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An integration of multi-objective goal programming and linear assignment models based on grey relational analysis for the collaborative robot assignment problem in Human-Robot Collaboration (HRC): An application of industry 5.0

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Abstract

This research presents a novel two-step assignment method for forming cobot workstations to facilitate collaboration between humans and cobots, in alignment with the Industry 5.0 concept. The method is based on Grey Relational Analysis (GRA) to address limitations in existing cobot task allocation approaches, which typically focus on single-objective optimization. The first step involves a lexicographic goal programming model with dual objectives, optimizing cobot-job and job-cobot assignments. These objectives aim to maximize the mean of the total grey relational grade for both assignments, resulting in optimal cobot-job pairings. In the second step, the integrated GRA assignment model determines the appropriate worker for each cobot set. An illustrative example and comparative analysis demonstrate the advantages of the proposed method over traditional approaches.

Keywords: Cobots, Collaborative robots, Cobot assignment problem, Lexicographic goal programming model, Grey relational analysis

1. Introduction

Regarding the Industrial Revolution after mass production in the centralization era, Industry 4.0 focused on integrating industrial robots into high-volume production processes in order to improve efficiency by addressing the limitations of manual labor, such as inconsistency and fatigue, within tight deadlines and across varying product types [1-3]. Moving into Industry 5.0, a human-centered approach has emerged, introducing collaborative robots, or "cobots," which are designed to safely and efficiently interact with humans in shared workspaces [4, 5]. In contrast to traditional industrial robots, which typically function in isolation and are less adaptable to small-scale and complex tasks, cobots enable seamless human-robot collaboration, combining human creativity with robotic precision to enhance productivity and execute intricate operations [5-8]. In recent years, the global cobot market has experienced significant growth, increasing from $819.6 million in 2020 to $1.117 billion in 2023, marking a 36.27% growth since 2018. Furthermore, projections indicate that the cobot end-effector market will reach $2.655 billion by 2030 [9]. This rapid expansion highlights the pivotal role of cobots in optimizing resource utilization and meeting the evolving requirements of modern, flexible production systems, particularly in industries such as automotive manufacturing, where dynamic and efficient workflows are critical.

In terms of utilizing cobots in production, the interaction between humans and cobots is a major concern. In addition to evaluating production outcomes, such as work efficiency and productivity, it is also crucial to consider the capability of the cobot, particularly when selecting the most suitable type of cobot. A wide array of cobots is available in the manufacturing industry, each of which has unique performance capabilities, functionalities, tools, material properties and component availability, and operational limitations. As highlighted by El Zaatari et al. [10], the effectiveness of cobot integration depends heavily on selecting the right cobot that matches the specific tasks at hand, considering factors such as precision, flexibility, and compatibility with existing systems. Furthermore, Human-Robot Collaboration (HRC) [11-13] entails close interaction between cobots and humans, meaning the workers tasked with controlling and working alongside these cobots must possess the necessary availability and skills related to cobots to perform their assigned tasks accurately and safely.

Planning for HRC is often accompanied by various problems. One of the most common issues is the assignment of tasks to either operators or cobots considering various criteria and limitations. This challenge is known as task allocation. A widely recognized solution to address this problem is the traditional use of mathematical programming models, commonly in terms of assignment models [14]. Conventionally, assignment models have been applied to assign workers to specific jobs, focusing on a single aspect such as performance, cost, time, or productivity. Moreover, production planners who are unaware of the skills and availability of the workers usually resort to the commonly used First-Come First-Served (FCFS) concept [15] for convenience, which might accidentally assign a non-skilled worker to a cobot workstation. However, several popular methods have been presented in various studies. These include metaheuristics, such as Genetic Algorithms (GA) [13, 16-20], and mathematical programming models, such as Mixed-Integer Linear Programming (MILP) [21, 22] and Constraint Programming (CP) [23-25]. Logic-based methods have also been proposed for the

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operational planning of Human-Robot Collaboration (HRC) assembly lines [2]. Thus, it is crucial to consider both the suitability of the cobot for the task and the appropriateness of the worker for the cobot workstation.

The methodologies, objective functions, and resources considered for Human-Robot Collaboration (HRC) planning are summarized in Table 1. The table outlines perspectives employed in the reviewed research, providing a concise overview of the criteria utilized in HRC planning.

Table 1 Summary of research papers concerning planning for human-robot collaboration

Authors	**Method**			**Objective Function**			**Focused resources**			**Number of perspectives considered**		
	M_1	M_2	M_3	O_1	O_2	O_3	R_1	R_2	R_3	1-3	4-10	>10
Takata and Hirano [26]			✓	✓			✓	✓			✓	
Chen et al. [27]		✓			✓				✓		✓	
Malvankar-Mehta and Mehta [28]		✓			✓		✓				✓	
Tsarouchi et al. [29]			✓		✓		✓	✓			✓	
Faber et al. [30]			✓	✓					✓	✓		
Ranz et al. [31]			✓	✓					✓	✓		
Tsarouchi et al. [32]			✓	✓					✓	✓		
Blankemeyer et al. [33]			✓		✓			✓				✓
Gombolay et al. [21]		✓		✓					✓	✓		
Bilberg and Malik [34]			✓	✓				✓		✓		
Dalle Mura and Dini [19]	✓				✓			✓		✓		
Dalle Mura and Dini [20]	✓				✓			✓		✓		
Ijtsma et al. [35]			✓	✓					✓	✓		
Malik and Bilberg [36]			✓	✓					✓	✓		
Bänziger et al. [17]	✓			✓				✓		✓		
Bettoni et al. [37]			✓		✓			✓			✓	
Liau and Ryu [13]	✓				✓				✓	✓		
Mokhtarzadeh et al. [23]		✓		✓					✓	✓		
Raatz et al. [18]	✓			✓					✓		✓	
Evangelou et al. [38]			✓		✓			✓			✓	
Kinast et al. [39]	✓			✓					✓		✓	
Lee et al. [40]			✓	✓					✓	✓		
Liau and Ryu [16]	✓				✓				✓	✓		
Messeri et al. [41]			✓	✓					✓	✓		
Pabolu et al. [42]			✓	✓			✓		✓		✓	
Stecke and Mokhtarzadeh [24]		✓			✓		✓	✓		✓		
Sun et al. [43]			✓	✓			✓	✓		✓		
Zhang et al. [44]			✓	✓			✓	✓		✓		
Dauzère-Pérès et al. [45]	✓			✓				✓			✓	
Faccio et al. [46]		✓			✓				✓		✓	
Mao et al. [22]		✓		✓			✓		✓	✓		
Guo [25]		✓		✓					✓	✓		
Wang et al. [47]			✓	✓			✓	✓		✓		
Proposed method		✓			✓	✓	✓	✓	✓			✓

Notes: M_1 = Metaheuristics, M_2 = Mathematical programming model, M_3 = Logic-based, Algorithm based, Planning process, Decision-Making based Method, O_1 = Single objective function, O_2 = Multiple objective function, O_3 = Lexicographic multiple objective function, R_1 = Collaborative robot, R_2 = Worker, R_3 = Job

Table 1 highlights significant gaps in current cobot task allocation methods, revealing a lack of systematic, multi-objective frameworks that can simultaneously optimize cobot-job-worker assignments. Traditional methods typically focus on single objectives, such as selecting the most suitable robot for a task or matching workers to jobs. However, these approaches often neglect critical factors such as cobot limitations and worker performance, which are essential for effective human-robot collaboration. A gap in the existing literature is the absence of an integrated approach that considers the complexity of real-world manufacturing environments, where multiple criteria must be balanced to optimize overall performance.

