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***RESEARCH ARTICLE***

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# Multi-objective genetic algorithm for the assembly line worker assignment and balancing problem: A case study in the automotive supply industry

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**Abstract**

The primary challenge in assembly line design is the need for more appropriately allocating tasks and workers to workstations. This study addresses the problem of line balancing and worker assignments, considering the performance disparities among workers during the line balancing process. In the relevant literature, this problem is known as the Assembly Line Worker Assignment and Balancing (ALWAB) problem. This research examines a multi-objective ALWAB Type-2 problem, simultaneously evaluating cycle time and squared load assignment objectives. The study is conducted based on a real-life scenario in a sub-industry automotive industry that manufactures cable equipment. To solve this problem, a multi-objective genetic algorithm approach is proposed. Recognising that the selection of parameter values will influence the algorithm's performance, parameter calibration has been performed. A full factorial experimental design and the **irace** method have been utilised for this purpose. The results are compared with those using parameter values utilised for similar problems in the literature. Furthermore, a sensitivity analysis has been carried out to examine the impact of various relative weight values of the objectives on the result. The results indicate that the experimental design generally yields superior results compared to other methods.



*Keywords:* Genetic Algorithm; Assembly Line Worker Assignment and Balancing; **irace**; Design of Experimental Design; Type-2

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## 1. Introduction

Production is a primary activity for enterprises producing goods and services [1]. Flow-line production systems have become increasingly crucial for enterprises aiming to increase production quantities, enhance productivity, and reduce costs. Assembly lines are specialised flow production systems crucial in the industrial manufacture of highly standardised products [2]. Designed to meet large production quantities, assembly lines have become foundational to production systems. The workload between workstations must be balanced to achieve more efficient and rapid production on assembly lines. This balanced distribution of tasks across stations is termed assembly line balancing (ALB). The challenge of determining which individual will perform a given task, taking into account performance differences among workers in addition to line balancing, is known as the assembly line worker assignment and balancing (ALWAB) problem [3]. This type of problem is viewed as an extension of the basic ALB problem [4]. The introduction of worker-dependent durations for defined tasks and the integration of worker assignment decisions with workstations in the ALWAB approach enhance the applicability of ALB problem-solving in the manufacturing sectors [5]. ALB problems are categorised into four groups based on their objective functions. This classification can be briefly described as follows:

*(i)* Type-1: In Type-1 problems, the cycle time is fixed and known. The objective is to minimise the number of workstations.
*(ii)* Type-2: The number of workstations is determined. The objective is to minimise the cycle time according to this number. By minimising the cycle time, it is aimed to increase the production amount per unit of time.
*(iii)* Type-E: It is a problem type that tries to simultaneously minimise the cycle time and the number of workstations.
*(iv)* Type-F: It is a feasibility problem type which is to determine whether a feasible line balance exists for a given number of workstations and cycle time [6].

In this study, Type-2 was utilised. The proposed algorithm in this study seeks to minimise cycle time and enable quadratic load assignment. This ensures a balanced distribution of tasks to the workstation while taking into account precedence relationships among the jobs, worker-specific task durations, and worker walking times. The ALWAB problem is known as the NP-hard problem [7,8]. Hence, a multi-objective genetic algorithm (GA) has been proposed to solve a real-life problem faced by an automotive sub-industry that produces cable equipment. A multi-objective mathematical model was presented to define this problem.

Parameters used in algorithms are crucial to attaining optimal solutions. In this study, a full factorial experimental design was employed to calibrate and control these parameters. Additionally, using **irace**—a method for parameter calibration—the optimal parameters were identified, allowing the problem to be resolved. Moreover, the algorithm proposed by Mutlu et al. [9] for the ALWAB problem has been employed in the literature. This study also compares the results derived from it. Sensitivity analysis is applied to check the outcome of a decision-maker, to see the risks involved and to analyse the values of parameters [10]. Here, sensitivity analysis was conducted to study the impact of varying relative weight values of objectives on the outcomes.

The rest of this study is organised as follows: Section 1 offers an in-depth review of the ALWAB problem. Section 2 introduces a detailed explanation of the problem, the mathematical model, the proposed GA algorithm, and the calibration of the GA algorithm's parameters and presents both experimental and comparative results. The final section encapsulates the study's concluding observations.

## 2. Experimental method

### *2.1. Literature review*

The study of the ALB problem in the existing literature was first addressed by Bryton in 1954 and many studies on ALB have been carried out until today [8]. A detailed literature review has been carried out to understand the depth of the work discussed in this study and identify the missing points. This is summarised in Table 1.

In the first stage, ALB studies in the literature were analysed. In ALB studies, task processing times do not vary depending on worker performance. In this problem type, the performance of each worker is neglected. However, this situation does not reflect real life. Since the task processing times vary depending on the worker performances in the real-life problem considered in this study, in the second stage, the studies on ALWAB in the literature were examined. Analysing the accessed studies, it was observed that the setup/transport (walking) times are generally ignored or included in the processing times since they are much smaller than the processing times. Considering that ignoring walking and transport times in problems does not reflect the real situation, walking times are handled separately from work times in this study. In the study of Karsu & Azizoğlu [16], the objective function of minimising the squared load assignment was developed and the walking time was added, and a multi-objective mathematical model was obtained by aiming at workload balancing. This study aimed to contribute to the literature by addressing a real-life problem in the automotive sub-industry that produces cable equipment.

Table 1. Related literature on the ALB and ALWAB problems.

| **Category** | **References** | **Assembly line type** | **Used objective functions** | **Solution methods** | **TP/RLP** |
|---|---|---|---|---|---|
| ALB problems | Karsu & Azizoğlu [11] | Simple | Workload balancing (Min) | B&B, TS | TP |
| | Altunay et al. [12] | Parallel | Cycle time (Min) | MM | TP |
| | Arıkan [13] | Simple | Workload balancing (Min) | MM, TS | TP |
| | Delice et al. [14] | Two-sided U-type | Number of mated-stations (Min)<br>Number of workstations (Min) | ACO | TP |
| | Süer & Sadeghi [15] | Parallel | Assembly rate (Max)<br>Number of operators (Min) | MM | TP |
| | Karsu & Azizoğlu [16] | Simple | Total squared load (Min) | B&B | TP |
| | Meng et al. [17] | Simple | Cycle time (Min)<br>Task alteration (Min) | MM, WOA | RLP |
| | Erten [18] | Simple | Number of agents (Min)<br>Workload balancing (Min) | MM, SA | TP |
| | Tang et al. [19] | Simple | Cycle time (Min)<br>Task alteration (Min) | MM, MFEA | TP |
| | Petroodia et al. [20] | Mixed-model | Cost (Min) | MM, FOH, CM | TP |
| | Yin et al. [21] | Partial disassembly | Cycle time (Min)<br>Peak Energy Consumption (Min)<br>Total Energy Consumption (Min)<br>Hazardous index (Min) | MM, HDA | TP |
| | Meng et al. [22] | Mixed-model | Cycle time (Min)<br>Task alteration (Min) | MM, CCEA | TP |
| | Zhao & Zhang [23] | - | Cycle time (Min)<br>Task adjustments (Min) | IVNS | TP |
| | Deliktaş & Aydın [54] | Simple | Smoothness index (Min)<br>Line efficiency (Max) | IABC, HH | TP |
| ALWAB problems | Aryanezhad et al. [24] | Cellular | Cost (Min) | MM | TP |
| | Blum & Miralles [25] | Simple | Cycle time (Min) | MM, BS | TP |
| | Sungur & Yavuz [26] | Simple | Cost (Min) | MM | TP |
| | Borba & Ritt [27] | Simple | Cycle time (Min) | B&B | TP |
| | Vilà & Pereira [28] | Simple | Cycle time (Min) | B&B | TP |

