 \quad if\ task\ i\ is\ assigned\ to\ workstation\ s \quad 0 \quad otherwise$

Y_{sr}=$\{ 1 \quad if\ robot\ r\ is\ allocated\ to\ workstation\ s \quad 0 \quad otherwise$

Indices

i, j: Index of assembly tasks, i, j = 1, 2, …, Na
r: Index of robot types, r = 1, 2, …, Nr
s: Index of workstation, s = 1, 2, …, Nw

Parameters

N_a: total number of tasks
N_r: total number of robots
N_W: total number of workstations (robots) where $N_r = N_W$
T_{ir}: processing time of task i by robot type r
T_s: total execution time for workstation s
pre(i): set of immediate predecessors of task i
P_r: the energy consumed by robot r per unit time.
Eir: The energy consumption for task i executed by robot type r
EN: the total energy consumption.
CT: Cycle time
EF: assembly line efficiency.

The Mathematical Model

Minimize $\quad$ Z= $\alpha.CT+\beta \cdot EN$ (1)

Where:

α and β are weight factors such that α + β=1

- CT is the cycle time (maximum workstation time)
- EN is the total energy consumption

Model constraints

1. Task Assignment constraint

Each task must be assigned to exactly one workstation.

$$\sum_{s=1}^{N_w} X_{is} = 1 \qquad \forall_i \in N_a \tag{2}$$

2. Robot Assignment constraint

Each workstation is assigned exactly one robot.

$$\sum_{r=1}^{N_r} Y_{sr} = 1 \qquad \forall_s \in N_w \tag{3}$$

3. Workstation Load constraint

The total execution time of tasks in a workstation cannot exceed the cycle time.

$$\sum_{i=1}^{N_a} \sum_{r=1}^{N_r} T_{ir} X_{is} Y_{sr} \le CT \qquad \forall_s \in N_w \tag{4}$$

4. Precedence constraint

Tasks must follow their precedence order.

$$\sum_{s=1}^{N_w} s\, X_{is} \ge \sum_{s=1}^{N_w} s\ X_{js} \qquad \forall\ (j\epsilon\ \text{pre(j)}) \tag{5}$$

5. Total Energy Consumption calculation

The energy consumed per task is determined by processing time and robot power consumption.

$$\text{Eir} = P_r \cdot \text{Tir} \tag{6}$$

The total energy consumption is then,

$$EN = \sum_{s=1}^{N_w} \sum_{i=1}^{N_a} \sum_{r=1}^{N_r} P_r . T_{ir} . X_{is} . Y_{sr} \tag{7}$$

6. Cycle time Definition.

Cycle time is determined as the maximum execution time across all workstations.

$$CT \geq \sum_{i=1}^{N_a} \sum_{r=1}^{N_r} T_{ir} X_{is} Y_{sr} \qquad \forall_s \epsilon\, N_w \tag{8}$$

For binary constraint

$X_{is} \epsilon \{0,1\}$, $Y_{sr} \epsilon \{0,1\}$

Linearization of the model

The non- Linear terms are constraints arise due to the product of decision variables X_{is} and Y_{sr}(e.g. $T_{ir}X_{is}Y_{sr}$). To linearize these terms, we introduce an auxiliary variable.

New Auxiliary variable

$$\text{Define} \quad Z_{isr} = X_{is} \,.\, Y_{sr} \tag{9}$$

Which transforms the non-Linear expression into:

$$Z_{isr} \leq X_{is} \;, \quad \forall_{i,s,r} \tag{10}$$

$$Z_{isr} \leq Y_{sr} \;, \quad \forall_{i,s,r} \tag{11}$$

$$Z_{isr} \geq X_{is} + Y_{sr} - 1 \;, \quad \forall_{i,s,r} \tag{12}$$

Now replacing $X_{is}Y_{sr}$ $with$ Z_{isr}, we obtain Linear constraint.