In response to this gap, this study is motivated to propose a more comprehensive method for task allocation in human-robot collaboration. The aim is to enhance efficiency and optimize resource allocation by integrating a multi-criteria decision-making (MCDM) framework. This study introduces a two-step assignment method that combines the Grey Relational Analysis (GRA) with two mathematical models, including the GRA-based Lexicographic Goal Programming (*GRA-LGP*) model and the GRA-based Linear Assignment (*GRA-LA*) model. The primary motivation is to develop a method that not only addresses the complexity of cobot assignments but also ensures that the interactions between cobots, jobs, and workers are optimized for maximum productivity and efficiency.

The contribution of this research lies in its introduction of a novel, integrated approach to cobot assignment, which considers multiple criteria and addresses the challenges of modern manufacturing systems. The proposed method optimizes both cobot-job assignments and worker-cobot allocations, taking into account the non-uniform capabilities of workers and their ability to collaborate effectively with cobots. It also factors in the non-homogeneous limitations of cobots across different workstations. By balancing task suitability, worker expertise, and cobot capabilities, the proposed method improves operational and worker efficiency, providing a robust tool that enhances human-robot collaboration. This approach aligns with the principles of Industry 5.0, advancing cobot performance and overall productivity in smart manufacturing environments.

The subsequent sections of this paper are outlined as follows: Section 2 gives the details of the proposed methodology. In Section 3, an illustrative example and results are provided to demonstrate the effectiveness of the proposed method. Discussions concerning the relationship between all related elements in the cobot workstation, and multiple criteria consideration in the cobot assignment problem are presented in Section 4. Finally, Section 5 presents the conclusion, summarizing the key findings and offering concluding remarks.

2. Materials and methods

Recent studies have highlighted the importance of using Multi-Criteria Decision-Making (MCDM) techniques to manage complex, multi-dimensional criteria across various applications [48, 49]. This study proposes a two-step approach. The first step employs GRA-based Lexicographic Goal Programming (*GRA-LGP*) for cobot-job matching, while the second step applies GRA-based Linear Assignment (*GRA-LA*) for worker allocation. By integrating GRA, LGP, and LA, the method prioritizes cobot-job pairings and optimizes worker allocation to cobot workstations. This dual approach enhances cobot utilization, improves task performance, and increases worker efficiency.

This study introduces a two-step methodology to optimize cobot assignment, ensuring that tasks align with the cobot's capabilities, thus improving efficiency and safety. Unlike single-step approaches that may overlook essential criteria, this method avoids the risk of assigning unsuitable tasks to cobots, which can lead to inefficiencies and safety concerns. The two-step process streamlines decision-making by first evaluating cobots' functional capabilities and job requirements, and then assigning suitable workers based on their skills. This systematic approach enhances productivity and ensures more effective human-robot collaboration by addressing both the cobot-job fit and worker compatibility with cobot workstations. The details of the proposed method are as follows.

2.1 Conceptual framework

The introduction of this paper highlights the significance of considering the aspects of cobots, jobs, and workers when addressing cobot assignment problems. Certain jobs may exceed the capabilities of specific cobots, while certain cobots may require specific job qualifications. The skills and availability of workers in cobot functions and job requirements should also be taken into account. Therefore, a comprehensive approach is imperative. To overcome these challenges, this paper suggests an MCDM approach for resolving assignment issues in HRC.

This paper introduces a two-step cobot assignment method. Firstly, cobots and jobs are grouped based on their respective aspects. Secondly, workers are assigned to collaborate at cobot-job workstations. The decision-making process follows these steps:

- *Determining the appropriate cobot type for a specific job (cobot-job assignment)*
- *Selecting the most suitable job for a cobot (job-cobot assignment)*
- *Assigning the most suitable worker to a cobot-job set (worker-cobot workstation assignment)*

By identifying these aspects, the proposed method aims to enhance assignment efficiency and optimize collaboration between cobots, jobs, and workers. The illustrative framework of the proposed method framework is demonstrated in Figure 1.

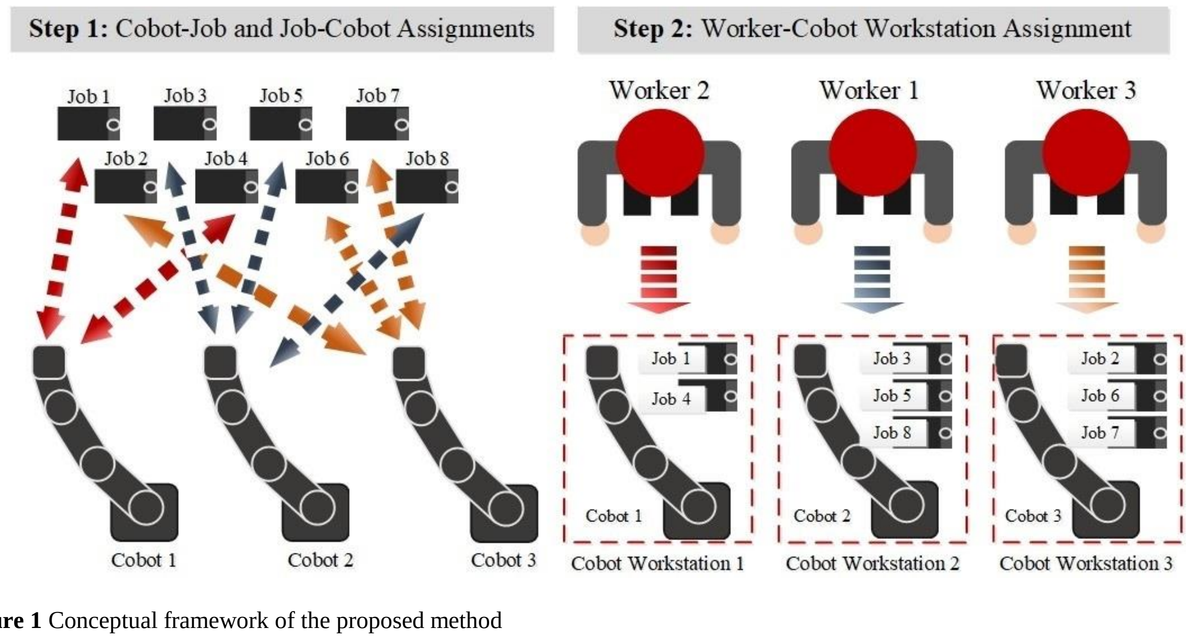

Figure 1 Conceptual framework of the proposed method

As depicted in Figure 1, the initial step is the determination of a suitable cobot type for the specific job and the identification of a job appropriate for the cobot. For instance, Cobot 1 is assigned to jobs 1 and 4, indicating it has a superior performance score for these tasks. Cobot 2 is assigned to jobs 3, 5, and 8, while Cobot 3 is assigned to jobs 6 and 7. Following the first assignments, the next step involves assigning workers to the cobot workstations established in the previous step. Worker 1 collaborates with Cobot 2 and jobs 3, 5, and 8, emphasizing his or her compatibility with this workstation. In the same way, Worker 2 is assigned to Cobot 1 for jobs 1 and 4, while Worker 3 is allocated to Cobot 3 for jobs 6 and 7.