| | | | | |
|---|---|---|---|---|
| | | Number of workstations (Min) | | |
| Ritt & Miralles [29] | Simple | Cycle time (Min) | MM, SA | TP |
| Polat et al. [30] | Simple | Cycle time (Min) | VNS | RLP |
| Zacharia &Nearchou [4] | Simple | Cycle time (Min)<br>Smoothness index (Min) | EA | TP |
| Janardhanan & Nielsen [31] | Two-sided | Cycle time (Min) | MM, MBO | TP |
| Yılmaz & Demir [32] | Simple | Cycle time (Min) | MM | TP |
| Janardhanan et al. [33] | Two-sided | Cycle time (Min) | ABC | TP |
| Yıldız et al. [34] | Simple | Cycle time (Min)<br>Number of workers (Min) | MM, Arena Simulation | RLP |
| Zhang et al. [35] | U-shaped | Cycle time (Min)<br>Ergonomic risks (Min) | MM, RIPG, OCRA | TP |
| Karaş & Özçelik [36] | Simple | Weighted sum of the relative percent deviation from the lower bounds (Min) | MM, ABC | TP |
| Campanaa et al. [37] | Simple | Cost (Min) | MM, H, VNS | TP |

Table 1. (Cont.) Related literature on the ALB and ALWAB problems.

| Category | References | Assembly line type | Used objective functions | Solution methods | TP/RLP |
|---|---|---|---|---|---|
| ALWAB problems (Cont.) | Gräßler et al. [38] | Manual | Skill improvement (Max)<br>Cycle time (Min) | MM | TP |
| | Katiraee et al. [39] | Simple | Cycle time (Min)<br>Physical effort (Min) | $\varepsilon$-constraint | RLP |
| | Küçükkoç [40] | Simple | Number of workstations (Min)<br>Disparity between workstations (Min) | MM, Hybrid GA | TP |
| | Akpınar & Bayhan [41] | Parallel | Number of workstations (Min) | MM, GA | TP |
| | Moreira et al. [42] | Simple | Cycle time (Min) | MM, Hybrid GA | TP |
| | Mutlu et al. [9] | Simple | Cycle time (Min) | MM, IGA | TP |
| | Oksuz et al. [43] | U-type | Line efficiency (Max) | MM, GA, ABC | TP |
| | Fathi et al. [44] | Simple | Number of workstations (Min)<br>Workload balancing (Min) | MM, GA, VNS | TP |
| | Liu et al. [45] | Simple | Cost (Min)<br>Energy consumption (Min) | MM, NSGA- II, SA | TP |
| | Kılınççı [46] | Simple | Number of workstations (Min) | MM, GA | TP |

***Solution methods:***
**ABC:** Artificial Bee Colony Algorithm, **ACO:** Ant Colony Optimization, **B&B:** Branch and Bound Algorithm, **CCEA:** Cooperative Co-evolutionary Algorithm, **CM:** Constructive Matheuristic, **EA:** Evolutionary Algorithm, **FOH:** Fix-and-optimize Heuristic, **H:** Heuristic, **HDA:** Hybrid Driving Algorithm, **HH:** Hyper-heuristic; **IABC:** Improved Artificial Bee Colony Algorithm, **IGA:** Iterative Enhanced Genetic Algorithm, **IVNS:** Improved Variable Neighborhood Search, **MFEA:** Multifactorial Evolutionary Algorithm, **MM:** Mathematical Model, **NSGA- II:** Non-dominated Sorting Genetic Algorithm-II, **OCRA:** Occupational Repetitive Action Tool, **RIPG:** Restarted Iterated Pareto Greedy Algorithm, **SA:** Simulated Annealing, **TS:** Tabu Search, **VNS:** Variable Neighborhood Search, **WOA:** Whale Optimization Algorithm
**TP:** Test Problem, **RLP:** Real-life problem

## *2.2. Problem description*

This study was conducted at an automotive company that produces electrical equipment for passenger vehicles. Each passenger vehicle has its own electrical equipment. The company produces these electrical components for vehicles. The assembly area of the company consists of a line system, with each line composed of 20 conveyors and an assembly table for each conveyor based on the production quantity. Fig. 1 shows the conveyor system for a vehicle.

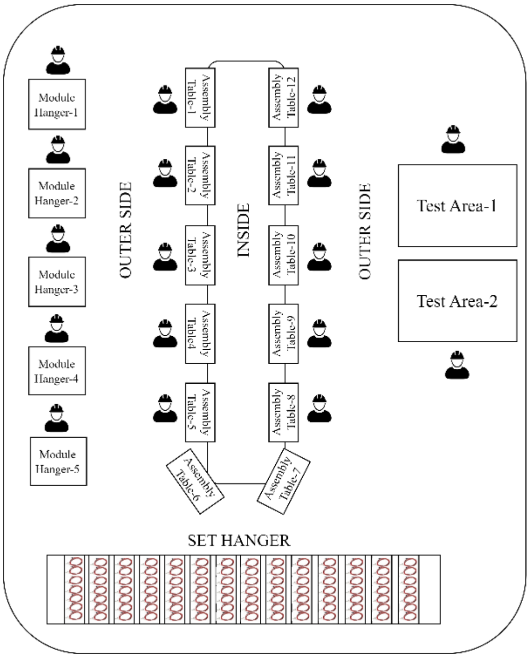



Fig. 1. An example of the assembly line in the cable industry.

