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Multi-Role Collaborative Behavior in the Construction Industry through Training Strategies

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Abstract: From a stakeholder perspective, the personal growth of industrial personnel is important for the promotion of the sustainable development of the construction industry. As an important part of knowledge management, training is a common way to improve the personal knowledge and skills of construction practitioners. Group role assignment with a training plan is thought to optimize group performance and the assignment of personnel with collaborative behaviors. However, existing mathematical models or approaches have mainly considered the loss of downtime caused by training while ignoring the different costs of training programs and personal capabilities, which affect the overall benefits. Hence, to solve the training-related role assignment problem, the intention of this study is to formulate a new model that integrates comprehensive training costs with various personal capabilities. After training, all roles need to be reassigned to maximize the overall benefit. Four experiments were conducted. The results show that training strategies can increase the total benefit, but also weaken it when the training costs are too high. Training strategies have a cumulative effect, i.e., training performance is positively related to the knowledge and skill levels of construction practitioners. Finally, training performance varies with the industrial role.

Keywords: sustainable development; collaborative behavior; group role assignment; GRATP; training cost

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Citation: Yan, X.; Yang, R.; Chong H.-Y.; Feng, M. Multi-Role Collaborative Behavior in the Construction Industry through Training Strategies. *Buildings* **2023**, *13*, 482. https://doi.org/10.3390/buildings13020482

Academic Editors: Tao Wang, Hanliang Fu and Zezhou Wu

Received: 30 November 2022
Revised: 30 January 2023
Accepted: 8 February 2023
Published: 10 February 2023

1. Introduction

The completion of a construction project requires the collaboration of multiple practitioners, such as decision makers, surveyors, program designers, construction workers, acceptance personnel, and maintenance operators. The professional competence of each practitioner has an impact on the quality of a project, as well as on the sustainable development of individual practitioners, i.e., on the improvement of practitioners' professional skills and knowledge [1]. As an important part of knowledge management, training is an important path toward enhancing the sustainable development of construction practitioners. Moreover, training can improve teams' benefits [2–4] and decision making [5,6]. In order to better promote the sustainable development of individuals, this paper focuses on the impact of training strategies on multi-role collaboration among construction practitioners.

In the existing research on collaboration, role-based collaboration (RBC) has been introduced as a new problem-solving paradigm that uses the E-CARGO model to facilitate modeling [7–11]. RBC includes three main tasks: role negotiation, role assignment, and role implementation [12]. Role assignment is an important component of RBC research, and it is accomplished by assigning personnel to roles according to their qualification values [13,14]. The qualification values represent the performance of personnel in their corresponding roles [15,16]. In order to obtain the optimal role assignment scheme, group role assignment (GRA) has been proposed [17]. The ultimate goal of GRA is to maximize the total performance or benefit of a team. The total performance is defined as the sum of the qualification values of all personnel, and the total benefit is defined as the cumulative group performance of the final team [18,19]. The definition of this total performance is positively related to the overall ability of a group, i.e., the total performance can reflect the quality of different role assignment plans in order to find the optimal role assignment plan for the group. Choosing different optimization indicators according to different problems can lead to the effective solution of practical collaboration problems. The cost of training has received little attention, despite the fact that starting times, durations, and training plans have all been studied [20]. Among the various practical problems, training cost is also an important factor that affects the total benefit of a team [21–23]. For different training projects, the training costs are generally different [24–26]. Therefore, it is necessary to consider the training cost when formulating training plans to solve collaboration problems.

Considering the influence of the training cost, this paper studies the problem of GRA with a training plan (GRATP) and with a training cost (GRATPC) in the construction industry. An algorithm for obtaining the optimal training plan is proposed according to this problem. Here, the training cost refers to the cost that a company needs to pay to training institutions for different training programs. In this article, the cost of each training project is measured in days. For different projects, the cost of training and the effects of capacity improvement are different. According to the RBC and E-CARGO models, this problem can be abstracted as an optimization problem. The cost of training varies according to the role. This paper comprehensively considers the influences of the training cost and the final improvement in the abilities of personnel on the team's total benefit, and the optimal training duration and training scheme are found to maximize the team's total benefit. The initial role assignment before training is determined by the personnel's ability to play a role. After training, the abilities of the personnel are differently improved because different personnel have different training projects. At this time, the initial training plan may not be optimal, so roles are reassigned after training to achieve the goal of maximizing the team's benefits. Finally, the effectiveness of the algorithm is verified with experiments.

The rest of this paper is organized as follows. Section 2 presents papers with related work. Section 3 describes the specific definitions for constructing the relevant E-CARGO models. Section 4 describes the experiments that were conducted and analyzes the experimental results. Finally, the conclusions and directions for further research are given in Section 5.