2.2 Criteria

The criteria used to evaluate each perspective are crucial as they guide decision-making by providing the necessary data to select the most appropriate alternative. In this research, once data aligned with these criteria are gathered and analyzed, it informs subsequent assignment phases. Therefore, the chosen criteria directly impact work allocation to maximize efficiency across all perspectives. Effective assignments from these viewpoints require comprehensive criteria that encompass all production aspects. Criteria differ across perspectives, focusing on cobot allocation to specific jobs, job suitability for cobots, and worker assignment to cobot-job sets or cobot workstations. The criteria used in GRA will be described in the following subsection. The details of the criteria are provided in Table 2.

The criteria outlined in Table 2, derived from key research studies and performance metrics for collaborative robots, emphasize critical factors that influence their operational effectiveness. Key Performance Indicators (KPIs) such as cycle time, utilization, efficiency, and wait time are essential for assessing the success of human-robot collaboration [50]. Specifically, assembly time and task switch times are pivotal metrics that can directly impact the efficiency of task execution [27, 46]. Furthermore, motion planning plays a crucial role in optimizing robot operations. As highlighted by Shen and Reinhart [51], effective motion planning allows robots to adaptively select assembly poses, improving task feasibility, reducing scrap, and enhancing operational efficiency. Additionally, research by Unhelkar et al. [48] introduces algorithmic approaches to human-robot interaction (HRI), which support adaptive behavior and facilitate smoother task transitions. By minimizing task switch times, these algorithms further improve system responsiveness and performance. Together, these factors are vital for the successful implementation of collaborative robots in dynamic environments, where flexibility and operational efficiency are essential.

Table 2 Criteria and type of analysis

Criteria | Type of analysis	References
a) Cobot-job assignment	
C_1: Efficiency (%) | benefit	Raatz et al. [18]; Takata and Hirano [26]; Faber et al. [30]; Ranz et al. [31]; Blankemeyer et al. [33]; Bilberg and Malik [34]; Pabolu et al. [42]; Gombolay et al. [52]; Gualtieri et al. [53]; Zanella et al. [54]
C_2: Performance (%) | benefit	Simões et al. [11]; Takata and Hirano [26]; Malvankar-Mehta and Mehta [28]; Pabolu et al. [42]; Faccio et al. [46]; Drexl and Kimms [55]
C_3: Defect (%) | non-benefit	Chen et al. [27]; Bettoni et al. [37]; Robotiq [50]
C_4: Utilization (%) | benefit	Michalos et al. [2]; Raatz et al. [18]; Chen et al. [27]; Tsarouchi et al. [32]; Evangelou et al. [38]; Robotiq [50]
b) Job-cobot assignment	
C_5: Cobot motion (cm) | non-benefit	Robotiq [50]; Shen and Reinhart [51]; Chen et al. [56]
C_6: Tool changing (times) | non-benefit	Raatz et al. [18]; Blankemeyer et al. [33]; Lee et al. [40]; Robotiq [50]
C_7: Continuous production per setup (lots) | benefit	Chen et al. [27]; Robotiq [50]
C_8: Job switch time (min) | non-benefit	Chen et al. [27]; Robotiq [50]; Drexl and Kimms [55]
c) Worker-cobot workstation assignment	
C_9: Availability (scores) | benefit	Tsarouchi et al. [29]; Kinast et al. [39]; Ritt et al. [57]
C_{10}: Skill (scores) | benefit	Simões et al. [11]; Raatz et al. [18]; Dalle Mura and Dini [19]; Dalle Mura and Dini [20]; Ranz et al. [31]; Blankemeyer et al. [33]; Bilberg and Malik [34]; Pabolu et al. [42]; Zhang et al. [44]; Oliff et al. [58]
C_{11}: Additional training required (hr) | non-benefit	Simões et al. [11]; Chen et al. [27]; Robotiq [50]

Furthermore, it is essential to emphasize the consideration of worker skills when assigning workers to cobot workstations [59, 60]. Workers are expected to have availability, knowledge, and skills relevant to their jobs, including training in robot operations [31]. As mentioned previously, the criteria can influence each other. For instance, insufficient worker training time with robots can negatively impact utilization. Conversely, skilled workers can enhance utilization and improve overall cobot performance. Therefore, considering the interrelation and influence of these criteria is significant.

2.3 Grey relational analysis

In the early 1980s, Professor Deng Ju-long developed the Grey Relational Analysis (GRA) as an integral component of the Grey System Theory [61]. GRA is known for its quantitative and sequence analysis capabilities [62] and is used to analyze partially known or unknown information [63]. It evaluates each alternative based on multiple criteria, comparing numerical raw data with target values, making it a valuable tool for decision-makers. GRA is commonly used in scientific studies as a scoring or classification method to select top-ranked alternatives from a set of choices.

GRA has been widely applied to provide valuable insights. For instance, Cenglin [64] used GRA to help car sellers identify factors that can boost customer satisfaction and increase sales volume. Furthermore, GRA has been utilized in building venture capital investment models and assessing the relationship between company attributes and financial performance [65, 66]. Additionally, GRA has found utility in supplier selection decisions [67-70]. Descriptions of the variables of GRA are shown in Table 3.

Table 3 Descriptions of the variables of the GRA method

Variable	Descriptions
x_{ij}	Raw data for alternative *i* criteria *j*
x_{0j}	The target sequence for criteria *j*
x_{ij}^*	Comparison sequence for alternative *i* criteria *j*
Δ_{ij}	Deviation sequence for alternative *i* criteria *j*
ξ_{ij}	The grey relational coefficient for alternative *i* criteria *j*
ξ	Distinguishing coefficient
w_j	Priority weight for criteria *j*
γ_i	The grey relational grade for alternative *i*

The procedure of the GRA method is described as follows:

2.3.1 Grey Relational Generating (GRA)

In the initial step, the raw data are transformed into a standard scale of [0-1], known as the comparison sequence. The comparison sequence is then analyzed according to the objectives of each criterion, which are classified as "*benefit* (*B*)" or "*non-benefit* (*NB*)" types. Equations (1) and (2) can be employed to determine the comparison sequence for the *benefit* and *non-benefit* analyses, respectively.

$$x_{ij}^* = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}, \tag{1}$$

$$x_{ij}^* = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}}. \tag{2}$$

2.3.2 Deviation sequence

The deviation sequence quantifies the extent of deviation between the comparison sequence acquired during the grey relational generation step and the target sequence. The calculated deviation sequence is shown below:

$$\Delta_{ij} = \left| x_{0j} - x_{ij}^* \right| \tag{3}$$

2.3.3 Grey Relational Coefficient (GRC)

When the raw data correspond exactly to the types of analyses, the Grey Relational Coefficient (GRC) is 1. The distinguishing coefficient has a range of [0, 1], and it is commonly set to 0.5 [71]. The calculation of the GRC can be done using the following equations:

$$\xi_{ij} = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_{ij} + \xi \Delta_{\max}}, \tag{4}$$

where,

$$\Delta_{\min} = \min\{\Delta_{ij} | \forall i, \forall j\}, \tag{5}$$

$$\Delta_{\max} = \max\{\Delta_{ij} | \forall i, \forall j\}. \tag{6}$$

2.3.4 Grey Relational Grade (GRG)

In this step, a priority weight is assigned to each criterion to rank each alternative. These weights are utilized to compute the total sum of the GRC and the priority weight for each criterion. This calculation results in a Grey Relational Grade (GRG) for each alternative. The GRG can be computed using Equation (7):

$$\gamma_i = \sum_{j=1}^{J} (\xi_{ij} \times w_j)\,. \tag{7}$$

The proposed method incorporates multiple aspects simultaneously using GRA. The GRG obtained from GRA will be utilized in Step 1 to assign cobots to jobs, and in Step 2 to assign workers to sets of cobot-job workstations.