The assembly tables on the conveyor are set to face outwards. Therefore, as can be seen in Fig. 1, they work on the outer side of the assembly tables and cannot enter the inner side. The conveyor system works in such a way that there is one operator at each assembly table. Each assembly table corresponds to a licence plate where the wiring of the respective car is addressed. Each vehicle has its own electrical equipment. This equipment includes different cable colours, cross-sections, lengths and routes. Accordingly, each worker has to perform the cable addressing on the assembly table, taking into account the tasks assigned to her/him. A sample section of the assembly table Fig. 2 shows a sample assembly table of the line where the ceiling installation equipment from the project groups is produced. In this line, there are cable addressing and harness taping processes on the conveyor. In the cable addressing process, each cable has an address (A1-A6, B1-B6 and C1-C5) and the cable routes to these addresses (purple and blue solid lines, red dashed lines) on the assembly table. In Fig. 2, the blue and purple solid lines and the red dashed line are the paths that the cables must follow. In order to ensure correct electrical conductivity, each cable must be taken from its own defined places.

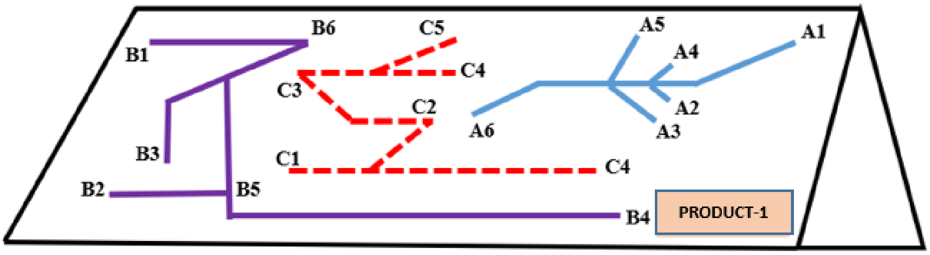



Fig. 2. An example of the assembly table in the cable industry.

In simple assembly line balancing problems, setup/transport (walking) times are usually ignored in studies since they are much smaller than the processing times, and in some cases, they are added to the processing times. Andres et al. [47] separately evaluated the setup times in the simple ALB problem and defined a new sequence-dependent assembly line balancing problem with setup times. No studies consider walking times in the ALWAB Type-2 problem type. In the considered enterprise, in order for each workstation to start working, the cable bundles in the set hangers must be transported to the workstations. The distance of each station to the set hanger where the cable bundles are located is different. The walking times here were not ignored, and a line balancing study was carried out by evaluating the station-based preparation times.

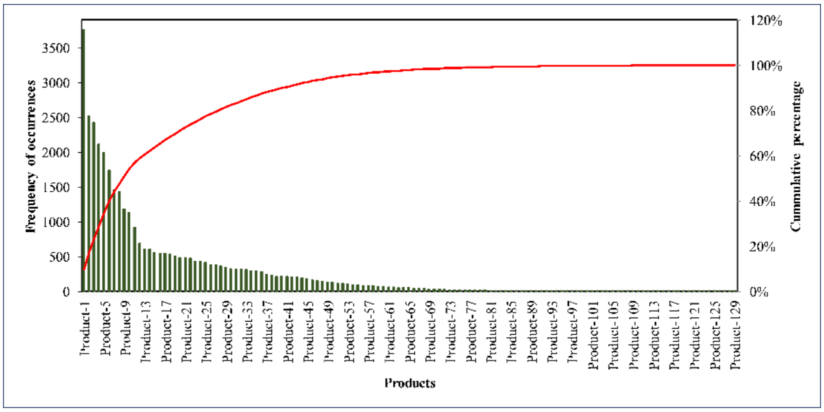



Fig. 3. Pareto analysis for the produced products in the last 6 months.

Pareto analysis, as a decision-making technique, statistically isolates a limited set of input factors, whether they are desirable or undesirable, that exert the most significant influence on the overall outcome. In order to determine the model type that will be the most produced according to the order rates received from the customer, a Pareto analysis was performed on the order quantity of 129 products for the last 6 months. As seen in Fig. 3, Product-1 is the product with the highest number of orders. The number of workers and workstations is determined for the problem to be balanced in the enterprise. The performance of all workers is different from each other. There are priority relations between the tasks. Product-1 consists of 48 jobs, and 8 workers work on the line to be assembled.

### 2.3. Mathematical model

The assumptions of the proposed mathematical model for the assembly line worker assignment and balancing problem are as follows:

- The processing times of each task of each worker are known deterministically.
- The processing times of each job vary depending on the worker.
- Each worker can do every job.
- The setup time of the worker at each station is included in the processing times.
- A worker cannot be assigned to more than one workstation.
- A task can be assigned to one and only one worker.
- Assignment of more than one worker to a workstation is not allowed.
- Precedence relationships between tasks exist, and precedence relationships are known.
- Each worker can perform more than one task.
- Stations can be assigned more than one task.
- There is a single type of product production.
- Tasks are indivisible.

*Notations:*

| | | |
|---|---|---|
| $J$ | : | Set of the workers, $j \in J = \{1,2,\ldots m\}$ |
| $I$ | : | Set of the jobs, $i, k \in I = \{1,2,\ldots n\}$ |
| $S$ | : | Set of the workstations, $s \in S = \{1,2,\ldots p\}$ |
| $m$ | : | The number of workers |
| $n$ | : | The number of jobs |
| $p$ | : | The number of workstations in the initial state |
| $D_i$ | : | The set of immediate predecessors of job $i$ in the precedence network |
| $P_{ij}$ | : | Processing time of job $i$ when worker $j$ executes it |
| $R_s$ | : | Cable transport time for workstation $s$ |
| $M$ | : | A large positive number |

*Decision variables:*

| | | |
|---|---|---|
| $CT$ | : | Cycle time |
| $X_{sij}$ | : | 1, if the job $i$ is assigned to the worker $j$ in the workstation $s$; 0, otherwise |
| $Y_{sj}$ | : | 1, if the worker $j$ is assigned to the workstation $s$; 0, otherwise |