2. Related Work

2.1. Sustainable Development of the Individual

Contemporary buildings are created and managed through the use of large amounts of energy and materials, and the construction process has a negative impact on human health and the natural environment [27]. Sustainability in the construction industry is often understood to mean that the construction activity itself should meet the requirements of sustainable development [28]. Specifically, the construction materials, program selection, construction technology, and construction waste disposal involved in construction activities during the entire life cycle should meet the requirements of protecting the environment and reducing energy consumption to achieve sustainable development [29]. Shurrab et al. [30] identified seven green building factors from data collected from 120 respondents and showed through their findings that the adoption of green building factors by construction companies can improve sustainability performance. Carlo et al. [31] argued that life cycle assessments (LCAs) of the energy efficiency and environmental performance of buildings are essential for addressing sustainability issues.

In addition to this, sustainable development in the construction industry also has another layer of meaning, namely, the continuous and stable development of the industry itself. In an open economy, the sustainable development of employees is considered essential in order to help achieve sustainable corporate growth, which includes employee quality, employee competencies, etc. [32]. Loosemore and Malouf [33] demonstrated that employee training can improve the overall quality and competence of construction companies and address the shortage of workers in the Australian construction industry. Demirkesen and Arditi [34] believed that formal, well-organized, and effective safety training is effective in reducing the frequency and severity of safety incidents. With the advent of the Industry 4.0 era, the construction industry is transforming toward informationization, digitalization, and intelligence [35], and new technologies and techniques are being applied more and more, making construction more and more difficult [36]. Therefore, it is necessary to ensure the sustainable development of the construction industry by providing continuous training for practitioners according to the requirements of projects.

2.2. RBC Theory and the GRATP Model

Collaboration and training come with certain losses, which are related to financial knowledge, and RBC and E-CARGO models can be used as emerging methods for studying such problems. For example, Zhu [37] put forward a new requirement for adapting the RBC model to the creation of sustainable groups; they explained the problem of an agent training plan for a sustainable group for the first time and proposed an efficient algorithm. Setting matching threshold values for each position and deciding whether to train an agent for that position based on that value will allow for future progress.

Huang et al. [38] discussed the last-mile assignment problem (LMAP) for fresh agricultural products. To formalize the problem, they used the group role allocation framework. In addition, they proposed a role awareness method by using adaptive clustering based on task granularity to solve the problem.

Liu et al. [39] proposed a method associated with the method of "one clause at a time", which is related to the factors that decision makers consider when making decisions. The method was proposed to solve the problem of group role allocation and balance.

Zhang et al. [40] suggested task assignment when using a human and robot in an intuitive fuzzy environment, which broadened the scope of the GRA theory and its specific applications.

Zhang et al. [41] formalized the high-order set assignment problem (HOTP) by using group role assignment (GRA), and they proposed a role negotiation method by using the hierarchical clustering and analytic hierarchy process (AHP) algorithms based on GRA.

The aforementioned studies demonstrated the significance of RBC in various role assignment problems. In particular, the GRATP model aims to solve a GRA problem with a training plan. Table 1 shows the development of GRATP. Zhang et al. [2] first studied how training can affect character competence. They studied the group role assignment problem according to redundant agents to avoid a situation in which no one would replace an agent after the agent left. Guo et al. [3] proposed the GRATP problem for the first time. They investigated the GRATP problem and introduced the training start time into the training plan. Zhang et al. [20] considered the correlations between roles, and they proposed a GRATP (RCCS-GRATP) algorithm based on role correlation and the current state to solve the adaptive GRATP (RCA_GRATP) problem based on role correlation.

Table 1. The development of the GRATP.

Paper Name	Innovation
Group role assignment with a training Plan [2]	GRA + training program (Redundant agent)
Adaptive collaboration with a training plan [3]	GRATP + training program + training start time
Adaptive collaboration with a training plan considering role correlation [20]	GRATP + role correlation
This paper	GRATP + training program + training start time + training cost

There are many areas in which the RBC theory has been used. Liu et al. [42] developed and solve the problem of UAV deployment for signal relays via the RBC theory.

Ma et al. [43] utilized RBC to formalize and solve the problem of cloud service composition for data-intensive applications. Jiang et al. [44] formalized the refugee resettlement problem by using the E-CARGO model, and they designed a new solution for refugee resettling (RS) by extending the RBC theory.

3. The Proposed Model

3.1. Basic Assumptions

Several logical assumptions are proposed for the formulation of the cooperation problem in question. These assumptions are the premise of the model. They follow the existing literature, a continuation of the literature, or observations in the real world.

Assumption 1 ([37])**.** *The qualification value is used to represent the ability of an agent to play the corresponding role.*

Assumption 2. *In the entire collaborative process, there are no redundant personnel, and the number of agents just meets the requirements for the normal progress of the project, which means that the project will stop when the training starts. Additionally, training takes place during working hours, and the project's end time cannot be later than the end of the training. This is because if the end time of the training is later than the project's end time, even if agents' abilities are improved, they will not make any contributions to the project.*

Assumption 3 ([2,3])**.** *The training plans are different, but all personnel are trained at the same time. The personnel will experience comparable capacity enhancements after the training.*

Assumption 4. *A certain loss is incurred during training. Training costs and lost work costs are calculated in days. In the real world, there are examples of targeted skill training that is charged by day. For example, in the e-commerce industry, some companies charge for anchor training by day. In order to facilitate the calculation of comprehensive training costs, we also calculate the downtime loss by day.*

Assumption 5 ([45])**.** *We assume that the functional ability of the personnel in a role is as follows:*

$$q(t) = \alpha \sin(\omega t + \theta) + \beta, \tag{1}$$

where the initial value of the ability is based on the parameters α, θ, and β, and ω represents the fluctuation speed. Their ranges of values will be discussed in the next section.