- Workstation Load constraint

$$\sum_{i=1}^{N_a} \sum_{r=1}^{N_r} T_{ir}\, Z_{isr} \leq CT \qquad \forall_s \,\epsilon\, N_w \tag{13}$$

- Total Energy calculation (Linearized)

$$EN = \sum_{s=1}^{N_w} \sum_{i=1}^{N_a} \sum_{r=1}^{N_r} P_r \,.\, T_{ir} . Z_{isr} \tag{14}$$

- Cycle time constraints (Linearized)

$$CT \geq \sum_{i=1}^{N_a} \sum_{r=1}^{N_r} T_{ir} Z_{isr} \qquad \forall_s \epsilon\, N_w \tag{15}$$

Thus, the MILP model is now totally linearized and can be solved with Lingo.

Final model summary

$$\text{Minimize} \quad Z = \alpha . CT + \beta \cdot EN \tag{16}$$

5. Design of Experiment for RALB Optimization

5.1. Analysis of the effect of different parameters on CT: EN and efficiency

The primary goal of the experiment is to analyze the impact of the number of robots, the number of stations, and the cycle time-to-energy weight ratio on the cycle time, energy consumption, and efficiency in a robotic assembly line balancing (RALB) problem. Additionally, the study will examine how these parameters determine the sensitivity of the decision variables to different configurations. Table 1 shows the experimental factors and their levels while Table 2 shows the Robot and Station Configurations.

Table 1. Experimental Factors and Levels

Factor	Levels Considered
Assembly Line Size	11, 25, 35 tasks
Number of Robots	Based on task size (see below)
Number of Stations	Based on task size (see below)
Weight Ratios (Cycle Time: Energy)	1:0, 0.5:0.5, 0:1
Robot Configurations	Varies based on problem size
Task Assignment Strategy	ILP-based optimization

Table 2. Robot and Station Configurations

Task Size	Number of Robots	Number of Stations
11 Tasks	1, 3, 5	2, 3, 4, 5

25 Tasks	1, 3, 4, 5, 6	4, 5, 7, 9, 12
35 Tasks	1, 3, 5, 7, 9, 12	4, 5, 9, 12

Single-Robot Case: One specific robot type is chosen for all tasks.
Multiple Robots Case: Robots with different task execution times and energy consumption levels are used.
The following are to be examined:

- Dual-objective mathematical model: Evaluate the effect of cycle time and energy consumption under different robotic configurations.
- Effect of robot variety: Analyze if increasing the number of available robot configurations impacts cycle time, energy consumption, and efficiency across different problem sizes.
- Effect of cycle time-to-energy ratio: Study how varying weight ratios in the weighted sum optimization impacts performance.
- Determination of dominance: Identify at which weight ratio, either cycle time or energy becomes the dominant factor in optimization.
- Effect of number of stations: Study how varying the number of stations affects cycle time, energy consumption, line efficiency and WEST ratio.

The experiment will evaluate the following:

- Cycle Time (CT) – The longest station time in each solution.
- Energy Consumption (EN) – The total energy used by all robots in the system.
- Efficiency (line Efficiency) – Computed as the ratio of total work time to available time across stations.

Line Efficiency $EF = \frac{CT \times N_W - \sum_{i=1}^{N_a} \sum_{s=1}^{N_W} \sum_{r=1}^{N_r} x_{is}\, y_{sr} T_{ir}}{CT \times N_W}$ (17)

- WEST Ratio: The Workstation Efficiency and Synchronization Tradeoff (WEST) Ratio is a performance metric that evaluates the tradeoff between cycle time and energy consumption in a robotic assembly line.

Experimental Structure is a full factorial design. For each scenario, the same precedence constraint matrix and task time for each robot will be used.
The precedence diagrams and robot time for each task are given in the data files mentioned in the data availability section.
Analysis Techniques:

- Trend Analysis: Examine how results change across different problem sizes to identify consistent behavior.
- Threshold Identification: Detect the weight ratio at which cycle time or energy becomes dominant.