*Multi-objective mathematical model:*

$$Min\ f_1(x) = CT \quad (1)$$

$$Min\ f_2(x) = \sum_{s\in S}\sum_{j\in J}\left(\sum_{i\in I}\left(\left(P_{ij} \times X_{sij}\right) + R_s\right)^2\right) \quad (2)$$

$$\sum_{s\in S}\sum_{j\in j} X_{sij} = 1, \quad \forall i \quad (3)$$

$$\sum_{j\in J} Y_{sj} \leq 1, \quad \forall s \quad (4)$$

$$\sum_{s\in S} Y_{sj} \leq 1, \quad \forall j \tag{5}$$

$$\sum_{s\in S}\sum_{j\in J} s \times X_{sij} \leq \sum_{s\in S}\sum_{j\in J} s \times X_{skj}, \quad \forall i,k/i \in D_i \tag{6}$$

$$\sum_{i\in I}\left(\left(P_{ij} \times X_{sij}\right) + R_s\right) \leq CT, \ \ \forall s,j \tag{7}$$

$$\sum_{i\in I} X_{sij} \leq M \times Y_{sj}, \quad \forall j \tag{8}$$

$$M > \sum_{s\in S}\sum_{j\in J}\left(\left(P_{ij} \times X_{sij}\right) + R_s\right), \ \ \forall i \tag{9}$$

$$X_{sij}, Y_{sj} \in \{0,1\}, CT \geq 0, \forall i, j, i \neq j, s \tag{10}$$

While Eq. (1) aims to minimise the cycle time, Eq. (2) aims to balance the task loads by quadratic load assignment. Eq. (3) ensures that each operation is assigned to a worker and a workstation. Eq. (4) guarantees that each workstation has only one worker. Eq. (5) ensures that each worker is assigned to only one workstation, respectively. Eq. (6) defines the priority relationships between tasks. Eqs. (7)-(8) ensure that the sum of the assigned task processing and walking times do not exceed the cycle time. Eq. (9) states that each worker assigned to a workstation can perform more than one task as long as the cycle time is not exceeded, where $M$ is a large enough constant. Eq. (10) specifies the decision variables. Since the problem considered has two objective functions, the objective functions are combined using the weighted-sum method (WSM). WSM is one of the most well-known methods for obtaining Pareto efficient solutions [48]. The mathematical model of WSM is formulated in Eq. (11).

$$Min\ WSM(x) = [w_1 \times CT] + \left[w_2 \times \sum_{s\in S}\sum_{j\in J}\left(\sum_{i\in I}\left(\left(P_{ij} \times X_{sij}\right) + R_s\right)^2\right)\right] \tag{11}$$

Here $w_1$ and $w_2$ represent the importance weights for $CT$ and $\sum_{s\in S}\sum_{j\in J}\left(\sum_{i\in I}\left(\left(P_{ij} \times X_{sij}\right) + R_s\right)^2\right)$. Assuming $w_1 + w_2 = 1$, it will be in the form of $w_1, w_2 \geq 0$ and all the constraints in Eqs. (3)-(10) must be satisfied.

The average walking distances of each worker from the set hanger where the harnesses are located to the workstations are given in Table 2. These times depend on the distance between the workstation and the set hanger and do not change according to the job. The precedence relationship of each job is given in Fig. 4.

Table 2. Average walking distance from set hanger to workstations.

| Workstation no | $R_s$ | Workstation no | $R_s$ |
|---|---|---|---|
| 1 | 39.8 | 5 | 18.5 |
| 2 | 32.9 | 6 | 15.3 |
| 3 | 27.2 | 7 | 12.0 |
| 4 | 22.6 | 8 | 10.1 |

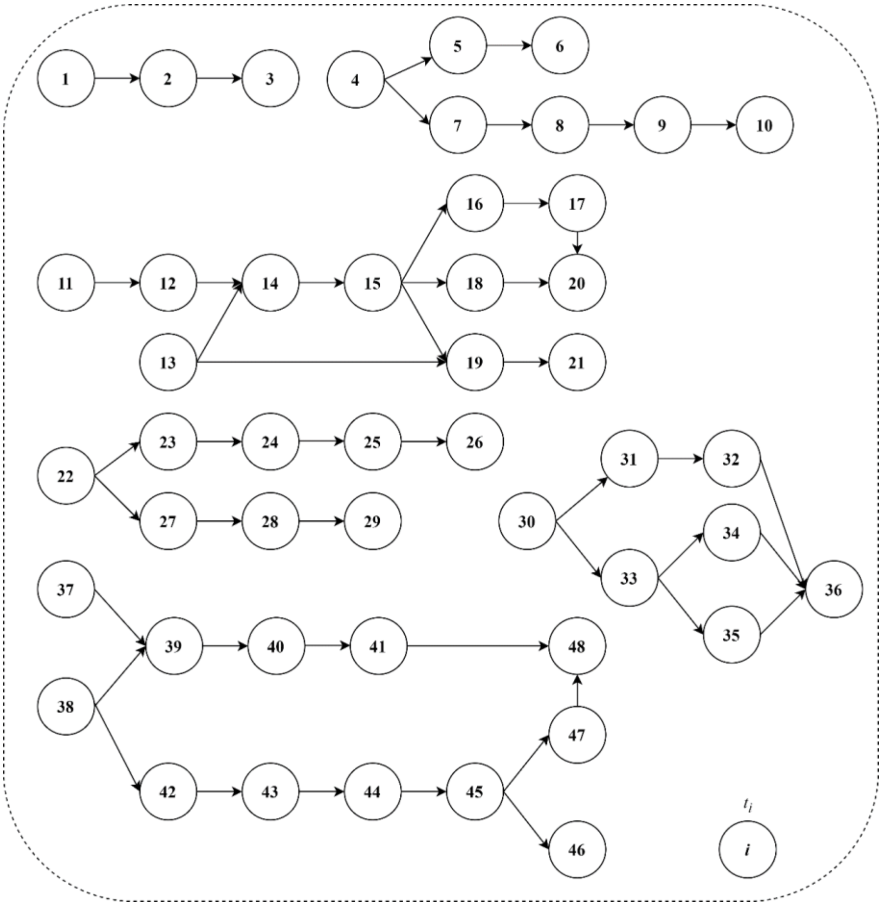



Fig. 4. Precedence relationship diagram for ceiling installation harness of Product-1.

### *2.4. Multi-objective genetic algorithm*

Due to the NP-hardness of the ALWAB Type-2 problem and the problem size limitation of exact solution methods, approximation procedures are needed to solve the problem [49]. Therefore, (meta)heuristic procedures have been developed for solving the ALWAB Type-2 problem. The pseudo-code of the proposed algorithm is given in Table 3.

Table 3. Pseudo-code of the proposed algorithm.

Algorithm 1: Pseudo-code of the proposed algorithm

**Input:** *I, J, S,* $D_j$, $P_{ij}$, $R_s$, $w_1$, $w_2$, $Tournament_{size}$, $C_{rate}$, $M_{rate}$, $UD_{Max}$

**Output:** Job-workstation-worker matrix, $f_1(x)$, $f_2(x)$, $WSM^{Norm}(x)$

**begin**

Randomly generate an initial population ($Pop_{init}$)

Compute of the fitness values ($Pop_{init}$) $\triangleright$ $see\ Eq.(17)$

$Pop_{current} \longleftarrow Pop_{init}$

**while** termination criteria not satisfied **do**

Parents ←Tournament selection ($Pop_{current}$, $Tournament_{size}$)

Childs ← *WMX* ($Parents$)

$Pop_{current}$ ←Swap ($Childs$)
Calculate of the fitness values ← ($Pop_{current}$) ⊳ $see$ Eq. (17)
**end while**
**return** the best individual in $Pop_{current}$
**end**

This study computes the cycle time by using the modified bisection search method proposed by Mutlu et al. [9]. Unlike the studies in the literature, walking times differ according to the distance between workstations. In order to achieve a balanced line distribution, walking times according to the station distance were added to the method. As a result, the bisection search method was modified, and the temporary cycle time was calculated.