Assumption 6 ([2,3])**.** *The abilities of agents are increased after training. The improved ability Δq is calculated as follows:*

$$\Delta q = (1 - q_0) \times k_0 \times q_0 \times (1 - |\alpha| - \beta) \times (1 - e^{-k_1 t}), \tag{2}$$

where $q_0 (0 \leq q_0 \leq 1)$ is the qualification of the personnel at time t, and $k_0 (0 \leq k_0 \leq 4)$ and $k_1 (k_1 \geq 0)$ are constants. When $t = +\infty$, Δq reaches its maximum, which indicates the maximum increase in capacity of the personnel in the entire training process. So, $\Delta q_{\max}$ is calculated as follows:

$$\Delta q_{\max} = (1 - q_0) \times k_0 \times q_0 \times (1 - |\alpha| - \beta), \tag{3}$$

where k_0 controls the degree of capacity growth. For convenience,

$$r(t) = 1 - e^{-k_1 t}, \tag{4}$$

where k_1 is the learning rate. Based on Equations (1)–(3), $\Delta q = \Delta q_{\max} \times r(t)$.

Assumption 7 ([2,3])**.** *The agents' qualification values vary when the agents are on duty, but they remain the same when they are not working.*

3.2. The Basic Definition of GRATP

According to the assumptions in Section 3.1, this paper proposes several definitions for formalizing the problem. In the existing RBC theory, some basic definitions of the E-CARGO model have been extensively used and familiarized. The contribution matrix λ, the role range vector L, the contribution vector w, and the assignment matrix T can be easily obtained according to the available comprehensive literature [46–48].

Definition 1. *We assume that the qualification function of agent* i $(0 \leq i < m)$ *for role* j $(0 \leq j < n)$ *is the following sine function:*

$$Q[i,j](t) = \alpha_{ij}\sin(\omega_{ij}t + \theta_{ij}) + \beta_{ij}(0 \leq t \leq t_d), \tag{5}$$

where the meanings of parameters α_{ij}, β_{ij}, ω_{ij}, *and* θ_{ij} *are the same as those in in Assumption 5.*

Definition 2. *The group performance at time t is defined as* $\sigma(t) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Q[i,j](t) \times T[i,j] \times \lambda[i,j]$. *Thus, the total benefit during* $[0,t]$ *is represented as:*

$$\sigma = \int_0^t \sigma(t)dt = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\int_0^t T[i,j] \times Q[i,j](t) \times \lambda[i,j]dt. \tag{6}$$

Definition 3. *Given* $Q(0)$, *the best role assignment matrix before training* T_{before} *can be obtained based on GRA:*

$$max \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\{Q[i,j](0) \times T_{before}[i,j] \times \lambda[i,j]\right\}$$

s.t.

$$T_{before}[i,j] \in \{0,1\}(0 \leq i < m, 0 \leq j < n), \tag{7}$$

$$\sum_{i=0}^{m-1} T_{before}[i,j] = L[j](0 \leq j < n), \tag{8}$$

$$\sum_{j=0}^{m-1} T_{before}[i,j] \leq 1(0 \leq i < m). \tag{9}$$

where expression (7) means that an element of T_{before} *can only be 0 or 1; (8) guarantees that the group is workable; (9) represents that each agent can be assigned at most one role.*

Definition 4. *Based on Equation (4), the function of the capabilities of the personnel after training is expressed as*

$$q_1 = q_0 + \Delta q = q_0 + \Delta q_{\max} \times r(t_{duration}), \tag{10}$$

where q_0 $(0 \leq q_0 \leq 1)$ *is the qualification of the personnel before training, i.e., at time* t_{start}, q_1 $(0 \leq q_1 \leq 1)$ *is the qualification of the personnel after training,* $\Delta q_{\max}$ *denotes the maximum value of the capability improvement, and* $r(t_{duration})$ *is the proportion of growth. Their expressions are shown below.*

$$\Delta q_{\max} = (1 - q_0) \times k_0 q_0 \times (1 - |\alpha| - \beta), \tag{11}$$

$$r(t) = 1 - e^{-k_1 t_{duration}}, \tag{12}$$

where k_0 $(0 \leq k_0 \leq 4)$ *and* k_1 $(k_1 \geq 0)$ *are constants.*

To illustrate the change in the abilities of multiple personnel during, the function is revised as follows:

$$Q'[i,j](t_{end}) = Q[i,j](t_{start}) + (1 - Q[i,j](t_{start}))$$

$$\times k_0 Q[i,j](t_{start}) \times (1 - e^{-k_1 t_{duration}}) \times T_{train}[i,j]. \tag{13}$$

s.t.

$$t_{end} = t_{start} + t_{duration}, \tag{14}$$

where t_{end} denotes the end time of training.