2.4 GRA-based lexicographic goal programming model for cobot-job and job-cobot assignments (step 1)

Referring to Figure 1, this paper presents the lexicographic goal programming model [72-75] as a solution to cobot assignment problems incorporating two goals in Step 1. The primary goal is to assign cobots to jobs, while the secondary goal is to match jobs for cobots. The proposed method prioritizes achieving the first goal before addressing the second goal. In the assignment process, the GRG value obtained from the GRA is utilized. The relevant variables of the proposed model are outlined in Table 4.

Table 4 Relevant variables of a lexicographic goal programming model

Index sets:	
r	Index of cobots, $r = 1,2,3,\dots,R$
h	Index of jobs, $h = 1,2,3,\dots,H$
t	Index for goals, $t = 1,2,3,\dots,T$
Decision variables:	
x_{rh}	is 1 if a cobot r is assigned to a job h; otherwise, it is 0.
ρ_t	is an overachievement from the target of the goal t or positive deviation.
η_t	is an underachievement from the target of the goal t or negative deviation.
η_t^*	is the optimized negative deviation of the goal t.
Related Parameters:	
γ_{rh}^{RJ}	is a grey relational grade from ranking a cobot r for a job h.
γ_{rh}^{JR}	is a grey relational grade from ranking a job h for a cobot r.
τ_t	is the target of the goal t.
u	is the maximum number of jobs allowed for the cobot r.

2.4.1 Objective functions

The first objective function is maximizing the overall mean of the total GRG for assigning cobot *r* to job *h*:

$$\max Z_1(x_{rh}) = \frac{1}{R}\sum_{r=1}^{R}\left(\frac{\sum_{h=1}^{H}\gamma_{rh}^{RJ}x_{rh}}{\sum_{h=1}^{H}x_{rh}}\right). \tag{8}$$

The second objective function is maximizing the overall mean of the total GRG for selecting job h for cobot *r*:

$$\max Z_2(x_{rh}) = \frac{1}{H}\sum_{r=1}^{R}\sum_{h=1}^{H}\gamma_{rh}^{JR}x_{rh}\ . \tag{9}$$

2.4.2 Goals

Based on the objective functions in Equation (8) and Equation (9), the formulated goals can be expressed as illustrated below:

$$Z_1(x_{rh}) + \eta_1 = \tau_1, \tag{10}$$

$$Z_2(x_{rh}) + \eta_2 = \tau_2. \tag{11}$$

Equations (10) and (11) represent the goals for the first and second objectives, respectively. Since the targets of the goal will be set to 1 in both objective functions, which corresponds to the highest probable GRG, the positive deviations are eliminated. When the mean of the GRG (or objective value) cannot exceed 1, it is unnecessary to consider the positive deviation from the goal value of 1.

2.4.3 Lexicographic goal programming model

The proposed GRA-based Lexicographic Goal Programming (*GRA-LGP*) model is formulated based on the defined goals and constraints, as follows:

To achieve the maximum target value, this study minimizes the negative deviations for two objectives using lexicographic optimization, as detailed in Equation (12).

$$\text{lex min} = [\eta_1, \eta_2]. \tag{12}$$

To successfully attain both goals, establishing goal functions is crucial. These functions are derived from Equations (8) through (11), and are detailed in Equations (13) and (14), respectively.

$$\frac{1}{R}\sum_{r=1}^{R}\left(\frac{\sum_{h=1}^{H}\gamma_{rh}^{RJ}x_{rh}}{\sum_{h=1}^{H}x_{rh}}\right) + \eta_1 = \tau_1\ , \tag{13}$$

$$\frac{1}{H}\sum_{r=1}^{R}\sum_{h=1}^{H}\gamma_{rh}^{JR}x_{rh} + \eta_2 = \tau_2\ , \tag{14}$$

The constraints for cobot and job assignments comprise two conditions. The first condition, specified in Equation (15), ensures each job is assigned to only one cobot. The second condition, outlined in Equation (16), ensures that no cobot exceeds the maximum number of jobs, denoted as "u"

$$\sum_{r=1}^{R} x_{rh} = 1,\ \forall h, \tag{15}$$

$$\sum_{h=1}^{H} x_{rh} \leq u,\ \forall r, \tag{16}$$

The following constraint guarantees that, based on the optimization of the lower priority objective, the negative deviation of the higher priority objective will not deteriorate compared to the optimized value achieved when optimizing the first goal.

$$\eta_1 \leq \eta_1^*, \text{ for } t = 1, \ldots, T-1, \tag{17}$$

Given that the proposed model comprises only two goals, this restriction can be reorganized, as demonstrated in Equation (18).

$$\eta_1 \leq \eta_1^*, \tag{18}$$

The decision variables are defined as binary, taking on values of either 0 or 1, as presented in Equation (19).

$$x_{rh} \in \{0, 1\}, \forall r \text{ and } \forall h, \tag{19}$$

The last constraint guarantees that the negative deviations for both goals are limited to non-negative values, articulated in Equation (20).

$$\eta_1, \eta_2 \geq 0. \tag{20}$$

2.5 GRA-based linear assignment model for worker-cobot workstation assignment (Step 2)

After determining the assignments of cobots to jobs and jobs to cobots using the proposed *GRA-LGP* model in Step 1, Step 2 simultaneously employs the linear assignment model and GRA to assign workers to cobot workstations. Here, the GRG value is analyzed based on data for each criterion related to worker-cobot workstation assignments. The corresponding notations are listed in Table 5.

Table 5 Pertinent variables of the assignment model

Index sets:	
g	Index of workers, $g = 1,2,3,\ldots,G$
ω	Index of cobot workstation, $\omega = 1,2,3,\ldots,\Omega$. A cobot workstation ω consists of a cobot r and a list of jobs that x_{rh}= 1 (obtained from Step 1), for all *h*.
Decision variables:	
$x_{g\omega}$	is 1 if the worker g is assigned to a cobot workstation ω; otherwise, it is 0.
Related Parameters:	
$\gamma_{g\omega}$	is grey relational grade from ranking workers g in cobot workstation ω.