The lower bound ($C_{LB}$) is calculated as given in Eq. (12), and the upper bound ($C_{UB}$) as given in Eq. (13) [50]:

$$C_{LB} = Max\left\{\left(\frac{1}{S}\sum_{i\in I} Min\left(P_{ij}\right),\ \ \forall j \in J\right),\quad \left(Min\left(P_{ij}\right),\quad \forall j \in J\ \ \vee\ \ \forall i \in I\right)\right\} \tag{12}$$

$$C_{UB} = Max\left\{\left(\frac{1}{S}\sum_{i\in I} Max\left(P_{ij}\right),\ \ \forall j \in J\right),\quad \left(Max\left(P_{ij}\right),\quad \forall j \in J\ \ \vee\ \ \forall i \in I\right)\right\} \tag{13}$$

In this study, the modified bisection search method used the following equations to calculate the expected cycle time (see Eqs. (14)-(15)):

$$C_m = \frac{1}{S}\sum_{i\in I} avg\left(P_{ij}\right),\quad \forall j \in J \tag{14}$$

$$C_e = \frac{1}{6}\left(C_{LB} + 4 \times C_m + C_{UB}\right) + avg(R_s) \tag{15}$$

where $avg\left(P_{ij}\right)$ and $avg(R_s)$ represent the average of processing and walking times, respectively.

The initial population is created in the initialization phase. The chromosomes in the population are randomly generated between 1 and the number of jobs (*n*). Every job is denoted by a numerical value, which is positioned within a sequence of numbers referred to as chromosomes. The length of each chromosome corresponds to the total number of jobs, and the value of each gene within the chromosome signifies the specific job's position in the assembly line. The jobs are listed sequentially in accordance with their assigned order. Fig. 5 represents an example of solution string corresponding to a data set consisting 11 jobs.

| Job Number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Job Priority | 8 | 10 | 7 | 5 | 2 | 6 | 11 | 3 | 9 | 1 | 4 |

Fig. 5. Chromosome representation.

Workers are also assigned to workstations. The worker numbers given in the representation are assigned to workstations, respectively. An example representation is given in Fig. 6.

| Workstation Number | 1 | 2 | 3 |
|---|---|---|---|
| Worker Number | 2 | 3 | 1 |

Fig. 6. The initial worker assignment of the example problem.

In the proposed multi-objective genetic algorithm (MOGA), the job assignment is made by considering the precedence diagram between jobs according to the determined job priority values, initial chromosome and worker assignment results. In order for the worker to start working, s/he needs to fetch the cable bundles from the set hanger. The cable retrieval time defined for the first station is added, and jobs are started to be assigned to the relevant station, taking into account the ability of the assigned worker to do the jobs and the duration of the job. If there is a possibility of selecting more than one job according to the priority status, the job with the highest priority number initially assigned by the algorithm is selected. Jobs continue to be assigned to the first workstation until the specified cycle time is reached. In the solution of proposed algorithm, to perform the optimum assignment process, only the last job of the assigned workstation is ignored, and if other jobs can be assigned, they are assigned. After the jobs that can be assigned to the first workstation are finished, we move to the next workstation and repeat the process described above.

In this study, the proposed MOGA aims to minimise the cycle time and the squared load assignment. When assigning the jobs to the workstation according to the specified cycle time ($CT_{opt}$), all the remaining jobs are assigned to the last station according to the order of priority since each task needs to be done. This may not be a feasible solution as the last station is assigned without considering the cycle time constraint. The fitness function applied in study of Mutlu et al. [9] prevents the station time of the last station from exceeding the cycle time via a high penalty in given in Eq. (16). In this equation, $FS$ denotes the time by which the station time of the last station exceeds the cycle time.

$$Fitness\ value = CT_{opt}^{2} \times FS \tag{16}$$

A group of individuals is randomly selected from the population, and the individual with the highest fitness value is selected to be the parent of the next generation population, and the tournament size is taken as 2. In each generation, the selection method, crossover and mutation operators are applied to ensure genetic diversity in the population. In the proposed genetic algorithm, a two-point-based weight mapping crossover (WMX) is applied as a crossover operator. The applied WMX operator consists of four primary steps: (*i*) the selection of a random sub-vector from two randomly selected parents (see Step 1), (*ii*) the prioritization of jobs in ascending order based on their assigned priorities, with lower numbers indicating higher-priority jobs (see Step 2), (*iii*) the exchange of ranks between the selected sub-vectors and the subsequent rearrangement of priorities according to the new rankings (see Step 3), and (*iv*) the generation of offspring using the newly determined job priorities from Step 3 (see Step 4). An illustrative example for the applied WMX operator is shown in Fig. 7 [44].

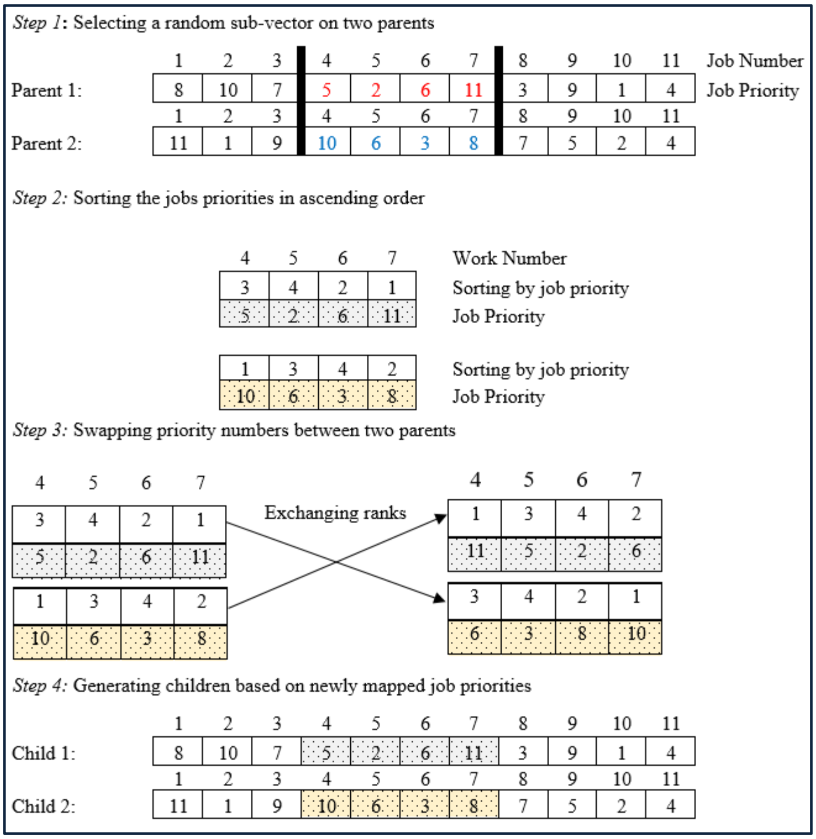



Fig. 7. Representation of the proposed WMX operator.