Since the capabilities of agents in a group will vary over time, it is necessary to draft an appropriate training plan $\mathcal{P}$ to maximize the total benefits; this plan contains the start time of training t_{start}, the end time of training $t_{duration}$, and the training assignment matrix T_{train}.

Definition 5. *The total benefit before training, i.e., the total benefit in $[0, t_{start}]$, is expressed as*

$$\sigma_0 = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \int_0^{t_{start}} T_{before}[i,j](t) \times Q[i,j] \times \lambda[i,j] dt. \tag{15}$$

Definition 6. *T_{after} is the role reassignment matrix after training.*

Note that T_{after} is equal to T_{train} when they are both optimal. This is because if one member of the personnel trains and is reassigned to different roles, the training will be wasteful, i.e., the result will not be optimal.

Definition 7. *Given t_{start}, $t_{duration}$, and $Q(t_{start})$, the training matrix T_{train} and re-assignment matrix after training T_{after} can be calculated as follows:*

$$\max \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} Q'[i,j](t_{end}) \times T_{after}[i,j] \times \lambda[i,j]. \tag{16}$$

s.t. (13) and (14) and

$$T_{after}[i,j] \in \{0,1\} (0 \le i < m, 0 \le j < n), \tag{17}$$

$$\sum_{i=0}^{m-1} T_{after}[i,j] = L[j] (0 \le j < n), \tag{18}$$

$$\sum_{j=0}^{m-1} T_{after}[i,j] \le 1 (0 \le i < m), \tag{19}$$

$$\sum_{j=0}^{m-1} T_{train}[i,j] \le 1 (0 \le i < m), \tag{20}$$

$$T_{after} = T_{train}, \tag{21}$$

where expressions (17)–(19) are the same as (7)–(9), respectively; (20) expresses that each person can only be trained in at most one role, and (21) is explained in Definition 6.

Definition 8. *The total benefit in $[t_{start} + t_{duration}, t_d]$ is denoted as:*

$$\sigma_1 = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \int_{t_{end}}^{t_d} Q'(t_{end})[i,j] \times T_{after}[i,j] \times \lambda[i,j] dt. \tag{22}$$

Definition 9. *The total benefit σ' is defined as the sum of the overall project performance $(0 \sim t_d)$:*

$$\sigma' = \sigma_0 + \sigma_1. \tag{23}$$

Definition 10. *The cost of the role-training vector h is an n-dimensional vector, and $h[j]$ denotes the cost of training agents in role j for one day.*

Definition 11. *The cost of the role-training vector H is an $m \times n$ matrix representing the cost of the training program.*

Definition 12. *The cost function of training is defined as:*

$$Cost{=}t_{duration} \times \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} T_{train}[i,j] \times H[i,j]. \tag{24}$$

Definition 13. *During the training, the losses caused by the suspension of the project are calculated as*

$$Loss{=}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\int_{t_{start}}^{t_{end}} Q[i,j](t) \times T_{before}[i,j] \times \lambda[i,j]dt. \tag{25}$$

Definition 14. *The total cost of training is defined as:*

$$Cost\_all = Cost + Loss. \tag{26}$$

Definition 15. *Given a group expressed by $Q(t)$, L, T_{before}, and H, the GRATPC problem is that of obtaining the optimal training plan $\mathcal{P}$ (t_{start}, $t_{duration}$, and T_{train}) to maximize the total benefit σ^*, i.e., obtaining*

$$\sigma^* = \max(\sigma' - Cost\_all). \tag{27}$$

s.t. (7)–(9), (17)–(19), (24)–(26), and

$$\sigma_0{=}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\int_{0}^{t_{start}} Q[i,j](t) \times T_{before}[i,j] \times \lambda[i,j]dt, \tag{28}$$

$$\sigma_1 = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\int_{t_{end}}^{t_d} Q'(t_{end})[i,j] \times T_{after}[i,j] \times \lambda[i,j]dt, \tag{29}$$

$$0 \le t_{start} < t_d, t_{start} \in \mathcal{N}, \tag{30}$$

$$0 \le t_{duration} \le t_d - t_{start}, t_{duration} \in \mathcal{N}, \tag{31}$$

where expressions (30) and (31) represent training that must take place during the project.

The whole algorithm has been presented in Algorithm 1.

3.3. Description of the Experiments

To verify the effectiveness and reliability of the model, four simulated experiments were conducted. The parameters α, β, ω, and θ in the experiments were randomly generated. On the one hand, from the perspective of the group, Experiment 1 compared the difference in the total benefits under the three algorithms of *reassignment*, *noreassignment*, and *notraining*. The average value, maximum value, and minimum value were obtained in repeated experiments to verify the universality of the model. In addition, changes in the parameters could affect the experimental results. Experiment 2 considered the influence of k_0 and k_1 on the total benefits under the condition of equal-step-size growth. Experiment 3 studied the impact of increasing the training cost. On the other hand, from the perspective of roles, Experiment 4 considered the influence of changes in the roles of k_0 and k_1 on the total benefit.