The GRA-based Linear Assignment (*GRA-LA*) model is formulated as follows:

The objective function is to maximize the average GRG of the total when assigning worker g to a cobot workstation ω, which encompasses cobot r and its associated jobs. This is expressed in Equation (21).

$$\max Z_3(x_{g\omega}) = \frac{1}{G}\sum_{\omega=1}^{\Omega}\sum_{g=1}^{G} x_{g\omega}\gamma_{g\omega}. \tag{21}$$

There are two requirements for the allocation of workers to cobot workstations. The first ensures that each cobot workstation is assigned to only one worker. Meanwhile, the subsequent condition is that each worker is assigned exclusively to one cobot workstation. These conditions are presented in Equations (22) and (23), respectively.

$$\sum_{g=1}^{G} x_{g\omega} = 1,\ \forall \omega, \tag{22}$$

$$\sum_{\omega=1}^{\Omega} x_{g\omega} = 1,\ \forall g. \tag{23}$$

The ultimate constraint establishes the decision variables as either 0 or 1, as illustrated in Equation (24).

$$x_{g\omega} \in \{0, 1\}, \forall g \text{ and } \forall \omega. \quad (24)$$

The proposed *GRA-LGP* and *GRA-LA* models utilize GRG values obtained from the GRA method as coefficients. Figure 2 illustrates the procedure of the proposed two-step assignment method for cobot assignment problems.

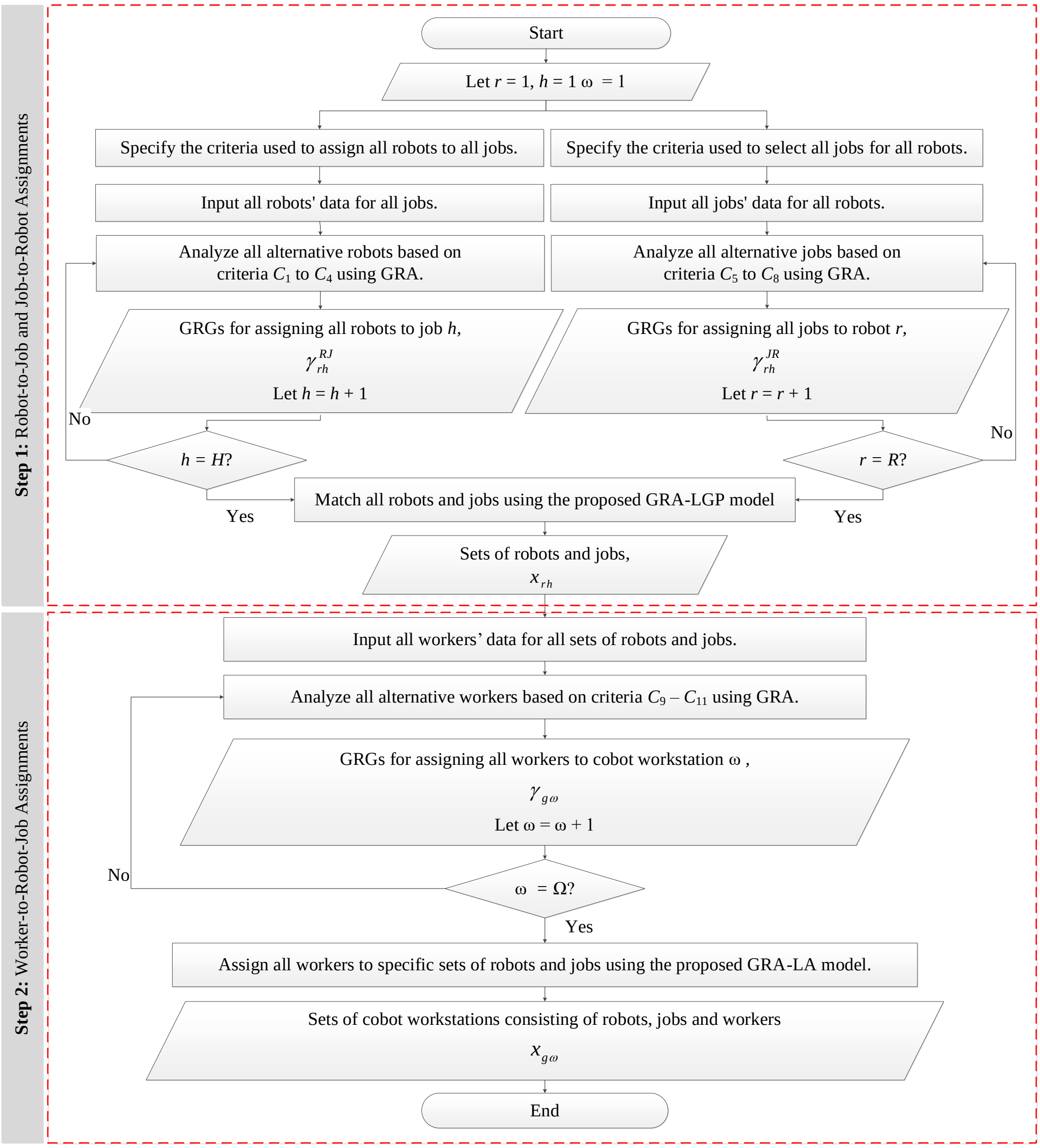

Figure 2 Procedure for the proposed two-step assignment method

3. Results

To demonstrate the effectiveness of the proposed two-step assignment method, a practical cobot assignment application in the article proposed by Kimaporn and Nunkaew [76] was studied and adapted as a cobot production line consisting of three cobots and three workers responsible for handling ten jobs, as depicted in Figure 3.

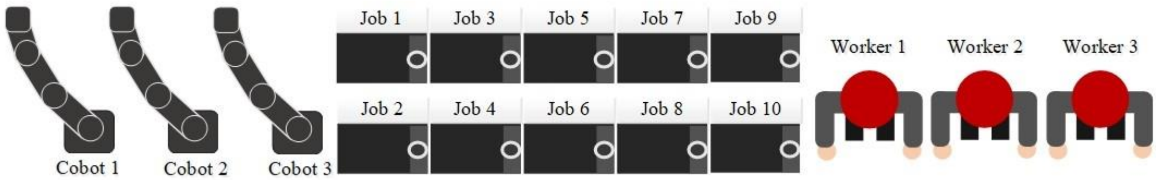

Figure 3 An example cobot production line

Additionally, the relevant data for evaluating cobots, jobs, and workers according to the established criteria are collected from industry experts with over 10 years of experience in robotics and production management, ensuring the reliability and relevance of the assessments. These experts, including production line managers, experienced workers, and individuals with expertise in robotics, play a crucial role in assessing each perspective. The data for subjective criteria were gathered to evaluate cobot-job-worker assignments in the next phase. Specifically, Table 6 presents data for criteria C_1 to C_4, evaluating the suitability of cobots for specific jobs, while Table 7 displays data for criteria C_5 to C_8, used for assessing the compatibility of jobs with cobots. After applying GRA to these data, the GRG values are calculated and integrated into the proposed *GRA-LGP* model in Step 1. The cobot-job sets are formed, with a limit of four jobs per set (u = 4). Subsequently, the suitability of workers for each cobot-job set is evaluated using GRA based on criteria C_9 to C_{11}, as shown in Table 8. The resulting GRGs are incorporated into the *GRA-LA* model in Step 2. The priority weights for criteria C_1 to C_8 and C_9 to C_{11} are assumed to be 0.25 and 0.33, respectively, ensuring a balanced approach to the assignment process.