5.2. ANOVA Analysis

The WEST Ratio quantifies how efficiently a given configuration balances two objectives relative to the best and worst observed values in a data set. It is derived from an efficiency metric (η), which accounts for the relative improvements in cycle time and energy consumption based on their maximum and minimum values observed in the dataset. The efficiency is defined as:

$$\eta = \frac{(CT_{max} - CT) + (EN_{max} - EN)}{(CT_{max} - CT_{min}) + (EN_{max} - EN_{min})} \times 100 \quad (18)$$

6. Results and Discussion

This section analyzes the outcomes derived from optimizing cycle time (CT) and energy consumption (EN) using the proposed dual-objective model. While the datasets and the results for problems involving 11, 25, and 35 tasks are comprehensively summarized in the tables provided in the data availability section, the focus here is on the 35-task scenario. To enhance clarity, the findings for this larger problem are illustrated through graphical representations, which highlight the interplay between CT and EN under varying configurations and weight ratios. The discussion delves into the trade-offs, trends, and implications observed in the optimization process for both objectives.

6.1. Effect of Stations and Robots on Cycle Time and Energy (35-Task Problem, Considering Different CT: EN Ratios)

The Robotic Assembly Line Balancing (RALB) problem involves optimizing both cycle time (CT) and energy consumption (EN) under varying configurations of stations, robots, and objective weight ratios. This analysis evaluates the interplay between these parameters based on results derived from a dual-objective mathematical model solved using MILP software (LINGO) with the weighted sum method. The study focuses on 35 tasks, examining CT, EN, and efficiency across three weight ratios (1:0, 0.5:0.5, and 0:1) and configurations involving 1 to 12 robots and 4 to 12 stations.

6.1.1. Effect of the Number of Stations on Cycle Time (CT)

Figures (1-3) illustrate the relationship between cycle time (CT) and the number of stations for 35-task problems at different numbers of robots under different ratios of CT:EN. The ratio of 1:0 gives cycle Time Prioritization, the ratio 0.5:0.5 considers balanced Optimization and 0:1 gives energy Consumption Prioritization.
The relationship between the number of stations and CT is heavily influenced by the CT:EN weight ratio and the number of robots deployed is presented in figures (1-3).

CT-Prioritized Scenarios (1:0 Ratio):

Increasing stations in CT-focused optimization significantly reduces cycle time by distributing tasks more evenly and minimizing sequential bottlenecks. This observation can be depicted in figure 1. With **1 robot**, increasing stations from 4 to 12 reduces CT by **66%** (494 to 170). With **12 robots**, CT drops by **68%** (302 to 98) as stations increase from 4 to 12.
While adding stations initially reduces CT by distributing tasks, precedence constraints and inherent task durations limit further improvements beyond 9 stations. The rigid structure of task dependencies and static robot assignments create a "saturation point" where additional stations yield minimal gains. CT Reduction Rate:

- 4 to 9 Stations: $\Delta CT = 270$ (494 →224), ~54 units/station.
- 9 to 12 Stations: $\Delta CT = 54$ (224 →170), ~18 units/station.

The slowdown in CT reduction aligns with the theoretical limits of task divisibility and synchronization overhead.

Balanced Scenarios (0.5:0.5 Ratio):

Balanced optimization achieves moderate CT reductions. For instance, with **9 robots**, increasing stations from 4 to 12 reduces CT by **68%** (345 to 112) as shown in figure 2. However, CT remains **15–20% higher** than CT-prioritized scenarios due to energy trade-offs. Generally, increasing the number of stations improves CT but are constrained by energy-aware task allocation.

EN-Prioritized Scenarios (0:1 Ratio):

Energy-focused optimization severely penalizes CT. For example, with **1 robot**, CT spikes to **1,481** (4 stations) and **1,785** (12 stations). Adding robots mitigates this: **12 robots** reduce CT to **153** (12 stations), but it remains **56% higher** than CT-prioritized scenarios as shown in figure 3. As Key **insight,** Stations alone cannot resolve CT penalties caused by energy prioritization; robot scaling is critical.

6.1.2. Effect of Number of Stations on Energy Consumption (EN)

Energy consumption trends inversely with CT priorities, modulated by robot count and weight ratios. The results are represented in figures (4-6) at the three CT:EN ratios under consideration.

CT-Prioritized Scenarios (1:0 Ratio):

Stations reduce energy consumption indirectly by shortening CT, which lowers per-task energy. For example, with **3 robots**, EN decreases by **22%** (1,149.9 to 894.9) as stations increase from 4 to 12. However, uneven task allocation at intermediate stations (e.g., 9 stations) can temporarily increase EN by **8%** (973.1). These results are presented in figure 4. As key insight: Stations enable energy savings through faster task completion but risk inefficiency if unbalanced.