Algorithm 1 The algorithm for the GRATPC problem

Require:
$Q(t)$, T, λ, H.
Ensure:
The training program matrix T^*_{train}, the total benefit σ^*, the training start time t^*_{start}, and the training duration $t^*_{duration}$.

$\sigma^* \leftarrow 0$;
for $t_{start} \in [0, t_d]$ **do**
  for $t_{duration} \in [0, t_d - t_{start}]$ **do**
    Calculate $Q(t)'$ with Definition 10;
    Calculate T_{train} and T_{after} with Definition 13;
    $Cost\_all = Cost + Loss$, $Cost$, and $Loss$ are calculated with Equations (24) and (25), respectively;
    $\sigma' = \sigma_0 + \sigma_1$, σ_0, and σ_1 are calculated with Equations (28) and (29), respectively;
    Calculate $\sigma = \sigma' - Cost\_all$;
    if $\sigma^* < \sigma$ **then**
      $\sigma^* \leftarrow \sigma$, $T^*_{train} \leftarrow T_{train}$, $t^*_{start} \leftarrow t_{start}$, $t^*_{duration} \leftarrow t_{duration}$;
    end if
  end for
end for

4. Results

In this section, to verify the effectiveness and reliability of the model, we describe the four simulated experiments that were conducted. The parameters and experimental settings are illustrated, and the model was tested for its correctness and effectiveness according to multiple experimental results.

4.1. Preparation of the Experiments

According to the Code of Construction Organization and Design, the construction procedures for general construction projects in China, such as highway projects, large bridge projects, and water conservancy projects, can be summarized into four stages: the investment decision stage, survey and design stage, project construction stage, and completion acceptance and operation stage. For general construction projects, many practitioners are involved in the four stages; these include decision makers, surveyors, program designers, construction workers, acceptance personnel, and maintenance operators. The contributions of the required positions and staffing are shown in Table 2.

Table 2. Required positions and their contributions.

Positions	Decision Maker	Surveyor	Program Designer	Construction Worker	Acceptance Personnel	Operator	Maintainer
Required Number	1	2	1	3	1	1	1
Contribution Rate	20%	11%	12%	30%	8%	9%	10%

Different roles have different training priorities. For decision makers, training should focus on market insight, organizational and coordination skills, interpersonal and communication skills, and decisive ability. For construction workers, training should focus on enterprise regulations, job responsibility education, learning basic skills, and safe and civilized production. For other practitioners, the training should focus on understanding the development of the industry and learning the latest research results in the profession, such as those concerning new technologies, new equipment, and new materials. Taking into account that training can expedite a project's progress, this paper set a training budget. Since the costs of training are different for different roles, this paper lists the initial prices of training positions based on experience, as shown in Table 3. This paper also takes into account that the abilities of the personnel may change over time. To maximize the effectiveness of the budget, this paper is intended to obtain the best training plan $\mathcal{P}$ (t_{start}, $t_{duration}$, and T_{train}).

Table 3. Initial training cost list.

Position	Decision Maker	Surveyor	Program Designer	Construction Worker	Acceptance Personnel	Operator	Maintainer
cost	10	20	30	13	11	14	20

The cost is calculated in units of one hundred dollars.

In the next experiments, the parameters α, β, ω, and θ in the equation were randomly generated. It was reasonable to set $k_1 = 0.8$ and $k_0 = 4$. According to Assumption 2, the training could only be carried out on working days, that is, the project stopped during the training period and did not produce any benefits. This can be regarded as the loss caused by the training. Different training programs require different costs. In consideration of the real situation, the remaining period of the project was set to 130 working days.

4.2. Experiment 1

In the experiment, we used the E-CARGO model to first calculate the redistribution scheme and then infer the training plan. In order to prove that our conclusion is reliable, we have shown the results of the three strategies in Figures 1–3. In these figures, t_{start} indicates the training start time, $t_{duration}$ indicates the training duration, and the total benefit indicates the total benefit. Taking Figure 1 as an example, (4, 14, 264.342) indicates that the training starts on the fourth day and lasts for 14 days, and the final total benefit is 264.342. According to the results in the three figures, training and redistribution can significantly improve the total benefit, and the optimal total benefit of our method is 8.19% and 28.06% higher than that of the the new allocation and no-training strategies, respectively. Although costs would be incurred in the training process, we can see from the results that the total benefit can be increased as long as reasonable training and redistribution are carried out. At the same time, the experimental results show that after training, the total benefit increases, and the training redistribution causes the gap to be further widened.