The formulated models for solving this example by the proposed method are as follows:

3.1 Cobot-job and job-cobot assignments using the proposed GRA-LGP model (initial step)

$$\text{lex min} = [\eta_1, \eta_2]. \tag{25}$$

Subject to:

$$\frac{1}{3}\sum_{r=1}^{3}\left(\frac{\sum_{h=1}^{10}\gamma_{rh}^{RJ}x_{rh}}{\sum_{h=1}^{10}x_{rh}}\right)+\eta_1=1, \tag{26}$$

$$\frac{1}{10}\sum_{r=1}^{3}\sum_{h=1}^{10}\gamma_{rh}^{JR}x_{rh}+\eta_2=1, \tag{27}$$

$$\sum_{h=1}^{10}x_{rh}\le 4,\ \text{for } r=1,\ 2,\ \text{and } 3, \tag{28}$$

with Equation (15) and constraints (17) to (20).

Table 6 Data for criteria C_1 to C_4 (cobot-job assignment)

Job	Cobot	**C_1: Efficiency**			**C_2: Performance**				**C_3: Defect**			**C_4: Utilization**		
		Cobot Motion Times	**Available Time**	**Efficiency**	**Average Cycle Time**	**Total Units Produced**	**Total Running Time**	**Performance**	**Number of Defects**	**Total Units Produced**	**Defect**	**Total Running Time**	**Available Time**	**Utilization**
		min	**min**	**%**	**min**	**units**	**min**	**%**	**units**	**units**	**%**	**min**	**min**	**%**
	1	282	420	0.6714	4.20	75	416	0.7572	5	75	0.0667	416	420	0.9905
1	2	262	420	0.6238	4.20	80	398	0.8442	10	80	0.1250	398	420	0.9476
	3	260	420	0.6190	4.20	90	416	0.9087	6	90	0.0667	416	420	0.9905
	1	284	420	0.6762	2.10	152	402	0.7940	18	152	0.1184	402	420	0.9571
2	2	288	420	0.6857	2.10	149	401	0.7803	20	149	0.1342	401	420	0.9548
	3	314	420	0.7476	2.10	168	400	0.8820	13	168	0.0774	400	420	0.9524
	1	300	420	0.7143	1.40	257	400	0.8995	21	257	0.0817	400	420	0.9524
3	2	275	420	0.6548	1.40	236	401	0.8239	24	236	0.1017	401	420	0.9548
	3	282	420	0.6714	1.40	258	402	0.8985	32	258	0.1240	402	420	0.9571
	1	300	420	0.7143	4.67	50	413	0.5650	5	50	0.1000	413	420	0.9833
4	2	283	420	0.6738	4.67	59	411	0.6699	7	59	0.1186	411	420	0.9786
	3	300	420	0.7143	4.67	82	413	0.9266	12	82	0.1463	413	420	0.9833
	1	319	420	0.7595	1.50	244	410	0.8927	18	244	0.0738	410	420	0.9762
5	2	274	420	0.6524	1.50	224	412	0.8155	25	224	0.1116	412	420	0.9810
	3	319	420	0.7595	1.50	239	411	0.8723	21	239	0.0879	411	420	0.9786
	1	308	420	0.7333	2.47	127	383	0.8192	12	127	0.0945	383	420	0.9119
6	2	303	420	0.7214	2.47	147	400	0.9079	12	147	0.0816	400	420	0.9524
	3	289	420	0.6881	2.47	116	401	0.7147	19	116	0.1638	401	420	0.9548
	1	304	420	0.7238	5.25	46	415	0.5819	7	46	0.1522	415	420	0.9881
7	2	311	420	0.7405	5.25	64	413	0.8136	8	64	0.1250	413	420	0.9833
	3	296	420	0.7048	5.25	42	414	0.5326	10	42	0.2381	414	420	0.9857
	1	302	420	0.7190	21.00	10	388	0.5412	5	10	0.5000	388	420	0.9238
8	2	304	420	0.7238	21.00	14	418	0.7033	2	14	0.1429	418	420	0.9952
	3	307	420	0.7310	21.00	10	419	0.5012	2	10	0.2000	419	420	0.9976
	1	281	420	0.6690	5.60	41	405	0.5669	5	41	0.1220	405	420	0.9643
9	2	289	420	0.6881	5.60	58	418	0.7770	7	58	0.1207	418	420	0.9952
	3	317	420	0.7548	5.60	57	406	0.7862	10	57	0.1754	406	420	0.9667
	1	308	420	0.7333	1.35	241	418	0.7811	13	241	0.0539	418	420	0.9952
10	2	298	420	0.7095	1.35	234	382	0.8299	19	234	0.0812	382	420	0.9095
	3	308	420	0.7333	1.35	260	418	0.8427	24	260	0.0923	418	420	0.9952

Table 7 Data for criteria C_5 to C_8 (job-cobot assignment)

Job	Cobot 1				Cobot 2				Cobot 3			
	C_5: Cobot motion	C_6: Tool changing	C_7: Continuous production per setup	C_8: Setup time	C_5: Cobot motion	C_6: Tool changing	C_7: Continuous production per setup	C_8: Setup time	C_5: Cobot motion	C_6: Tool changing	C_7: Continuous production per setup	C_8: Setup time
	cm	times	lots	min	cm	times	lots	min	cm	times	lots	min
1	97	3	2.1	32	97	3	0.9	49	45	9	3.9	21
2	43	8	0.2	32	98	9	1.3	41	48	5	3.6	37
3	58	3	1.5	34	70	5	2.8	40	118	3	4.5	23
4	96	3	1.9	35	91	7	1.8	39	46	2	3.6	36
5	98	1	0.7	18	55	4	1.9	32	54	8	3.8	20
6	47	10	2.0	34	56	4	1.1	28	112	8	4.4	53
7	56	5	0.8	33	73	8	1.3	49	58	4	3.7	35
8	41	4	2.1	36	58	10	1.0	37	85	2	4.9	28
9	52	4	1.8	48	100	7	0.8	42	106	4	0.0	53
10	46	5	0.1	37	99	6	1.7	34	84	9	4.0	34

Table 8 Data for criteria C_9 to C_{11} (worker-cobot workstation assignment)

Set of Cobot and Jobs	Worker 1			Worker 2			Worker 3		
	C_9: Availability	C_{10}: Skill	C_{11}: Additional Training required	C_9: Availability	C_{10}: Skill	C_{11}: Additional Training required	C_9: Availability	C_{10}: Skill	C_{11}: Additional Training required
	score	score	hr	score	score	hr	score	score	hr
1	8	10	0	7	10	4	9	9	0
2	7	7	16	8	6	40	8	9	0
3	5	8	8	10	8	8	5	5	56

3.2 Worker-cobot workstation assignment by the proposed GRA-LA model (final step)

$$\max Z_3(x_{g\omega}) = \frac{1}{3}\sum_{\omega=1}^{3}\sum_{g=1}^{3} x_{g\omega}\gamma_{g\omega}, \tag{29}$$

with Equation (22), Equation (23), and constraint (24).