Balanced Scenarios (0.5:0.5 Ratio):

Balanced optimization achieves deliberate energy reductions. For example, with **5 robots**, EN decreases by **19%** (862.9 to 702.4) as stations increase from 4 to 12 as shown in figure 5. Energy savings are **30% slower** than CT-prioritized scenarios due to competing objectives. It can be concluded that stations contribute to energy savings but are less impactful than robot scaling.

EN-Prioritized Scenarios (0:1 Ratio):
Energy consumption plateaus with station scaling. For example, with **3 robots**, EN drops by only **6%** (822.5 to 772) as stations increase from 4 to 12 as shown in figure 6. Further station additions yield marginal gains (e.g., **2% reduction** from 9 to12 stations). Generally, energy minimization is largely robot-driven; stations play a secondary role.

6.1.3. Effect of Number of Stations on Efficiency

Efficiency—defined as the harmonization of CT and EN—depends on the interplay between stations, robots, and weight ratios. The results of the effect of the number of stations and number of robots at different CT:EN ratios are presented in figures (7-9)

CT-Focused Efficiency (1:0 Ratio):
Efficiency remains high (90–99%) as stations balance workloads. For example, with **5 robots**, efficiency stays at **98%** across 4–12 stations as shown in fig 7. Idle time is minimized through parallel task allocation. High station counts enable rapid task completion, aligning with CT goals. However, energy inefficiency limits overall effectiveness. In general, Stations sustain efficiency by preventing resource underutilization.

Balanced Efficiency (0.5:0.5 Ratio):
Efficiency declines moderately (71–97%) due to conflicting priorities. For example, with **12 robots**, efficiency drops to **71%** (12 stations) as energy constraints disrupt load balancing as can be depicted in fig 8. Intermediate stations (7–9) maintain efficiency at **85–89%**. As a key insight, stations partially offset efficiency losses but cannot reconcile CT/EN trade-offs. These configurations avoid energy waste while maintaining competitive CT, exemplifying the model's ability to reconcile conflicting objectives.

EN-Focused Efficiency (0:1 Ratio):
Efficiency collapses (9–89%) due to imbalanced workloads as shown in fig 9. For example, with **1 robot**, efficiency drops to **9.1%** (12 stations) as energy optimization creates idle time. Adding robots improves efficiency (e.g., **12 robots**: 56.2% at 12 stations), but it remains suboptimal. Consequently, stations cannot compensate for efficiency losses caused by energy-driven task sequence.

In conclusion, stations enhance CT and efficiency in CT-prioritized Scenarios, as increasing stations reduce cycle time by up to **68%** and maintain efficiency above **90%** through balanced task allocation. It also diminishing returns occur beyond 9 stations. In **Balanced Scenarios Require Trade-offs**, stations improve CT and EN moderately but fail to fully resolve efficiency losses (e.g., **71%** at 12 stations). While in **EN-Prioritized Scenarios Demand Robot Scaling**, stations alone cannot mitigate CT penalties or efficiency collapse; **12 robots** reduce CT by **90%** and improve efficiency to **56%**.

The RALB problem underscores the necessity of aligning robotic configurations, station counts, and objective weights with operational goals. The weighted sum method effectively quantifies trade-offs, enabling managers to make data-driven decisions. Future work could explore dynamic weight adjustment during production or integrate real-time energy pricing for adaptive optimization. Ultimately, this analysis demonstrates that optimal assembly line performance hinges on harmonizing speed, energy, and resource allocation. a balance achievable through rigorous multi-objective modeling.