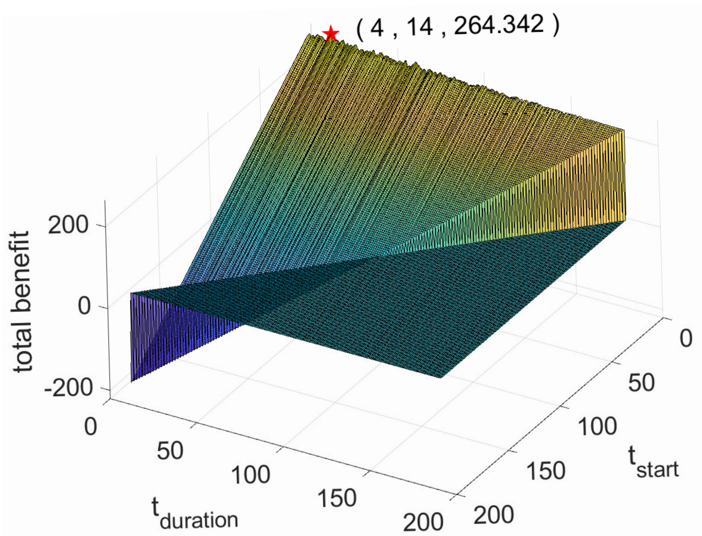

Figure 1. The results of the reassignment algorithm.

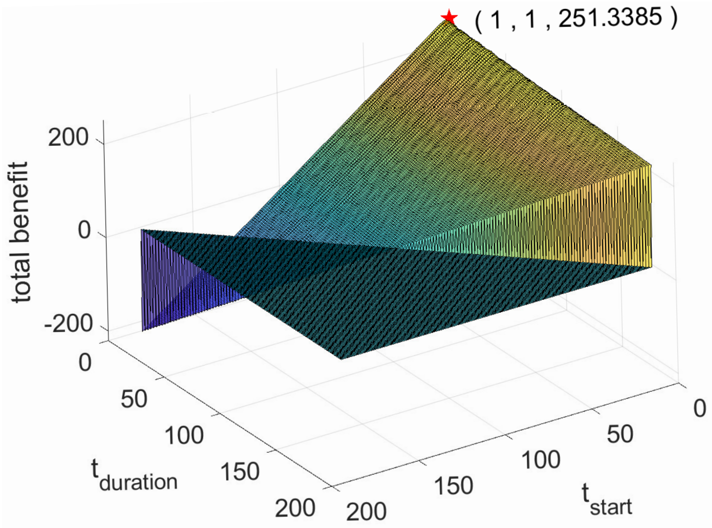

Figure 2. The results of the noreassignment algorithm.

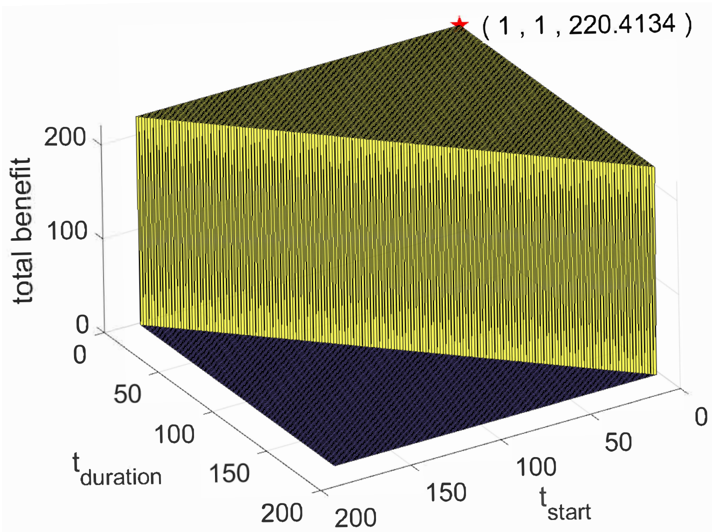

Figure 3. The results of the notraining algorithm.

To further demonstrate the generality of the model, we ran multiple experiments while using the randomly generated parameters α, β, ω, and θ. The average, maximum, and minimum values of each of the 20 experiments are included in Table 4. From the table, we can see that our theoretical derivation is correct, that is, training and redistribution are obviously better than the two cases of no training and no distribution.

Table 4. The result matrix.

Method / **Total Benefit**	**Reassignment**	**Noreassignment**	**Notraining**
Average	260.15	238.71	212.55
Max	271.44	259.25	231.99
Min	246.66	215.84	189.44

4.3. Experiment 2

In this subsection, the impacts of k_0 and k_1 on the proposed model are explored.

Without loss of generality, the values of k_0 and k_1 were set to be different for each role. The original values of the two parameters were set to: $K_1 = [0.3, 0.5, 0.2, 0.12, 0.33, 0.21, 0.34]$, $K_0 = [3, 5, 2, 2, 3, 1, 4]$. Then, k_0 and k_1 were incremented by 0.05 at each step. For generality, the experiments were randomly repeated 10 times. The results for k_0 and k_1 are shown in Figures 4 and 5, respectively.

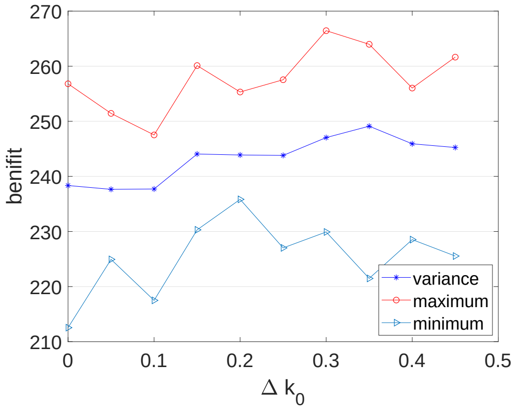

Figure 4. The changes in the total benefit with the increase in Δk_0 (a step of 0.05).