Swap-mutation ($S_{wap}$) operator was applied in the proposed genetic algorithm to ensure diversity. For the crossover rate ($C_{rate}$) and mutation rate ($M_{rate}$), the values determined from parameter tuning are used. The fitness value of the new population ($Pop_{current}$) is calculated. After the stopping condition is met, the best individual in the current population constitutes the output of the algorithm.

## *2.5. Parameter tuning*

The selection of appropriate parameters is pivotal for genetic algorithms to achieve optimal solutions. Ensuring the correct parameters for a given problem can profoundly influence the results. By making fine adjustments to these parameters, algorithms often demonstrate enhanced performance, leading to improved results [51]. These parameters are preset at the algorithm's onset based on the specifics of the problem at hand. The critical parameters to be determined include the population size, the crossover rate, and the mutation rate. In this study, the parameters for the proposed MOGA were ascertained using both the **irace** and design of experimental (DoE) methods. The real-life problem was then addressed using the suitable parameters derived from each approach.

The algorithm was executed for the problem under consideration with objective weights $w_1=0.5$ (representing the weight of the cycle time objective function) and $w_2=0.5$ (for the weight of the squared load assignment objective function). The algorithm was run 31 times with objective weights set at $w_1=0.0$ ($w_2=1.0$) to obtain the nadir value associated with the cycle time objective. Similarly, the algorithm was initiated 31 times with objective weights configured at $w_1=1.0$ ($w_2=0.0$) to pinpoint the nadir value for the squared load assignment objective function.

Given the diverse magnitudes present among the objective values, it is essential to normalise these values by dividing the corresponding objective function by its nadir value [52]. When scaled using the weighted sum method, the fitness function is normalised as outlined in Eq. (17). In this equation, $N_i$ denotes the nadir point of the $i$th objective function ($i = 1,2$).

$$Min\ WSM^{Norm}(x) = \left[w_1 \times \frac{CT}{N_1}\right] + \left[w_2 \times \frac{\sum_{s \in S}\sum_{j \in J}\left(\sum_{i \in I}\left((P_{ij} \times X_{sij}) + R_s\right)^2\right)}{N_2}\right] \tag{17}$$

Additionally, the obtained results were executed using the determined parameters for the genetic algorithm used in the study of Mutlu et al. [9] and the obtained results were compared with the obtained results of the **irace** and DoE methods. For the **irace** method, the parameter ranges used for each genetic operator (population size, crossover rate, and mutation rate) are presented in Table 4.

Table 4. Ranges of the parameters for the proposed MOGA and the best parameter configuration obtained with the **irace** method.

| Factors | Parameter Values | Selected Parameter ($w_1$=0.5 ; $w_2$=0.5) |
|---|---|---|
| Population Size | U ~ [20 ; 200] | 35 |
| Crossover Rate | U ~ [0.7 ; 1] | 0.87 |
| Mutation Rate | U ~ [0.05 ; 0.4] | 0.06 |

The stopping criterion for the algorithm has been considered based on the maximum fitness value ($UD_{Max}$). This value is obtained by multiplying the number of tasks by a fixed number. As seen the convergence graph given in Fig. 8, this constant number is determined to be 10,000 after various trials.

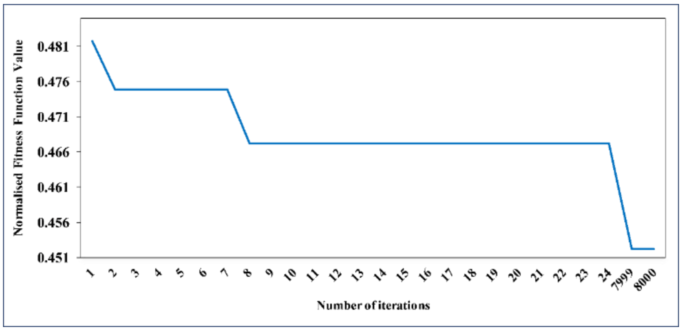



Fig. 8. Convergence graph for the normalized objective function values.

A design of experimental was implemented to determine the appropriate parameter values for genetic operators. Accordingly, the levels associated with the considered operators are given in Table 5.

Table 5. Factors and levels of factors.

| | Levels | | |
|---|---|---|---|
| Factors | Level 1 | Level 2 | Level 3 |
| Population Size | 20 | 60 | 100 |
| Crossover Rate | 0.70 | 0.85 | 1.00 |
| Mutation Rate | 0.05 | 0.10 | 0.40 |

The proposed MOGA, with a stopping condition and tournament size similar to those considered in the **irace** method, was analysed using Minitab 21.0 software for each determined factor level. In the DoE, due to 27 different combinations and each experiment being run 31 times, a total of $27 \times 31 = 837$ experiments were conducted.

Accordingly, an analysis of variance (ANOVA) was carried out to determine the critical parameters and their interactions. In the variance analysis, the main effect is a value that indicates the degree of a factor's impact on the result. The main effects plot is used to examine the difference between the level averages of the factors [53]. According to the analysis results shown in Fig. 9, the *p*-values related to population size, crossover rate, and mutation rate are below 0.05 with a 95% confidence interval. Hence, these factors have been selected as critical factors in minimising the average normalised results.