The results of solving this example using the proposed method are summarized in Table 9. Three cobot workstations are formed: Cobot 1 is assigned to Worker 1 to handle Jobs 3, 5, and 10, while Cobot 2 is assigned to Worker 3 for Jobs 6, 7, 8, and 9, and Cobot 3 is assigned to Worker 2 to deal with Jobs 1, 2, and 4. The optimal objective values for cobot-job, job-cobot, and worker-cobot workstation assignments are 0.8405, 0.6562, and 0.8872, respectively. These values indicate that the alternatives with high GRG scores based on the considered criteria have been selected. Furthermore, finding solutions using the proposed models can be achieved easily using general optimization software, such as Excel Solver, as observed in this example.

3.3 Comparison between the proposed method and traditional methods

To validate and demonstrate the effectiveness of the proposed two-step assignment method, other traditional methods were selected and compared in this section. The first method is First-Come First-Served (FCFS), which assigns employees to cobots based on their skills in working with cobots. Jobs are then transferred to a set of workers and cobots in the order of jobs from 1 to 10, resulting in a cobot workstation consisting of workers, cobots, and jobs. The second method is a conventional assignment method that focuses on assigning employees to cobots based on the employee's availability for each cobot. Jobs are assigned to sets of employees and cobots based on their performance in previous jobs. The results obtained from comparing the two methods with the proposed method are shown in Table 10.

From the comparison results in Table 10, it was revealed that the solution obtained from the proposed method outperformed the two other compared methods. The proposed method provided better results in 9 out of 11 criteria (C_1 to C_8, and C_{11}) compared to both the FCFS and conventional assignment methods. However, the proposed method achieved the same results as the two methods in the remaining two criteria (C_9, and C_{10}). The conventional assignment method obtained a value of 9.00 for criterion C_9 (Availability), whereas the FCFS method achieved a value of 8.76 for criterion C_{10} (Skill).

The enhanced performance of the proposed method is attributed to its multi-criteria optimization framework, unlike the single-criterion approaches of the traditional methods. The normalization of the average overall normalized value of the proposed method reached 1.0000, significantly surpassing the conventional method's value of 0.3244. These results underscore the effectiveness of the proposed *GRA-LGP* and *GRA-LA* models in optimizing cobot assignments across multiple criteria.

Table 9 Summary of the results of solving this example by the proposed two-step assignment method

Step	Assignment	Item	Cobot 1	Cobot 2	Cobot 3
Step 1: GRA-LGP Model	Cobot-job Assignment	Job	Job 1 Job 3 Job 4 Job 5	Job 6 Job 7 Job 8 Job 9	Job 2 Job 10
		Negative Deviation	Goal 1: 0.1595		Goal 2: 0.4174
		Grey Relational Grade	Z_1^*: 0.8405		Z_2: 0.5826
	Job-cobot Assignment	Job	Job 3 Job 5 Job 10	Job 6 Job 7 Job 8 Job 9	Job 1 Job 2 Job 4
		Negative Deviation	Goal 1: 0.1595		Goal 2: 0.3438
		Grey Relational Grade	Z_1: 0.8405		Z_2^*: 0.6562
Step 2: GRA-LA Model	Worker-Cobot Workstation Assignment	Worker	Worker 1	Worker 3	Worker 2
		Job	Job 3 Job 5 Job 10	Job 6 Job 7 Job 8 Job 9	Job 1 Job 2 Job 4
		Grey Relational Grade		Z_3^*: 0.8872	

Note: Z_1^*, Z_2^*, and Z_3^* are the optimized values of objectives 1, 2, and 3, respectively.

Table 10 Comparison of results obtained from the FCFS method, conventional assignment method, and the proposed method

Cobot assignment		FCFS method			Conventional assignment method			Proposed method		
	Cobot	Cobot 1	Cobot 2	Cobot 3	Cobot 1	Cobot 2	Cobot 3	Cobot 1	Cobot 2	Cobot 3
	Worker	Worker 2	Worker 3	Worker 1	Worker 3	Worker 1	Worker 2	Worker 1	Worker 3	Worker 2
	Job	Job 1 Job 2 Job 3 Job 4	Job 5 Job 6 Job 7 Job 8	Job 9 Job 10	Job 2 Job 3 Job 5	Job 6 Job 7 Job 8	Job 1 Job 4 Job 9 Job 10	Job 3 Job 5 Job 10	Job 6 Job 7 Job 8 Job 9	Job 1 Job 2 Job 4
Cobot-job assignment (C-J)	**C_1: Efficiency**	0.6714 0.6762 0.7143 0.7143	0.6524 0.7214 0.7405 0.7238	0.7548 0.7333	0.6762 0.7143 0.7595	0.7214 0.7405 0.7238	0.6190 0.7143 0.7548 0.7333	0.7143 0.7595 0.7333	0.7214 0.7405 0.7238 0.6881	0.6190 0.7476 0.7143
			0.7102[a] | 0.0000[b]			0.7157 | 0.9200			**0.7162** | 1.0000	
	C_2: Performance	0.7572 0.7940 0.8995 0.5650	0.8155 0.9079 0.8136 0.7033	0.7862 0.8427	0.7940 0.8995 0.8927	0.9079 0.8136 0.7033	0.9087 0.9266 0.7862 0.8427	0.8995 0.8927 0.7811	0.9079 0.8136 0.7033 0.7770	0.9087 0.8820 0.9266
			0.7885 | 0.0000			0.8475 | 0.9717			**0.8492** | 1.0000	
	C_3: Defect	0.0667 0.1184 0.0817 0.1000	0.1116 0.0816 0.1250 0.1429	0.1754 0.0923	0.1184 0.0817 0.0738	0.0816 0.1250 0.1429	0.0667 0.1463 0.1754 0.0923	0.0817 0.0738 0.0539	0.0816 0.1250 0.1429 0.1207	0.0667 0.0774 0.1463
			0.1096 | 0.0634			0.1104 | 0.0000			**0.0970** | 1.0000	
	C_4: Utilization	0.9905 0.9571 0.9524 0.9833	0.9810 0.9524 0.9833 0.9952	0.9667 0.9952	0.9571 0.9524 0.9762	0.9524 0.9833 0.9952	0.9905 0.9833 0.9667 0.9952	0.9524 0.9762 0.9952	0.9524 0.9833 0.9952 0.9952	0.9905 0.9524 0.9833
			0.9757 | 0.2000			0.9752 | 0.0000			**0.9776** | 1.0000	
Job-cobot assignment (J-C)	**C_5: Cobot motion**	97 43 58 96	55 56 73 58	106 84	43 58 98	56 73 58	45 46 106 84	58 98 46	56 73 58 100	45 48 46
			72.60 | 0.0000			66.70 | 0.6020			**62.80** | 1.0000	
	C_6: Tool Changing	3 8 3 3	4 4 8 10	4 9	8 3 1	4 8 10	9 2 4 9	3 1 5	4 8 10 7	9 5 2
			5.60 | 0.5000			5.80 | 0.0000			**5.40** | 1.0000	
	C_7: Continuous production per setup	2.10 0.20 1.50 1.90	1.90 1.10 1.30 1.00	0.00 4.00	0.20 1.50 0.70	1.10 1.30 1.00	3.90 3.60 0.00 4.00	1.50 0.70 0.10	1.10 1.30 1.00 0.80	3.90 3.60 3.60
			1.50 | 0.0000			1.73 | 0.8846			**1.76** | 1.0000	
	C_8: Setup time	32 32 34 35	32 28 49 37	53 34	32 34 18	28 49 37	21 36 53 34	34 18 37	28 49 37 42	21 37 36
			36.60 | 0.0000			34.20 | 0.8889			**33.90** | 1.0000	
Worker-cobot workstation assignment (W-C)	**C_9: Availability**	7	8	5	9	7	10	8	8	10
			6.67 | 0.0000			**8.67** | 1.0000			**8.67** | 1.0000	
	C_{10}: Skill	10	9	8	9	7	8	10	9	8
			9.00 | 1.0000			8.00 | 0.0000			**9.00** | 1.0000	
	C_{11}: Additional training required	4	0	8	0	16	8	0	0	8
			4.00 | 0.7500			8.00 | 0.0000			**2.67** | 1.0000	
Average overall normalized value (the normalization of the average overall normalized value)			0.2285 (0.0000)			0.4788 (0.3244)			1.0000 (1.0000)	

Note: Bold represents the best value, [a] is obtained values, and [b] is normalized values.