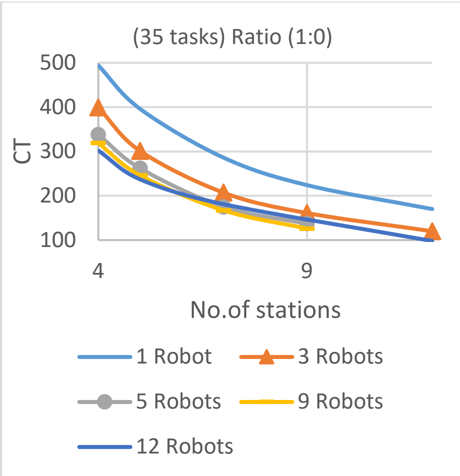

Figure 1. The cycle with number of stations ratio (1:0)

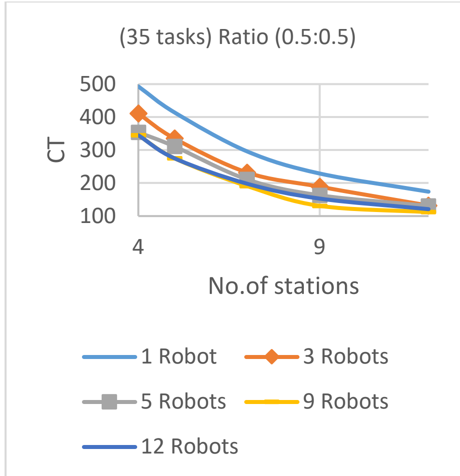

Figure 2. The cycle time with no. of stations ratio (0.5:0.5)

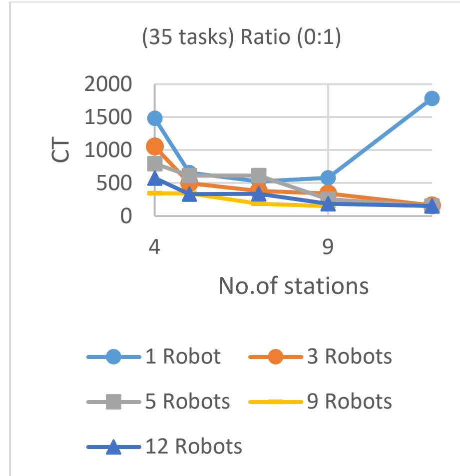

Figure 3. The cycle time with the number of stations ratio (0:1)

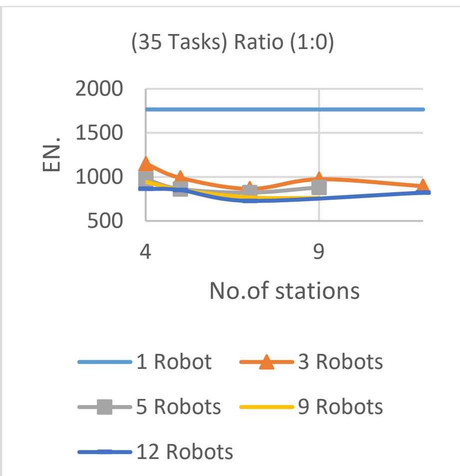

Figure 4. The Energy with the number of stations ratio (1:0)

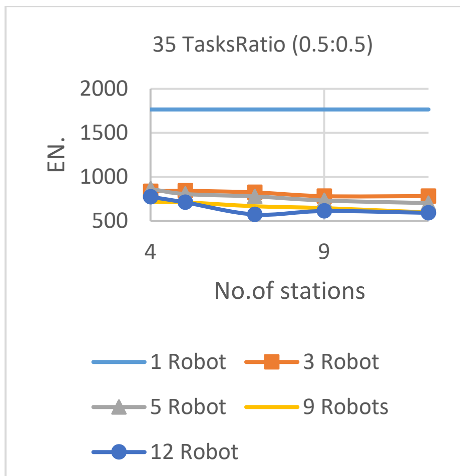

Figure 5. The Energy with the number of stations ratio (0.5:0.5)

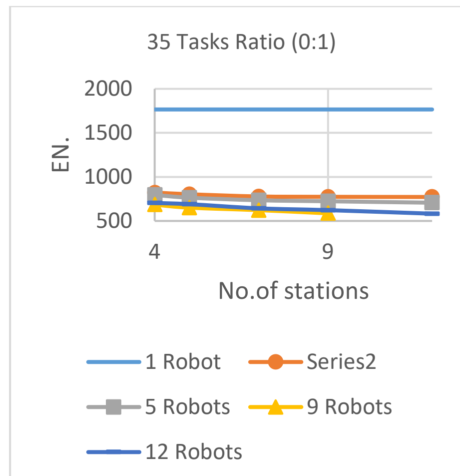

Figure 6. The Energy with the number of stations ratio (0:1)