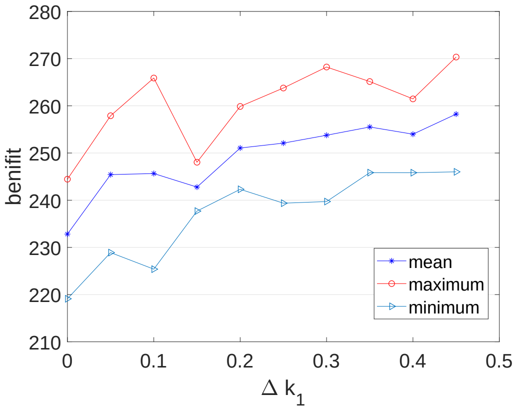

Figure 5. The changes in the total benefit with the increase in Δk_1 (a step of 0.05).

As shown in Figure 4, as Δk_0 increases, the improvement in capability brought about by the training becomes larger, thus leading to an increase in the total benefit. As shown in Figure 5, the total benefit becomes larger because the improvement brought about by the training becomes larger as Δk_1 increases.

4.4. Experiment 3

In this part of the experiment, we discuss the influence of $\Delta cost$ on the total benefit. The change in cost affects the total benefit. We set the cost to increase by 10 each time. In order to make the experiment general, we made the parameters of each experiment change randomly. The results of three experiments for $\Delta cost$ are shown in Table 5. It can be concluded from the experimental results that the total benefit decreases when the cost increases with the same step size. The results also show that companies in the construction industry need to harmonize the conditions related to cost on the basis of training in order to maximize the total benefits.

Table 5. $\Delta cost$ and total benefit.

ΔCost / Benefit	0	10	20	30	40	50	60	70	80	90
time 1	219.45	219.34	219.23	219.12	219.01	218.90	218.79	218.68	218.57	218.46
time 2	230.99	230.89	230.79	230.69	230.59	230.49	230.39	230.29	230.19	230.09
time 3	243.77	243.68	243.59	243.50	243.41	243.31	243.22	243.13	243.04	242.96

4.5. Experiment 4

The previous experiments were based on the perspective of the group, and this experiment was based on the perspective of the role. In order to avoid the influences of other factors, some elements were ignored, i.e., the values of W and the cost were the same for each role. That is to say, $W = [\frac{1}{7}, \frac{1}{7}, \frac{1}{7}, \frac{1}{7}, \frac{1}{7}, \frac{1}{7}, \frac{1}{7}]$ and $cost = [0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01]$. Moreover, for the original vector, $K_0 = [1, 2, 3, 4, 5, 6, 7]$. In Figure 6, $k_0 = 1$ means that the element with a value of 1 in K_0 is set to 0, i.e., $K_0 = [0, 2, 3, 4, 5, 6, 7]$. In the experimental scenario, this indicates a low quality of training for decision makers. Like K_0, $K_1 = 0.2$ mean that $K_1 = [0.1, 0, 0.3, 0.4, 0.5, 0.6, 0.7]$. In the experimental scenario, this indicates a low ability to understand training for decision makers. As shown in Figure 6, if k_0 or k_1 is larger, the total benefit further decreases after it is set to zero. The specific values and corresponding positions are shown in Table 6.

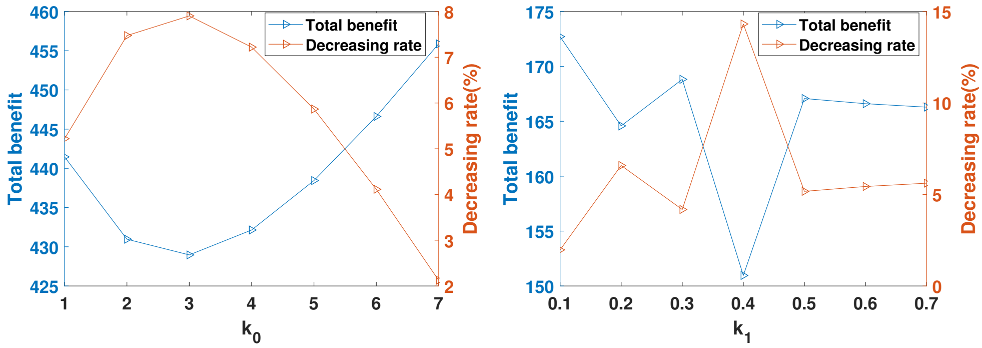

Figure 6. The impact of changes in k_0 and k_1 for a single role on the model.

Table 6. The impact of changes in k_0 and K_1 for a single role on the model.