**Analysis of Variance**

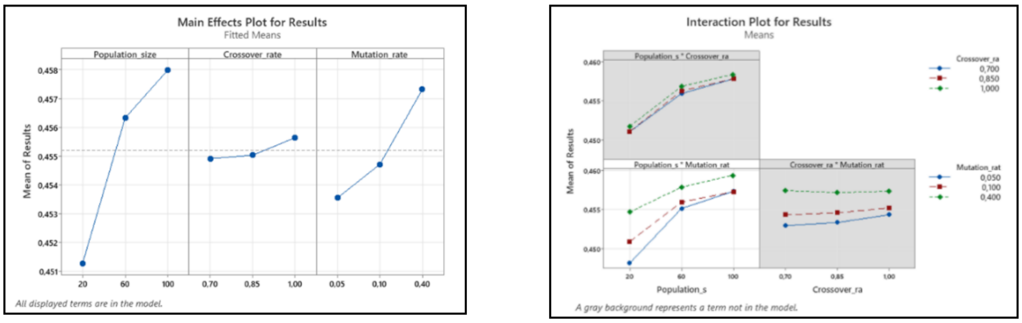
| Source | DF | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|
| Model | 10 | 0,000307 | 0,000031 | 111,86 | 0,000 |
| Linear | 6 | 0,000289 | 0,000048 | 175,71 | 0,000 |
| Population_size | 2 | 0,000220 | 0,000110 | 400,72 | 0,000 |
| Crossover_rate | 2 | 0,000003 | 0,000001 | 5,01 | 0,020 |
| Mutation_rate | 2 | 0,000067 | 0,000033 | 121,40 | 0,000 |
| 2-Way Interactions | 4 | 0,000018 | 0,000004 | 16,08 | 0,000 |
| Population_size*Mutation_rate | 4 | 0,000018 | 0,000004 | 16,08 | 0,000 |
| Error | 16 | 0,000004 | 0,000000 | | |
| Total | 26 | 0,000311 | | | |

**Model Summary**

| S | R-sq | R-sq(adj) | R-sq(pred) |
|---|---|---|---|
| 0,0005239 | 98,59% | 97,71% | 95,98% |

Fig. 9. The ANOVA result based on coded values.

Upon examining the main effect graph, the levels of the critical factors are determined. The number of experiments conducted is reflected in Figs. 10(a) and 10(b), where both the main effects and the interaction plots are displayed.




a) Main effects plot

b) Interaction plot

Fig. 10. The main effects and interaction plots for the proposed MOGA parameters.

According to the results obtained, the best values for the critical factors of population size, crossover rate, and mutation rate have been determined as 20 (Level 1), 0.7 (Level 1), and 0.05 (Level 1), respectively.

## *2.6. Comparative analysis*

In this subsection, for $w_1=0.5$ and $w_2=0.5$ objective weights, the results obtained from the appropriate parameters via the DoE are compared with the results obtained from the appropriate parameter values via the **irace** method, and the results obtained using the appropriate parameters suggested by Mutlu et al. [9]. The results obtained are displayed in a box plot in Fig. 11.

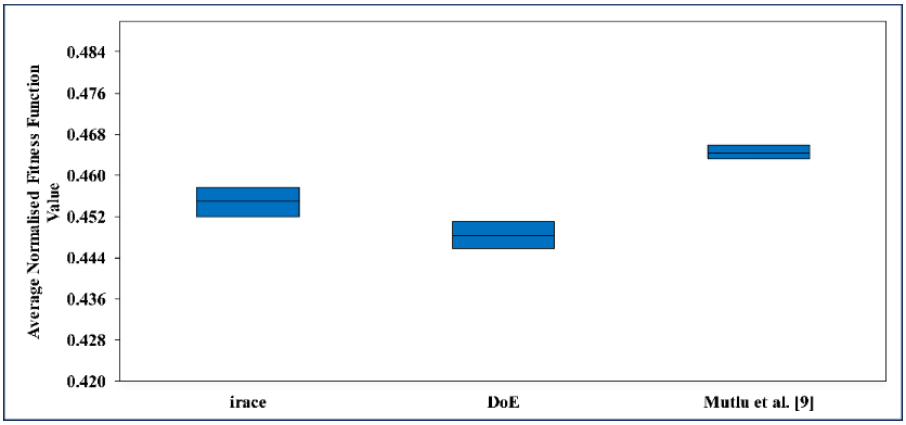



Fig. 11. Box plots of average normalised fitness values obtained from 31 runs of the MOGA with weighted-sum scalarisation for three different parameter determination methods.

The box plot shows that the average normalised fitness values obtained through the DoE have yielded better results than others. The results obtained with the **irace** method are more successful than the results achieved with the parameters proposed by Mutlu et al. [9].

## 3. Conclusions

Taking into account the task times specific to workers and the walking times of workers, the cycle time was intended to be optimised along with aiming for a balanced distribution of tasks assigned to workstations. For our proposed multi-objective genetic algorithm, the parameter selection and calibration were carried out using the full factorial experimental design and the **irace** method, one of the automatic parameter determination methods, considering the objective weights of $w_1=0.5$ and $w_2=0.5$. The real-life problem was resolved using the suggested MOGA approach with the identified suitable parameters. The worker assignments, task allocations, and station times for the best result among the 31 repetitions are presented in Table 6.

Table 6. Comparison of results of the proposed MOGA using appropriate parameters obtained from three different ways with the current situation of the cable industry.

| WS No | Parameter Method | Worker No | Assigned Jobs | | | | | | | | | WS Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **WS 1** | DoE | Worker-7 | 30 | 4 | 33 | 11 | 13 | 34 | 1 | 37 | | 159.0 |
| | Mutlu et al. [9] | Worker-6 | 13 | 4 | 7 | 8 | 30 | 33 | 35 | 38 | | 174.3 |
| | **irace** | Worker-3 | 38 | 11 | 4 | 7 | 37 | | | | | 147.3 |
| | CS | Worker-1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 30 | | 175.3 |
| **WS 2** | DoE | Worker-6 | 38 | 42 | 43 | 44 | 45 | 35 | 5 | | | 177.2 |
| | Mutlu et al. [9] | Worker-7 | 42 | 43 | 11 | 34 | 1 | 37 | | | | 178.1 |
| | **irace** | Worker-7 | 8 | 42 | 1 | 30 | 33 | 34 | 31 | 13 | | 178.5 |
| | CS | Worker-2 | 8 | 9 | 10 | 31 | 33 | 35 | 37 | | | 163.5 |
| **WS 3** | DoE | Worker-5 | 12 | 14 | 22 | 23 | 24 | 47 | | | | 174.4 |
| | Mutlu et al. [9] | Worker-8 | 39 | 22 | 23 | 24 | 40 | | | | | 175.7 |
| | **irace** | Worker-6 | 32 | 35 | 36 | 22 | 27 | 28 | | | | 173.6 |
| | CS | Worker-3 | 11 | 12 | 13 | 14 | 15 | 16 | 18 | 19 | 22 | 176.0 |
| **WS 4** | DoE | Worker-4 | 25 | 7 | 8 | 46 | 2 | 3 | 15 | | | 178.8 |
| | Mutlu et al. [9] | Worker-3 | 41 | 25 | 44 | | | | | | | 139.2 |
| | **irace** | Worker-4 | 29 | 23 | 24 | 25 | 9 | 43 | | | | 179.0 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | CS | Worker-4 | 17 | 20 | 23 | | | | | | 169.9 |
| **WS 5** | DoE | Worker-2 | 31 | 18 | 26 | 27 | 28 | 29 | 16 | 19 | 150.6 |
| | Mutlu et al. [9] | Worker-2 | 45 | 47 | 46 | 26 | 48 | 2 | 31 | 5 | 175.6 |
| | **irace** | Worker-5 | 44 | 45 | 47 | 46 | 10 | 12 | | | 154.7 |
| | CS | Worker-5 | 21 | 24 | 27 | 25 | | | | | 182.2 |
| **WS 6** | DoE | Worker-3 | 21 | 39 | 40 | 41 | | | | | 177.3 |
| | Mutlu et al. [9] | Worker-5 | 32 | 36 | 6 | 27 | 28 | 29 | 12 | | 178.3 |
| | **irace** | Worker-2 | 14 | 15 | 18 | 19 | 21 | 26 | 5 | 16 | 170.3 |
| | CS | Worker-6 | 2 | 34 | 28 | 29 | 38 | 36 | | | 177.6 |
| **WS 7** | DoE | Worker-1 | 17 | 20 | 9 | 48 | | | | | 162.1 |
| | Mutlu et al. [9] | Worker-4 | 14 | 15 | 16 | 19 | 21 | 18 | 17 | 9 | 174.4 |
| | **irace** | Worker-8 | 17 | 6 | 20 | 2 | | | | | 170.2 |
| | CS | Worker-7 | 26 | 39 | 42 | 43 | | | | | 182.9 |
| **WS 8** | DoE | Worker-8 | 6 | 10 | 32 | 36 | | | | | 135.8 |
| | Mutlu et al. [9] | Worker-1 | 3 | 10 | 20 | | | | | | 140.5 |
| | **irace** | Worker-1 | 3 | 39 | 40 | 41 | 48 | | | | 156.4 |
| | CS | Worker-8 | 40 | 41 | 44 | 45 | 45 | 47 | 48 | | 174.7 |