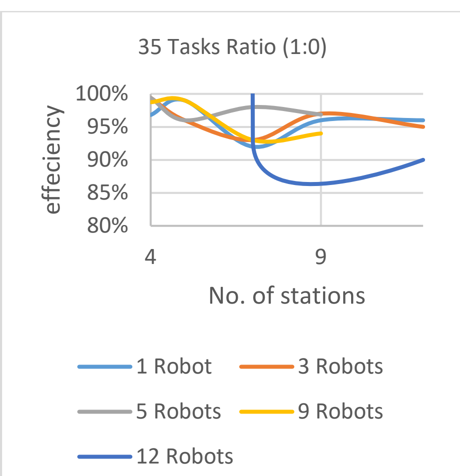

Figure 7. The Efficiency with the number of stations ratio (1:0)

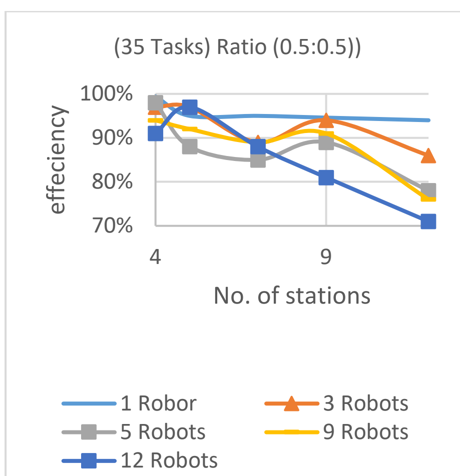

Figure 8. The Efficiency with the number of stations ratio (0.5:0.5)

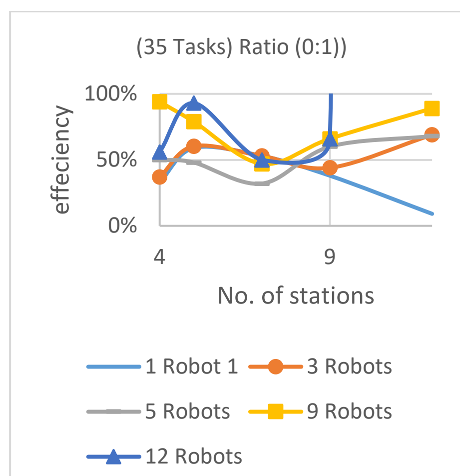

Figure 9. The Efficiency with the number of stations ratio (0:1)

6.2. Impact of Problem Size on Performance Metrics (for 11, 25, and 35 Tasks in the RALBP Problem)

To analyze the robotic assembly line balancing problem (RALBP) comprehensively, we compare the 11-task, 25-task, and 35-task results across different numbers of stations and robots. For the 11-task problem, it is depicted from Table 3 that the CT is relatively low, and the impact of increasing robots is less significant compared to larger task sets. As for the 25-Task Problem, the CT is noticeably higher compared to 11 tasks, indicating an increased complexity in task allocation. The benefit of increasing robots becomes more prominent, especially in setups with more than 6 stations. Higher robot counts (5-9) significantly lower CT, while single-robot setups show high CT due to workload bottlenecks. In the case of the 35-Task Problem, CT values are the highest among the three cases, demonstrating the increasing challenge of balancing more tasks. A single robot results in extreme inefficiencies, particularly when the number of stations is too high (e.g., CT spikes around 12 stations for 1 robot).