Position		Decision Maker	Surveyor	Program Designer	Construction Worker	Acceptance Personnel	Operator	Maintainer
k0	total benefit	552.33	541.84	539.836	543.01	549.32	557.49	566.75
	decreasing rate	4.22%	6.04%	6.38%	5.83%	4.74%	3.32%	1.72%
k1	total benefit	212.31	204.18	208.42	190.557	206.67	206.20	205.88
	decreasing rate	1.61%	5.38%	3.41%	11.69%	4.22%	4.44%	4.59%

5. Discussion and Conclusions

To explore the effects of training strategies on group performance and optimal personnel assignment for collaborative behavior in the construction industry, this paper explored GRATP in dynamic scenarios under the premise of considering the training cost. We investigated the impact of the training cost on the GRATP problem and proposed the GRATPC model. The correctness and validity of the inferences including all assumptions were confirmed and verified through the four experiments. The GRATP model is a highly abstract model, and it still requires more modelling and abstraction in practical applications. The main innovation of this paper was the description and modelling of the problem of collaboration in the construction industry from the perspective of RBC and the extension of the GRATP model.

The contributions of this paper include two aspects. First, to the best of our knowledge, this is the only model to consider the training cost with diverse personnel capabilities when studying GRATP, unlike in related studies [3,20], which only took the benefit generated by the group as the optimization target. Second, the proposed model extended the application of RBC and the E-CARGO model from three perspectives.

(a) By combining Experiment 1 and Experiment 3 (aligning with the proposed Assumptions 1, 2, 3 and 4), we found that training strategies could increase the total benefit, but also weaken it when the training cost was too high. This finding corroborates those of other research. For example, Clements and Josiam [49] showed that system training can be economically beneficial and that trainees can reach full production faster. Wang et al. [50] surveyed 93 training directors and construction managers from the U.S. construction industry and estimated that the benefit-to-cost ratio of training for industrial projects ranged from 1.5:1 to 3.0:1. These results contribute to the growing body of evidence showing that investment in practitioner training is essential to the sustainability of the construction industry. It is worth noting that excessive training costs can undermine the benefits of training. Lombardo [51] believed that training departments should use cost–benefit analysis when planning the long-term goals of training programs and use it as a way to improve organizational productivity and achieve training goals.

(b) Experiment 3 (aligning with the proposed Assumptions 5, 6 and 7) revealed that training strategies have a cumulative effect, i.e., training performance is positively related to the knowledge and skill levels of construction practitioners. Wang et al. [50] explained that in a community model where multiple companies participate in training programs, employers can still reap better training benefits, even when workers move from one company to another. For the construction industry, providing ongoing training for practitioners is beneficial to the sustainability of the industry. The Ministry of Housing and Urban–Rural Development of the People's Republic of China issued the "Essentials of Construction Education Reform and Development" and "Opinions on Vigorous Development of Construction Vocational Education", which pointed out the importance of training in the construction industry, as well as specific training requirements and training objectives.

(c) Experiment 4 (aligning with the proposed Assumptions 5, 6 and 7) clarified that training performance varies by industrial role, and among the seven types of construction practitioners, training targeting construction workers has a greater impact on the overall benefit. Recent studies have shown that shortages of labor and an unqualified workforce are the two most serious reasons for delays in large construction projects [52]. In addition, shortages of skilled workers are one of the most significant challenges facing the construction industry worldwide [53]. To address this issue, Johari and Jha [54] expressed that a constant supply of skilled workers can allow high productivity and quality in construction work to be achieved. This, in part, suggests that training construction workers has a significant impact on improving the performance of the construction industry.

However, there are still some deficiencies that have not been taken into account. In this study, the experimental data used were randomly generated, rather than using real data, which made the experimental results slightly different from those in the real world. Furthermore, the theoretical GRATP model was developed and tested via four simulated experiments, and it has not yet been specifically applied in the industry. The actual application and validation of the model in the practice will need to be carefully planned according to project requirements and organizational policies. Next, future studies should address the costs of role reassignments that vary with time, and they should consider certain adjustments in the model through the inclusion of dynamic human factors in the learning process. Last but not least, future studies should also consider extending the investigation to multi-objective programming in order to maximize other benefits of various project stakeholders, especially through interpersonal perspectives such as morale, job satisfaction, loyalty, etc.

Author Contributions: Conceptualization, X.Y. and H.-Y.C.; methodology, X.Y.; validation, X.Y. and M.F.; formal analysis, X.Y. and M.F.; investigation, X.Y.; experiments, X.Y. and R.Y.; writing—original draft preparation, M.F. and H.-Y.C.; writing—review and editing, X.Y., M.F. and H.-Y.C.; visualization, R.Y.; supervision, X.Y.; project administration, X.Y.; funding acquisition, X.Y. and H.-Y.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the National Nature Science Foundation of China (No. 72001112), the Humanities and Social Science Fund of Ministry of Education of China (Nos. 20YJCZH203 and 21YJCZH028), the Natural Science Foundation of Chongqing (Nos. cstc2021jcyj-msxmX0824 and cstc2021jcyj-msxmX0565).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

RBC	Role-based Collaboration
GRA	Group Role Assignment
GRATP	Group Role Assignment with a Training Plan
GRATPC	GRATP Problem with Training Cost
E-CARGO	Environment—Classes, Agents, Roles, Groups and Objects

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