A comparison of the decision variables between the proposed method and Mixed-Integer Linear Programming (MILP) demonstrates a significant reduction in complexity achieved by the proposed two-step approach, as shown in Table 11.

Table 11 Comparison of the number of variables in each method

Method		Mixed-Integer Linear Programming	Proposed Method	
			GRA-LGP	***GRA-LP***
Variable		x_{rhg}	x_{rh}	$x_{g\omega}$
Nature of variable		Binary	Binary	Binary
Variable count		$r \times h \times g$	$r \times h$	$g \times \omega$
Constraint	**(13)**	-	1	-
	(14)	-	1	-
	(15)	h	h	-
	(16)	r	r	-
	(17)	-	t	-
	(18)	-	1	-
	(19)	$r \times h \times g$	$r \times h$	-
	(20)	-	t	-
	(21)	1	-	1
	(22)	-	-	ω
	(23)	g	-	g
	(24)	-	-	$g \times \omega$
Sum		$2(r \times h \times g) + h + r + g + 1$	$2(r \times h) + h + r + t + 3(1)$	$2(g \times \omega) + g + \omega + 1$
Total number of variables for the case study		197	78	25

The performance of the proposed method demonstrates significant improvements in computational efficiency and solution quality compared to contemporary approaches such as Mixed-Integer Linear Programming (MILP). Table 11 illustrates that the MILP model requires 197 decision variables, which escalate rapidly as the number of cobots, jobs, and workers increases. This growth in variables leads to higher computational complexity and extended processing times. In contrast, the proposed two-step method reduces the total number of decision variables to 103, with 78 variables in step one and 25 in step two. This reduction simplifies the problem structure, enabling faster computations and more precise optimization tailored to specific objectives.

The reduction in decision variables provides critical advantages. Methods with excessive variables often result in complex computational and greater difficulty in achieving convergence within acceptable timeframes. In complex, dynamic manufacturing systems, such computational inefficiencies hinder real-time adaptability and practical implementation. The proposed method mitigates these challenges by focusing on specific problem dimensions and allowing separate prioritization of multiple objectives without requiring a unified optimization function. This streamlined approach enhances both the efficiency and clarity of the decision-making process.

4. Discussion

Concerning the study and the comparative results of the proposed method to the FCFS and the conventional assignment methods, we can underline two crucial keystones as follows:

a. The core elements of the cobot assignment problem in HRC that should be considered simultaneously are jobs, cobots, and workers. The proposed methodology then gathers these important issues manifested in terms of three relationships: cobots and jobs, jobs and cobots, and workers and cobot workstations (related to cobots and jobs). More precisely, the relationship between cobots and employment should be considered first to match the requirements of the job and the functions of the cobot. After that, workers are paired with those two elements.

b. Considering multiple criteria in solving the cobot assignment problem, as mentioned in this paper, reinforces the capability of the assignment solutions. Focusing only on a single selected criterion and ignoring other important criteria failed to achieve optimal overall results as solved by the FCFS and the conventional assignment methods. In addition, other research on the cobot assignment problem typically focused on only one aspect. For example, Malik and Bilberg [36] allocated work by considering employees' skills, while Ranz et al. [31] focused on evaluating the capabilities of workers and collaborative robots. Moreover, studies by Bettoni et al. [37] and Faccio et al. [46] emphasized the allocation of work to optimally distribute available resources. However, achieving effective production requires comprehensive consideration of a wide range of criteria to solve cobot assignment problems in HRC, as in the main conceptual idea of this paper. Therefore, this highlights the efficiency and suitability of the proposed two-step assignment method with multi-criteria consideration in solving cobot assignment problems.

5. Conclusions

To enhance the efficiency of simultaneous assignments for cobots, jobs, and workers in HRC, this paper developed a novel two-step assignment method. The proposed method integrates GRA, an MCDM approach, productively enabling decision-makers to concurrently assess alternatives across multiple criteria.

In the first step, the proposed multi-objective *GRA-LGP* model generates solutions for cobot-job and job-cobot assignments based on the GRG values analyzed from criteria C_1 to C_8. This step results in the formation of sets consisting of a specific cobot and its corresponding jobs as the cobot workstations. The multi-objective model assists decision-makers in proactively assigning the most suitable cobot to each job and matching the appropriate jobs for a given cobot. In the final step, workers are assigned to the most appropriate cobot workstation obtained in the previous step using the formulated *GRA-LA* model and the GRG values that are evaluated based on criteria C_9 to C_{11}. Through this step, complete cobot workstations are fully formed.

As illustrated in the example as well as the comparative study with the FCFS and the conventional assignment methods, the cobot workstation problem can be solved efficiently using the proposed systematic method. This approach is an easy but efficient tool for engineers and production planners to solve multiple-resources assignment problems concerning cobots, jobs, and workers for HRC in Industry 5.0.

In addition to its efficiency in resource allocation, the proposed assignment method contributes significantly to sustainability goals in manufacturing by fostering sustainable industrialization and optimizing resource utilization. The method supports *Industry, Innovation, and Infrastructure (SDG 9)* by driving innovation in manufacturing processes and developing resilient systems capable of adapting to evolving demands. Additionally, it aligns with *Responsible Consumption and Production (SDG 12)* by minimizing waste and enhancing resource efficiency. Through optimized task allocation between cobots and workers, the method not only boosts production efficiency but also reduces energy consumption and material waste, thereby supporting sustainable manufacturing practices.

This study incorporates certain limitations and assumptions that may affect its application in large-scale and complex manufacturing environments. The proposed model assumes constant task durations and uniform worker skills, which simplifies calculations but overlooks real-world factors such as worker fatigue, variable skill levels, and cobot downtime. Similarly, the task durations for cobots are treated as average values, disregarding potential disruptions such as technical failures or maintenance requirements. Furthermore, using Microsoft Excel for computation imposes constraints, making it unsuitable for large-scale applications, particularly when handling problems with more than 200 variables. While aiding initial model development, these simplifications limit its adaptability to dynamic and unpredictable manufacturing systems. Future research should address these limitations by incorporating dynamic factors such as real-time task adjustments, advanced computational tools, and additional criteria such as ergonomics, safety, and cost considerations. These enhancements would improve the robustness of the model and expand its utility in modern, flexible manufacturing environments.

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