Table 3. Comparisons and Key Trends Across Different Task Sets

Aspect	11 Tasks	25 Tasks	35 Tasks
Cycle Time (CT)	Low	Moderate	High
Effect of More Robots	Moderate Improvement	Significant Improvement	Essential for Optimization
Effect of More Stations	Helps Initially, But Plateaus	Reduces CT, but Only up to ~9-10 Stations	Essential at First, but Excessive Stations Can Be Inefficient
Best Robot Count	3-5	5-9	5-12
Best Number of Stations	3-5	6-9	6-10

It can be concluded that balancing both objectives (CT: EN = 0.5:0.5), a mid-range robot and station configuration gives the best results.
As the number of tasks increases, optimizing the balance between robots, stations, and energy efficiency becomes more critical as can be depicted from table 4. An excessive number of stations without enough robots leads to inefficiencies, while too few stations create workload bottlenecks. A balanced approach is required to optimize both cycle time and energy consumption, ensuring efficient robotic assembly line performance.

Table 4. Comparative Analysis of 35, 25, and 11 Tasks

Factor	11 Tasks	25 Tasks	35 Tasks
Cycle Time (CT) Range	Low (50-800)	Moderate (100-1500)	High (100-2000)
Energy Consumption (EN) Variation	Low	Moderate	High
Effect of Increasing Stations	Minimal impact beyond 4-5 stations	Balances CT and EN efficiently	Improves CT but excessive stations cause diminishing returns
Optimal Stations for Balance	4-5 stations	5-7 stations	5-7 stations
Efficiency Trend	Less sensitive to station count	Moderate dependence on station count	Highly dependent on configuration

It can be concluded that higher task numbers demand more stations to maintain efficiency, but beyond 7 stations, diminishing returns occur. The effect of energy consumption variation is more pronounced in the 35-task case, while in smaller task cases, EN remains more stable. For small tasks (11 tasks), fewer stations are required, and additional stations have less impact on CT and EN. 25 tasks show an intermediate trend, where adding stations significantly improves efficiency but do not exhibit as extreme variations as the 35-task case.

6.3. ANOVA analysis for 11 Tasks RALBP for all CT:EN ratios

To determine whether the number of robots and stations significantly impact the WEST Ratio (η), we will perform ANOVA to check statistical significance of the balancing results. The WEST Ratio (η) is first calculated, and the histogram shown in figure 10 is plotted to check for normality. The histogram suggests the data is somewhat skewed.

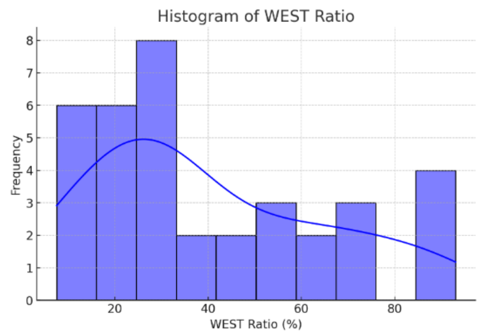

Figure 10. Histogram of WEST ratio

The factors analyzed are the number of Robots, number of Stations and interaction Effect (Robots × Stations). The ANOVA results are depicted in table (5).

Table 5. Results of ANOVA analysis for 11 tasks RALBP for different CT:EN ratios

Source	**Sum of Squares**	**df**	**F-value**	**p-value**
Number of Robots	13,961.94	2	14.16	0.000087 (Significant)
Number of Stations	2,934.34	3	1.98	0.143 (Not Significant)
Robots × Stations Interaction	294.82	6	0.10	0.996 (Not Significant)
Residual (Error)	11,833.20	24	-	-

The results show that the p-value (0.000087) for robot count is highly significant, meaning the number of robots has a strong effect on the WEST ratio. This indicates that increasing the number of robots significantly influences the efficiency of the system. From figure 11 the WEST ratio increases as the number of robots increases, confirming the significant ANOVA results. The variability of WEST ratio values is higher for fewer robots but stabilizes as more robots are added.

The effect of the number of Stations is not significant as the p-value (0.143), suggesting that the number of stations does not have a statistically strong effect on the WEST ratio. This implies that adjusting the number of stations alone may not improve system efficiency significantly. The interaction effect of the interaction of (Robots × Stations) has a very high p-value (0.996), meaning that the combined effect of robots and stations on WEST ratio is not significant. This suggests that the effect of robots on efficiency is independent of the number of stations. This can be seen in figure 12 where the WEST ratio does not show a clear increase or decrease trend with the number of stations. The variation in WEST ratio across different numbers of stations is small, supporting the ANOVA result that stations do not have a statistically significant effect. This suggests that optimizing efficiency is more dependent on the number of robots rather than the number of stations.