**Abbreviation(s):**
**CS:** Current Situation, **WS:** Workstation

The objective values obtained based on the parameter determination methods used in Table 7 and the current situation are provided. Accordingly, the cycle time obtained from the parameters of Mutlu et al. [9] preforms better than others. However, the squared load assignment obtained from the parameters of the DoE provides better performance than others.

Table 7. Comparison of the results of the proposed MOGA run using parameter values obtained in three different ways with the current situation in the cable industry.

| Parameters | Cycle Time | Squared Load Assignment |
|---|---|---|
| DoE | 178.8 | 217899.34 |
| Mutlu et al. [9] | 178.3 | 225129.09 |
| **irace** | 179.0 | 222100.68 |
| Current Situation | 182.9 | 245959.40 |

In this study, the effect of parameterisation methods on the results when run with different objective weights is analysed. The sensitivity analysis, as depicted in Fig. 12, indicates that the experimental design method for parameter determination with objective weights of $w_1=0.7$ and $w_2=0.3$ yields better results for all objective weights. However, it exhibits poorer performance when compared with the parameters proposed by Mutlu et al. [9]. Additionally, results obtained using the **irace** method for $w_1=0.7$ and $w_2=0.3$ objective weights have proven to be better. These findings show that the experimental design generally yields better outcomes across various objective weights when compared to other methods.

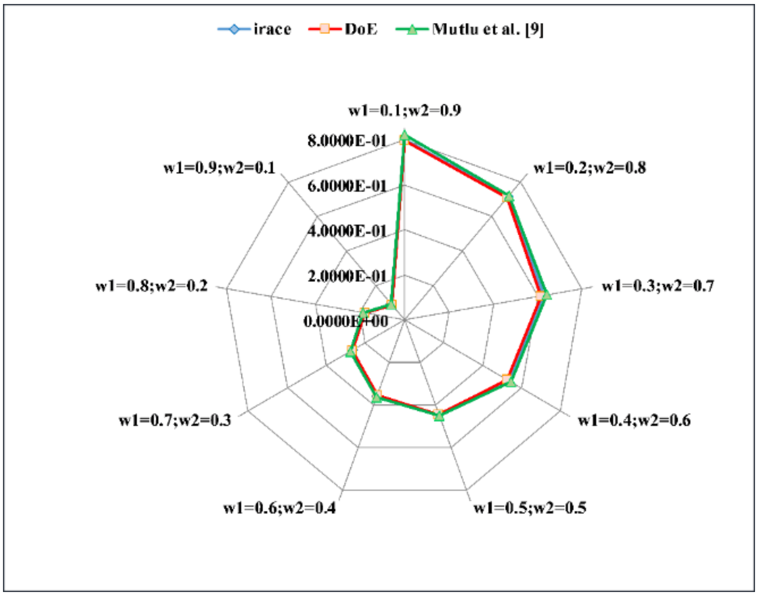



Fig. 12. Sensitivity analysis for the different objective weights.

While performing assembly line balancing, it should not be ignored that the characteristics and performances of the workers are different. It is accepted that each worker has different capabilities for the same task, and it is decided that worker assignments should also be made while performing line balancing.

This study considers the multi-objective assembly line worker assignment and balancing problem (ALWAB). The algorithm aims to minimise both the cycle time and the squared load assignment, striving for a balanced distribution of jobs assigned to the workstation. This is achieved by considering the predecence diagrams between jobs, the times of jobs for each worker, and the walking times of the workers. The proposed multi-objective algorithm is applied to a real-life problem in an automotive sub-industry that manufactures wiring harnesses. The product to be assembled in the plant belongs to the roof wiring harness of a vehicle, which consists of 48 jobs and 8 workers are assigned to this process. Since the problem is multi-objective and NP-hard, a multi-objective genetic algorithm (MOGA) approach is proposed to solve the problem. Since the parameter values used in the algorithm directly affect the result, it is of great importance to use appropriate values. A full factorial experimental design and the **irace** method, one of the automatic parameter determination methods, were proposed for the parameter calibration of the proposed MOGA. With the appropriate parameters found as a result of these two methods, the proposed MOGA was run for objective weights $w_1=0.5$ and $w_2=0.5$. In addition, the algorithm was also run with the parameters used in the study of Mutlu et al. [9], and the results obtained were compared. It was found that the full factorial experimental design performed better than the others. In addition, the performance of the parameterisation methods with different objective weights was tested by sensitivity analysis. According to the results, it was observed that the experimental design generally performed better than the others at different objective weights.

In future directions, the proposed algorithm can be solved by taking into account that not every worker is capable of every job. The performance of the proposed algorithm can be tested with benchmark problems in the literature, and the results can be compared. The problem can be extended by adding different objective functions. Also, ergonomic risk factors can be added to the ALWAB Type-2 problem. A decision support system with a user-friendly interface that can be used by the employees of the organisation can be designed.

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## Ethical Approval

This study was carried out as part of the master thesis [ID: 780444] prepared by Gözde KURADA under the supervision of Assoc. Prof. Dr. Derya DELİKTAŞ.

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