The WEST ratio tends to decrease as the weight on energy (EN) increases relative to cycle time (CT). When more emphasis is placed on minimizing cycle time (higher CT weighting), the WEST ratio remains higher, indicating better efficiency. As the weight shifts toward energy minimization (higher EN weighting), the WEST ratio becomes more variable and generally lower, implying trade-offs in efficiency. The effect of CT:EN ratio on WEST Ratio is shown in figure13.

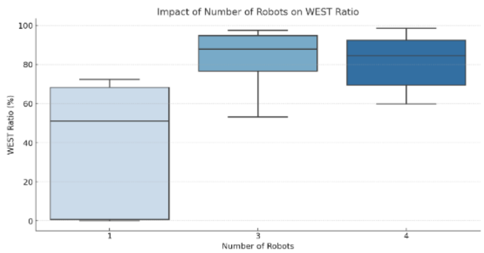

Figure 11. Effect of the number of robots on WEST ratio for all values of CT: EN

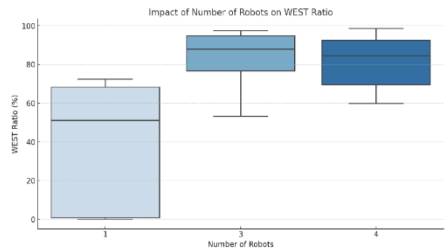

Figure 12. Effect of the number of stations on WEST ratio for all values of CT: EN

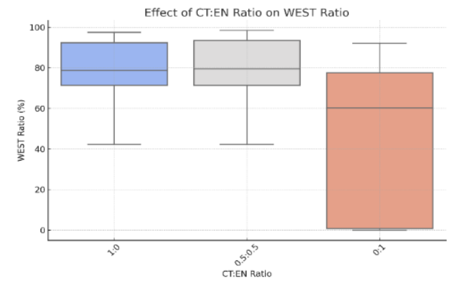

Figure 13. Effect of CT:EN ratio on WEST ratio

7.Conclusion

This study aims to optimize robotic assembly line balancing (RALBP) by analyzing the impact of different cycle time (CT) and energy consumption (EN) ratios across task complexities of 11, 25, and 35 tasks. The research investigates how varying the number of robots and stations affects performance efficiency under three different CT: EN priority ratios: 1:0 (cycle time prioritization), 0.5:0.5 (balanced optimization), and 0:1 (energy prioritization). A mathematical model was developed to simulate and optimize task allocation under these conditions, ensuring a trade-off between productivity and sustainability. The experimental design involved varying the number of robots (1 to 12) and stations (3 to 12), while conducting simulations to measure cycle time and energy consumption across different configurations. The results show that the optimization of robotic assembly lines is a delicate balancing act. While increasing resources improves performance, diminishing returns and energy trade-offs necessitate context-aware strategies. Stations mitigate sequential bottlenecks but risk inefficiency if overused. Larger problems necessitate proportional scaling of both resources to avoid performance collapse. Problem Size Dictates Optimization Strategy such that for small tasks (11–25 tasks) prioritize simplicity, as minimal robots/stations suffice, while for large tasks (35+ tasks) demand aggressive resource allocation to balance CT and EN.

Finally, the optimization of robotic assembly lines is a delicate balancing act. While increasing resources improves performance, diminishing returns and energy trade-offs necessitate context-aware strategies. For large-scale systems, a hybrid approach—leveraging parallelization for CT reduction while monitoring energy thresholds offers the most sustainable path forward. By aligning resource allocation with operational priorities, manufacturers can achieve both efficiency and sustainability in an era of increasingly complex automation**.**From ANOVA analysis, it is found that robots have a strong impact on efficiency, as shown by both ANOVA and box plots. Stations do not significantly affect the WEST ratio, meaning adding more stations does not necessarily improve efficiency. The interaction effect (Robots × Stations) is insignificant, meaning these two factors work independently rather than together.

8. Data availability

The datasets and the results for the problems used during the current study are available in this link.
https://doi.org/10.5281/zenodo.15025311

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